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User Innovation and Product Stickiness: Evidence From Video Games

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ABSTRACT

Prior research on user innovation fails to explain its low adoption rate and neglects its impact on increased product stickiness. To bridge these gaps, we conducted an empirical investigation into user innovations within the video game sector. Our study reveals that embracing user innovation leads to an upsurge in the number of active players for a game. Furthermore, the marginal effect of user innovations varies depending on their *recency* and *quality*, with low-quality user innovations leading to user attrition. The effect is also contingent on the stage in the product life cycle in which user innovation is adopted.

JEL Classification: L1, L86, M15, O36

1 | Introduction

While innovation has long been regarded as the domain of producers, the rapid development of information technology (IT) has greatly enhanced consumers' ability to modify, customize, and adapt products to meet their heterogeneous needs, making the demand side a supplementary source of product innovation (Abrate and Menozzi 2021; Baldwin and von Hippel 2011; von Hippel and Katz 2002). Researchers have been enthusiastic about the transformational power of user innovation, a form of distributed innovation that embraces elements of coinnovation, user communities, and user entrepreneurship (Bogers and West 2012; Dahlander and Wallin 2006; Shah and Tripsas 2007). The paradigm of user innovation differs from producer innovation in many respects: for example, a user–innovator typically engages in innovative activities to obtain use-value instead of pursuing pecuniary rewards, and the diffusion of the output occurs via peer-to-peer transfers rather than through markets (Gambardella et al. 2017). User innovation can lead to product prototypes that firms later build on von Hippel et al. (2012), and is pursued both individually and collaboratively (Huizingh 2011).

Earlier studies have established that user innovation brought about a range of benefits to producers, including a greater willingness to pay for the product and a higher level of customer satisfaction (Abrate and Menozzi 2021; Franke et al. 2006). Despite the progress, existing studies have not examined some other forms of the value associated with user innovations, one of which is the improvement in product stickiness. The aspect of product stickiness, or the tendency of users to keep returning to a product because it is engaging and valuable to them,[1] is a driver of continuous business growth and is particularly important in industries, such as computer software. In recent years, many software vendors, like, Microsoft and Adobe, have transitioned from selling licenses to the software-as-a-service (SaaS) paradigm, a business model based on subscription in which the source of revenue depends on active product use. Therefore, the value proposition of a product or service is strongly correlated with its customers' intensity of use. Another limitation of prior research on user innovation relates to the apparent discrepancy between theoretical predictions and industry practices. With research showing tremendous value associated with user innovation, it is surprising to observe that only a tiny fraction of producers have embraced this model. Current literature is silent on whether there are potential pitfalls of adopting user innovation for producers if it is not carefully managed. However, we contend that opening a product for user innovation often involves a delicate trade-off between harnessing network effects resulting from complementary goods (Abrate and Menozzi 2021) and losing platform control to some degree (K. Boudreau 2010), and one of the challenges that the producer faces is managing the quality provision of user innovation (Huang et al. 2022; Ye 2018).

We address these gaps in prior literature by examining user innovation in the video game industry. There are several reasons for us to choose this study context. First, user innovation in the form of game modifications (or simply called *mods* by game players), sometimes facilitated by toolkits provided by vendors, is popular among video game players (Koch and Bierbamer 2016). Second, many video games, particularly massively multiplayer online role-playing games, have adopted a subscription-based business model similar to SaaS.[2] Therefore, maintaining continued product use is of paramount importance because, for these game developers, revenue is generated only as long as the product is in use. Finally, there are huge variations in the quality of user innovations created for video games, which allows us to examine the heterogeneous effect of user innovations with different levels of quality.

Our empirical investigation uses data obtained from *Steam*, the largest digital distribution platform of PC video games. It introduced *Steam Workshop* (abbreviated *SW*)—a central hub and user community created for the development, distribution, and integration of user-generated game modifications—in 2011. We constructed a panel data set with 13,353 unique games hosted on Steam over the period of April 2015 to July 2022, among which 447 games have adopted the SW at different times. We collected data on each game's daily active users, retailing price, downloadable content (DLC)[3] packages, game mods, and other time-variant and time-invariant game characteristics. Using an event study method with a difference-in-differences (DiD) design, we first compare the daily active players of games that adopted SW with those that did not to identify the extensive margin of opening a game for external user innovation. To address the issue of self-selection associated with the adoption decision of a game developer, we use a propensity score matching (PSM) algorithm to construct a matched sample in which the treated (those that adopted SW) and control (those that did not) video games are similar in all observed characteristics. The results of the event study show that compared to games with similar characteristics that did not adopt SW, the adopters experienced a significant boost in daily active game players, with the average increase estimated to be 50.7% (or equivalent to an increase of 437.7 game players), and the effect appears to be long-lasting.

We then turn to the intensive margin of workshop items (i.e., the game modifications created by game players) on sustained product use by estimating a dynamic panel specification. As expected, we find that an additional workshop item contributes to an increase in the number of active daily players, with the average effect size estimated to be 0.375 added daily players in the model specification that accounts for the endogeneity of mods supply. Considering the average adopting game has a repository of 1411.4 cumulative workshop items in a month, the aggregate effect of user innovation translates to an increase of 529.3 additional active daily players for a game that adopted SW. Beyond this first-order effect, our investigation also reveals a few more interesting insights. *First*, we discover that the effect of a user innovation depends on its recency. By our estimate, a workshop item created in the month immediately before the current period on average leads to an increase of 1.58 daily game players, much higher than the average effect (of 0.375). In contrast, the average marginal effect of workshop items created earlier than 1 month before the current period is estimated to be 0.30, a fraction of that associated with a newly created workshop item. *Second*, our analyses highlight the importance of the quality of user innovation: when we bifork user innovation into high-quality and low-quality ones (using the quality scores assigned to game mods by Steam), we find that a high-quality workshop item helps attract 0.67 additional active daily players; in contrast, a low-quality one hurts user experience and leads to the *attrition* of 0.31 active daily players. *Finally*, we show that the effect of user innovation on stimulating product use also depends on the time of its adoption. Specifically, a positive effect is detected only when the game developer adopts user innovation when the game's user base is expanding, but not when the adoption takes place during the stage when the game's user base is shrinking.

Together, these findings lead to some useful insights for companies that plan to open their product and embrace user innovation. For example, results from our analyses imply that, because of obsolescence associated with the user-created complementary goods, a firm's provision of toolkits and engagement with user–innovators should not be a one-time effort but require consistent nurturing and maintenance over time. In doing so, the firm will harness a continuous stream of supply of user innovations that help stimulate sustained use of the product and extend the product's life. Our study also underscores the importance of managing the quality of user innovations. Because low-quality user creations negatively affect the game-play experience and lead to user attrition, firms should implement processes and systems that can detect and weed out low-quality or harmful user innovations and promote high-quality ones to reduce search costs. In addition, because the positive effect of user innovation on continued product use is most salient when a firm adopts it during the expansion stage of the product's life cycle, a firm should not delay the adoption of user innovation till beyond the product's heyday to take full advantage of the positive reinforcement between the growth of user base and the supply of user-created complementary goods.

2 | User Innovation and the Video Game Industry

2.1 | Literature Review

User innovation has emerged as an important source of new product and service designs in recent years (Ye and Kankanhalli 2018). By enlisting product users as codevelopers, sticky information related to user needs can be incorporated into product design with much lower costs (von Hippel 2006; von Hippel and Katz 2002). User innovation is often carried out by lead users, who experience needs ahead of the bulk of the product's users and derive the greatest benefits from their modification of the product (Franke et al. 2006; Urban and von Hippel 1988). In some cases, collaborations occur between users and producers, resulting in a model of open collaborative innovation (Baldwin and von Hippel 2011). Some researchers argue that firms should purposefully foster a user community to promote interactive learning among consumers, and extend product life through codevelopment (Peter and Sörhammar 2022; Jeppesen and Molin 2003).

The rapid rise of user innovation is attributed to two recent trends: better design toolkits provided by producers, and improvements in users' abilities to combine and coordinate innovation efforts (von Hippel 2006; von Hippel and Katz 2002). Given highly heterogeneous user needs, user innovation minimizes agency costs because users are inventing for themselves and thus the interests of the agent and principal are better aligned (Franke and von Hippel 2003). User–innovators often share their creations freely, and the quick diffusion of user-modified products is believed to increase social welfare (Henkel and von Hippel 2004). In addition, an innovation diffused freely by users may complement or substitute for products of the producers, therefore influencing firms' choices of innovation mode (Gambardella et al. 2017).

Empirical studies of user innovation have emerged under a variety of contexts. With self-designed watches, for example, Franke and Piller (2004) find that consumer preferences are highly diverse, and their willingness to pay for self-designed watches far exceeds that of standard watches. Kamali and Loker (2002) show that the involvement of consumers in the design of a T-shirt leads to higher customer satisfaction. Raasch et al. (2008) study the evolution of user innovation over time in the context of high-performance sailboats and find that the factors driving user innovation include technology complexity, technology maturity, and customer satisfaction, among others. Not surprisingly, many empirical studies relate to the context of IT and digital goods, as computer hardware and software producers often provide user toolkits or scripting languages for customization. For example, Franke and von Hippel (2003) find that users of Apache security software who modify the standard software to better serve their needs derive significantly higher satisfaction than those who do not. Nambisan et al. (1999) show that deliberate organizational design efforts can enhance technology users' propensity to innovate in IT. Morrison et al. (2000) identify characteristics of lead users who are more likely to innovate and share information in a computerized information search system.

Most relevant to our study is a stream of research on user innovation in the video game industry. With video games, toolkits such as level editors and character-building kits are widespread among user communities and are considered a critical boundary resource that developers use to guide and manage user contribution (Parmentier and Gandia 2013; Prugl and Schreier 2006). Studying game modifications for online multiplayer game engine platforms, K. J. Boudreau and Jeppesen (2015) find that the development rate of user innovation responds positively to the growing platform user base but negatively to the growth in user–innovators due to a competition effect. Through analytical modeling, Arakji and Lang (2007) show that when user innovations are complements to the commercial product, profit-maximizing game developers have an incentive to partially open game content to their users and to compensate the most innovative user–innovators for their effort. Some video game developers absorb user-generated innovations into their product offering, and research shows that the popularity, integrity, and maintenance services of a user innovation are the key considerations when game developers choose whether to adopt it (Ma et al. 2019). Abrate and Menozzi (2021) test the indirect and direct network effects in a user-producer system, and they show that user-generated complements boost the demand and reduce consumer price sensitivity for video games.

2.2 | Research Questions

Several gaps in the understanding of user innovation emerge from our review of the literature. *First*, while earlier empirical studies have tried to quantify the value of user innovation through measures of consumers' willingness to pay or the increase in product sales (Abrate and Menozzi 2021; Franke and Piller 2004), such studies painted an incomplete picture because the value of user innovation may take other forms, such as increased product stickiness or the extension of product life. This limitation is particularly relevant in the software industry as an increasing number of vendors are shifting from selling perpetual licenses toward a subscription model under which revenue is contingent upon active product use; the subscribers may terminate their subscriptions once they stop using the product (Zhang and Seidmann 2010). As a result, maintaining active product use and prolonging the life of a product become critical factors of success in these industries. However, the effect of user innovation on product stickiness remains unexplored.

Second, despite the significant benefits of user innovation highlighted by prior academic studies, only a small fraction of producers have embraced the approach of user innovation, even within industries such as software and video games, where the costs of providing and distributing toolkits are relatively low. This apparent contradiction begs the question: are there conditions under which user innovation may cause harm, rather than bring benefits, to product users so that the producers are reluctant to jump on the bandwagon of user innovation? For example, in the video game industry, a deluge of poor-quality games contributed to the collapse of the market in the early 1980s (Huang et al. 2022). Will there be a similar effect that user-contributed innovation of low quality hurts user experience and leads to reduced product use? The answer to this question may help explain the apparent contradiction between theory and reality.

Lastly, studies on producer strategies related to user innovation, such as Gambardella et al. (2017), have ignored its longitudinal dimension for the most part. As a result, there is little understanding of how firms should vary their user innovation strategies over the life cycle of a product. For example, it is unclear whether the benefits of user innovation remain constant, intensify, or attenuate over time within the life of a product. Relatedly, current literature offers very little insight into choosing the optimal time that a producer should open its product for external innovation by its users.

To address these limitations, we conduct an empirical investigation to evaluate the effect of user innovation on sustained product use in the video game industry. We are particularly interested in the elements that have been overlooked in prior studies of user innovation, such as the innovation's quality and the over-time change of its effect. The purpose of the study is to provide answers to the following questions:

1. Does user innovation help increase a product's stickiness and boost product use? How does its effect vary over time?
2. Does the quality of user innovation play a role in stimulating product use? Will low-quality user innovation hurt user experience and lead to reduced product use?
3. When is a better time for a producer to open its product for user innovation? When its user base is rapidly growing, or when it starts to decline?

3 | Empirical Context

As digital goods, video games are developed by either individual developers or corporate studios and can be played on different hardware platforms, including PCs, game consoles, and mobile devices. In addition to retail channels, many developers nowadays choose to distribute their games via digital channels, such as *Steam*. In recent years, some developers, in their efforts to create a more interactive experience, have offered users toolkits to create and integrate their own content (Prugl and Schreier 2006). One example is the map editor in *Warcraft 3*, which allows users to create new maps using modules from the game itself. These modules contain objects, sound, color, and even AI, and users can also create their own scripts and levels. During the early 2000s, many interesting maps were created by users, and some eventually evolved into separate games, like, *Dota 2*.

Steam is currently the largest digital distribution platform for PC games and distributes games released worldwide, commanding an estimated 75% market share of all digital game distribution sales.[4] In addition to video game sales, it also provides a variety of services, including “digital rights management (DRM), multiplayer gaming, and associated social networking and community” (Koch and Bierbamer 2016, p. 358). Steam introduced *SW*, a content-hosting service aimed at fostering player-created content, in 2011. The Workshop facilitates the creation and distribution of player-made game modifications (or *mods*),[5] which are used to enhance the gameplay experience. Mods vary in their scope, from small changes to an item (e.g., a different graphic for a sword) to entirely new items, characters, maps, or missions. Initially designed for use with *Team Fortress 2*, SW was later expanded to offer integration functionality with any game if its developer decides to open the game. Steam also provides a community and essential development tools for users to seamlessly integrate their content into games, significantly streamlining the process of creating and sharing such content.[6]

Game developers may choose what type of content players can upload to SW and distribute for their games. While the types of user-created mods may vary from game to game, most SW content includes new maps, skins, bots, game characters, interfaces, utility tools, and so forth. Some of these user-created mods greatly enhance the overall game experience, diversifying game content and simplifying game controls. Most user–innovators work to produce user-generated content voluntarily and do not make profits from distributing it.

4 | Data and Variables

Data of this study were collected from a variety of sources. First, we scraped the descriptive data of all video games available on *Steam*. The game features are mostly time-invariant, which include the game's publisher and developer, its genre, the number of DLCs, the category that the game belongs to, and its age requirement. The second part of the data, which relates to user innovation around the games, was collected from *SW*. We gathered information about each game mod (or workshop item), including the game it was developed for, its creation time, its quality score assigned by Steam, and its creator(s). To organize the data in a panel data format, we collapsed the workshop items into a monthly level for each game (i.e., monthly supply of new mods and the average quality of mods created in a month).

The third part of the data, which includes time-varying game characteristics, was collected from a third-party data services provider, *SteamSpy*. SteamSpy monitors games published on Steam worldwide. This data includes historical information on the number of active players in a month (which is the average of daily active players) for each game on Steam and the price of the game in a month (which is the average of its daily prices). While access to real-time data is provided by SteamSpy for free, one needs to pay for a subscription to access historical data. We obtained data for the period of April 2015 to July 2022. Lastly, we gathered information on firm sizes—in terms of employment—of game developers and game publishers from *LinkedIn*. Due to privacy concerns, the number of employees of the firms is typically not available in continuous values but is grouped into predefined buckets. This data is missing for some game developers and publishers as they are indie studios without a *LinkedIn* profile.

The definition of the primary variables used in our study, together with their summary statistics, is presented in Table 1. The average length of the panel is 35 months. Notably, some game genres, such as *Sports* and *Education*, have no adopters of SW by the end of our sample period, and we dropped games that belong to those genres from our sample, which leaves us with 13,353 games. Among them, a total of 447 games eventually adopted SW by the end of our sample period, equivalent to a 3.35% adoption rate. Once a game opens for user innovation, game players make significant contributions, with the cumulative number of mods for an average game-month being 1411.4. Figure 1 shows the average monthly contribution of mods by game players to a game that adopted SW. The peak of user contribution usually appears immediately after adoption, and contributions taper gradually over time.

We present the patterns of SW adoption by game genre in Table 2. Notice that on Steam, a game's genre is voted by players, and the game's most-voted genre becomes its primary genre. Although a game can be classified into multiple genres, it

TABLE 1 | Variable definition and summary statistics.

	Description	Count	Mean	SD	Minimum	Maximum
q_{it}	Game i's average active daily players in month t	488,422	191.775	6818.232	0	1,584,886.8
p_{it}	Game i's retailing price in US dollars in month t	488,422	10.669	11.469	0	399.99
n_{it}	Number of newly created workshop items for game i in month t	22,377[a]	30.561	108.131	0	4826
s_{it}	Average quality score of newly created workshop items for game i in month t	15,799[a]	0.341	0.235	0	0.957
N_{it}	Number of cumulative workshop items for game i till the end of month t	22,377[a]	1411.439	3778.618	1	48,329
S_{it}	Average quality score of cumulative workshop items for game i till the end of month t	22,377[a]	0.388	0.2	0	0.935
$Treated_i$	Dummy variable. Equals 1 if a game eventually adopted the Workshop	488,422	0.051	0.22	0	1
$Post_{it}$	Dummy variable. Equals 1 after a game adopted the Workshop in or before month t	488,422	0.046	0.209	0	1
DLC_{it}	Game i's cumulative count of released DLCs till the end of month t	488,422	1.118	17.976	0	2364

Note: The number of unique games is 13,353. The number of games that adopt the Workshop is 447.
Abbreviation: DLC, downloadable content.
[a]On the basis of postadoption observations, N_{it} is defined as $N_{it} = \sum_{T=1}^{t} n_{iT}$. S_{it} is defined as $S_{it} = \left(\sum_{T=1}^{t} n_{iT} * s_{iT}\right)/N_{it}$.

has a single primary genre. We observe that while *Action* games have more adopters of SW than any other game genre, the genre of *Animation & Modeling* has the highest adoption rate.

To explore the factors that may influence the adoption of SW, we run a simple logit model on games' Workshop adoption decisions using game-level, time-invariant characteristics, the preadoption average price, and the number of preadoption daily active players. The purpose of this analysis is explorative in nature, and we do not claim causality in any way. We present the results in Table 3. The omitted baseline game genre for comparison is *Action*. Consistent with the statistics of Table 2, we find that *Indie*, *Simulation*, and *Animation & Modeling* games are more likely to adopt SW compared to the baseline genre of *Action* games, while *Adventure* games are less likely to adopt. Another interesting observation relates to the presence of in-app purchases (aka microtransactions)[7] in a game. For games with in-app purchases, the game developers typically offer the game for free and make profits from selling add-on items, such as skins, weapons, and soundtracks, some of which can be partially substituted by user-created mods. As a result, game developers tend to limit the supply of these items and preclude the cannibalization from free, user-created mods. In contrast, the publishing of DLCs by the game developer is positively correlated to its adoption of user innovation, perhaps due to the incentive to prolong the product life to recoup development costs.

Besides the adoption decision, we also plot the number of user-created mods by game genre. As shown in Figure 2, *Action* games are the top genre that spawns the most user innovations on SW, followed by *Indie* games.

Figure 3 shows the quality distribution of mods, which is measured by a Steam-assigned quality score. Steam's scoring rules take both users' ratings (in the form of an up or down vote) and the popularity of the mod into consideration, and the quality score has a range between 0 and 1. To prevent rating manipulation, items with less than 20 votes receive a 0 score regardless of their user voting, as these items are unpopular. Items with more than 20 but less than 100 votes can only receive a score between 0 and 0.5, with the exact value determined by their fraction of upvotes. Workshop items start achieving a score higher than 0.5 once they become popular and receive enough votes. To receive a perfect score of 1, an item needs more than 200 votes with mostly positive ratings. As a result, there are two spikes around 0 and 0.5 scores, as shown in the figure.

It should be noted that our data collection was carried out in April 2023, and we only include workshop items created before July 2022, giving the mods in our data set at least 10 months to accumulate user ratings. Therefore, the low popularity of some workshop items (and therefore having a quality score of 0) is unlikely to be caused by their recency.

5 | Effect of Adopting User Innovation at the Game Level

As a first step, we evaluate if opening a game for user innovation leads to greater product use. In other words, we treat the

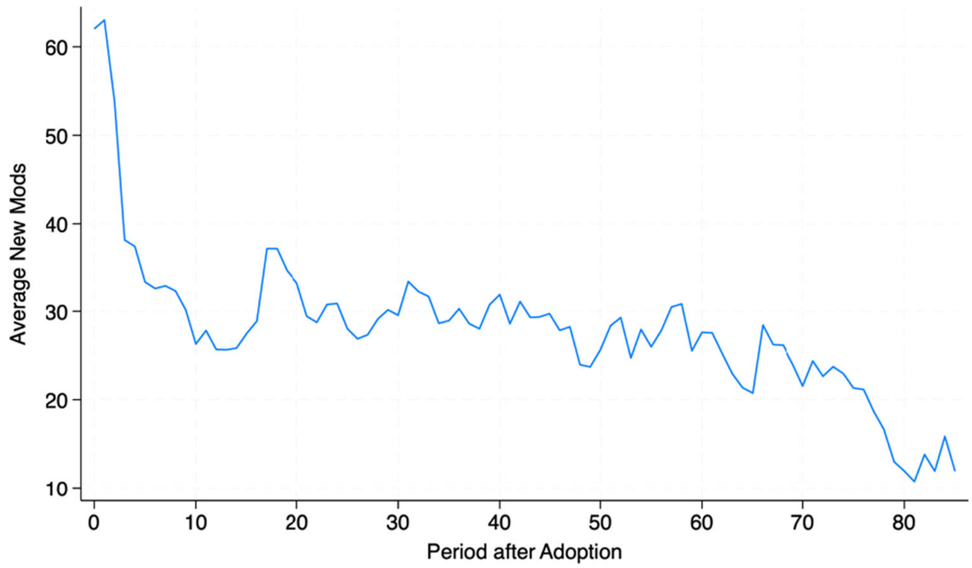

FIGURE 1 | Average number of new mods produced over time after adoption. [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 2 | Adoption of the Steam Workshop by game genre.

Primary genre	Number of games	Number of games that adopt the Workshop	Adoption rate
Animation & Modeling	83	16	0.193
Design & Illustration	30	4	0.133
Racing	105	9	0.0857
Simulation	403	31	0.0769
Indie	1255	92	0.0733
Utilities	80	5	0.0625
Action	5449	189	0.0347
Strategy	315	8	0.0254
Casual	2069	51	0.0246
RPG	295	7	0.0237
Free to Play	215	4	0.0186
Violent	88	1	0.0114
Adventure	2966	30	0.0101

Note: The adoption rate for a genre is defined as the fraction of games within the genre that have adopted Steam Workshop by the end of our sample period.

adoption of Stream Workshop by a game as a binary decision, and study whether there is an increase in product use by its users after the adoption. In our context, *adoption* means that (1) the game developer opens the game to external innovation, and (2) it also adopts a channel or marketplace to facilitate the distribution of user innovation among gamers. Notably, user innovations for a video game may have existed from other channels in various forms before SW was introduced. However, porting user innovations from other sources to Steam is not straightforward because it involves modifying Steam's platform-specific file structures without official guidelines or how-to documents, resulting in high development costs on the part of innovators. More importantly, even if one successfully ports an outside mod to Steam, the distribution of it was greatly limited before SW, and therefore, its impact on the population of game players on Steam would be very small.

Because the treatment (i.e., the adoption of SW) effect is likely dynamic,[8] we adopt an event study approach similar to that used in Autor (2003), in which we add the lags and leads of the treatment variable. There are two major challenges in identifying the treatment effect in our context. *First*, because the game developers make their own adoption decisions, the assignment of treatment in our study is not random. We address it by creating a matching sample where we match a treated game with a never-treated game with similar game characteristics while ensuring the parallel trends assumption holds for the treatment and control groups. Since most games in our sample did not adopt SW, we have a large pool of never-treated games from which we can construct a control group that is similar to the treated group in terms of observable game characteristics. *Second*, the games are released at different times, and the adoptions of SW are staggered. The staggered introductions of the intervention may lead to a biased estimate of the treatment effect in a two-way fixed effects (TWFE) model, because the model compares all games regardless of their treatment conditions, as long as there is "variation in treatment status" in the given time window (Callaway and Sant'Anna 2021). We address this issue by using an interaction-weighted (IW) estimator pioneered by Sun and Abraham (2021).

5.1 | Evidence From the Event Study

When treatment assignments are not randomized by researchers, matching samples are often used to address potential self-selection bias. Following prior literature (Dippel and Heblich 2021; Lysyakov and Viswanathan 2022), we use the PSM approach to mitigate the potential bias that may arise from unobservable covariates between treated and control units. Here, we use the time-invariant covariates of a game, including its genre, its game category, whether it has in-app purchases,

TABLE 3 | Logit model for adoption decision.

Dependent variable Model	(1)	(2) Steam Workshop adoption Logit	(3)
Log (*Number of DLCs* + 1)	0.526***	0.654***	0.644***
	(0.0558)	(0.0737)	(0.0744)
In-app purchase	−2.869***	−2.097***	−2.103***
	(0.487)	(0.559)	(0.562)
Game primary genre			
Strategy	−0.333	−0.973	−1.079
	(0.372)	(0.723)	(0.728)
RPG	−0.266	0.314	0.449
	(0.396)	(0.413)	(0.417)
Casual	0.0449	−0.260	−0.270
	(0.166)	(0.261)	(0.264)
Racing	0.249	−0.221	−0.279
	(0.383)	(0.632)	(0.658)
Indie	0.981***	1.086***	1.113***
	(0.138)	(0.184)	(0.186)
Adventure	−0.853***	−1.107***	−1.144***
	(0.205)	(0.315)	(0.316)
Simulation	0.865***	0.754**	0.746**
	(0.210)	(0.300)	(0.304)
Free to Play	−0.172	0.0647	0.110
	(0.521)	(0.608)	(0.610)
Animation & Modeling	2.897***	1.634***	1.698***
	(0.375)	(0.617)	(0.622)
Design & Illustration	1.875***	0.139	0.195
	(0.704)	(1.288)	(1.295)
Utilities	1.615***	0.253	0.313
	(0.520)	(1.043)	(1.044)
Violent	−0.800	−0.143	−0.121
	(1.012)	(1.017)	(1.018)
Game category dummies	Yes	Yes	Yes
Preadoption average price	No	Yes	Yes
Preadoption average daily players	No	Yes	Yes
Developer size dummies	No	No	Yes
Publisher size dummies	No	No	Yes
Constant	−3.818***	−4.193***	−4.350***
	(0.234)	(0.294)	(0.308)
Pseudo-R^2	0.110	0.125	0.135
Observations	13,353	13,127	13,127

Note: Standard errors in parentheses. The unit of observation is a game. The omitted base game genre is *Action*. Game category dummies include Single-player, Multiplayer, player vs. player (PvP), online PvP, and Co-op.
Abbreviation: DLC, downloadable content.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

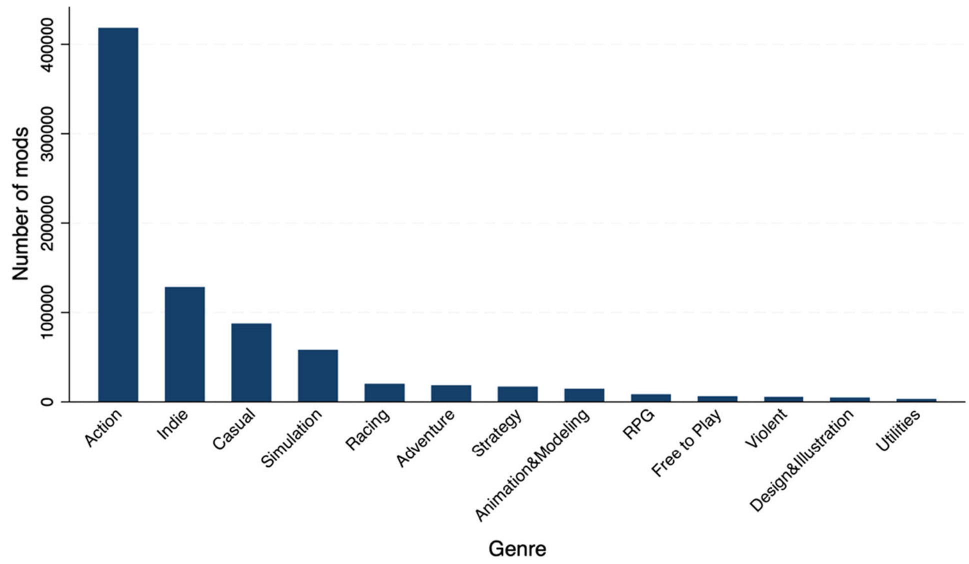

FIGURE 2 | Total number of mods created for each game genre. [Color figure can be viewed at wileyonlinelibrary.com]

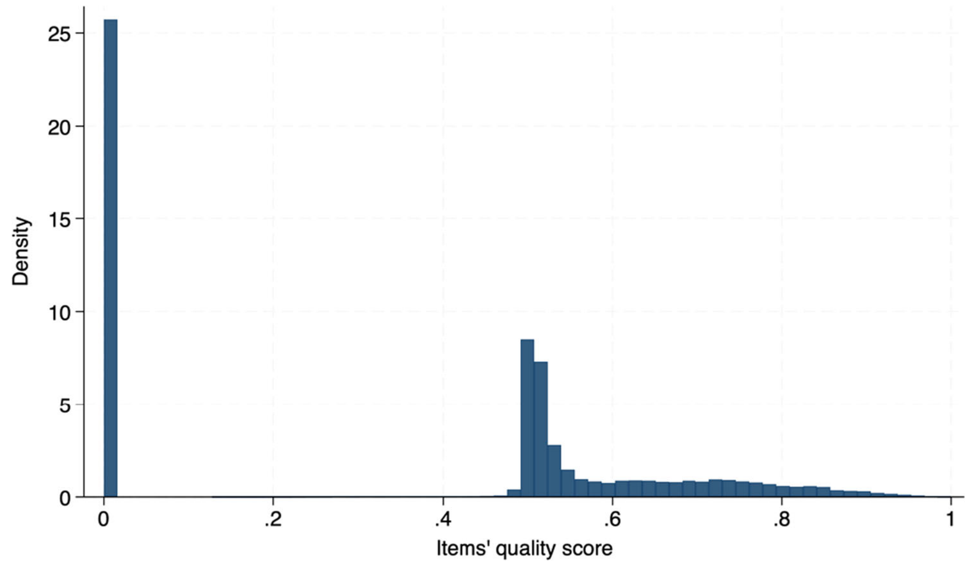

FIGURE 3 | Histogram of workshop items (mods) quality distribution. *Note:* Quality data are collected from Steam Workshop using official APIs (application programming interfaces). Total number of games is 447, and total number of mods is 730,117. [Color figure can be viewed at wileyonlinelibrary.com]

and its developer and publisher employment sizes to perform a one-to-one matching without replacement. The matching algorithm produced 438 games in both the treatment and control groups. Table 4 shows that the covariates are well-balanced between the treatment and control groups after matching. In addition, the kernel densities of the propensity score (p score), presented in Figure 4, show a significant improvement in terms of similarity in the likelihood of being treated between the treated and control groups after matching.

Having constructed a matched sample, we conduct the event study as follows: (1) we use five periods (months) both before and after the treatment—the adoption of SW—as the time window, with the rest of the periods outside the time window lumped into two dummies; (2) we drop the first lead period to break the collinearity (Borusyak et al. 2024). The TWFE estimator is specified as

$$\log(q_{it}) = \beta_{<-5} D_{it}^{<-5} + \sum_{l=-5}^{-2} \beta_l D_{it}^l + \sum_{l=0}^{5} \beta_l D_{it}^l + \beta_{>5} D_{it}^{>5} + u_i + v_t + \epsilon_{it}, \quad (1)$$

where i indexes the games, and t indexes the months. The data for the number of daily average active players, q_{it}, are highly skewed as a few hit games have significantly more active players than other games. Therefore, we take the log of it in the regression. D_{it}^l is the relative time indicator for unit i being l periods away from the treatment at calendar time t. u_i and v_t represent game and month fixed effects.

TABLE 4 | Covariates balance after propensity score matching.

	Mean		t test		
	Treated	**Control**	**% Bias**	***t***	***p* value**
Genres					
Strategy	0.018	0.023	−3.2	−0.480	0.634
RPG	0.016	0.018	−1.7	−0.260	0.795
Casual	0.116	0.114	0.7	0.110	0.916
Racing	0.021	0.018	2.0	0.240	0.807
Indie	0.205	0.210	−1.3	−0.170	0.868
Adventure	0.068	0.068	0.0	0.000	1.000
Simulation	0.059	0.059	0.0	0.000	1.000
Free to Play	0.009	0.009	0.0	0.000	1.000
Animation & Modeling	0.032	0.032	0.0	0.000	1.000
Design & Illustration	0.009	0.009	0.0	0.000	1.000
Utilities	0.011	0.014	−2.5	−0.300	0.762
Violent	0.002	0.002	0.0	0.000	1.000
Categories					
Single-player	0.900	0.895	1.8	0.220	0.824
Multiplayer	0.459	0.454	1.0	0.140	0.892
PvP	0.249	0.242	1.7	0.240	0.814
Online PvP	0.221	0.215	1.9	0.250	0.806
Co-op	0.290	0.279	2.9	0.370	0.708
In-app purchases	0.014	0.011	1.4	0.300	0.762
Developer employment size					
1–10 employees	0.285	0.297	−2.6	−0.370	0.710
11–50 employees	0.187	0.185	0.6	0.090	0.931
51–200 employees	0.050	0.050	0.0	0.000	1.000
201–500 employees	0.032	0.027	2.5	0.400	0.691
501–1000 employees	0.018	0.014	3.9	0.540	0.590
1001–5000 employees	0.005	0.007	−2.3	−0.450	0.654
5001–10,000 employees	0.005	0.005	0.0	0.000	1.000
10,001+ employees	0.002	0.002	0.0	0.000	1.000
Publisher employment size					
1–10 employees	0.226	0.233	−1.7	−0.240	0.810
11–50 employees	0.203	0.201	0.6	0.080	0.933
51–200 employees	0.066	0.066	0.0	0.000	1.000
201–500 employees	0.064	0.064	0.0	0.000	1.000
501–1000 employees	0.016	0.011	3.9	0.580	0.562
1001–5000 employees	0.018	0.016	1.4	0.260	0.795
5001–10,000 employees	0.002	0.002	0.0	0.000	1.000
10,001+ employees	0.007	0.007	0.0	0.000	1.000

Note: Genre *Action* is omitted as the baseline. Missing developer and publisher employment size are treated as the baseline. There are 438 games in the treatment group and 438 games in the control group.
Abbreviation: PvP, player vs. player.

The traditional, static TWFE estimators in a DiD design impose three assumptions: (1) pretreatment parallel trends, (2) no anticipation before the treatment, and (3) homogeneous treatment effect across cohorts, where observations with the same treatment time are referred to as a cohort (Sun and Abraham 2021). In our setting, to satisfy the first and the second assumptions, the estimate of β_l should be insignificant for $l \in [-5, -2]$. While the third assumption usually holds in a

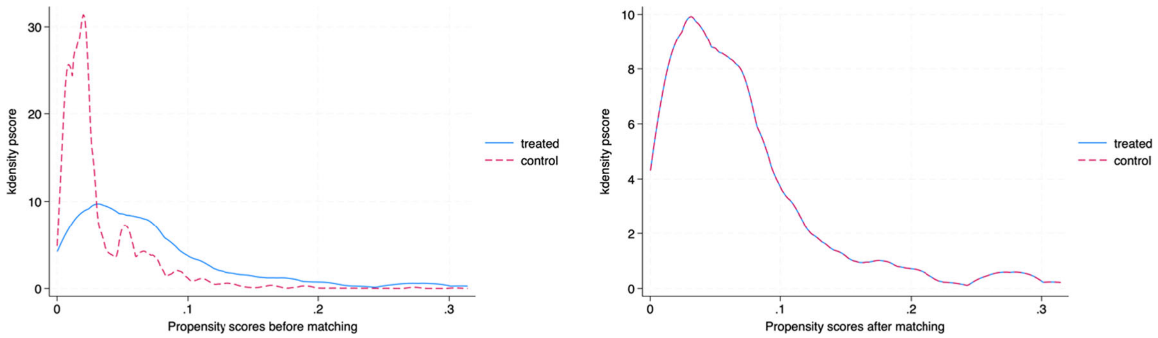

FIGURE 4 | *p* Score before and after propensity score matching. [Color figure can be viewed at wileyonlinelibrary.com]

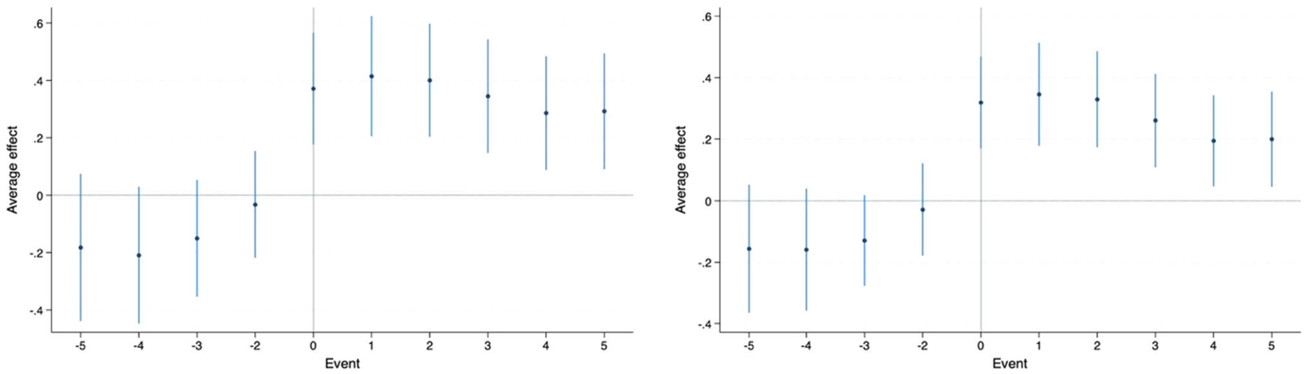

FIGURE 5 | Effects of adopting Steam Workshop. [Color figure can be viewed at wileyonlinelibrary.com]

normal DiD design with a uniform treatment time, it can be questionable where treatments are staggered because the treatment effects can be heterogeneous across cohorts. Under such conditions, the static TWFE specification may fail to identify a reasonably weighted average of heterogeneous treatment effects (Borusyak et al. 2024).[9] To address this issue, Sun and Abraham (2021) proposed an alternative method, the IW estimator, that incorporates the heterogeneous treatment effect among cohorts. They use the shares of cohorts as the weights and follow the procedure in Callaway and Sant'Anna (2021) to accommodate the covariates. We include this method as a robustness check in addition to the TWFE estimator in our event study.

The TWFE and IW estimates of β_l's, together with their 95% confidence intervals, are shown graphically in Figure 5; for brevity, we present the regression results in Supporting Information Appendix A as Table A1. In both models, the estimated coefficients of time periods before the treatment are not significantly different from zero, suggesting that the parallel trends assumption is valid. In addition, we observe a strong treatment effect: the coefficient estimates of β_l's are positive and significant for all posttreatment periods in both models. The effect size of opening a game for user innovation appears to peak 1 month after the treatment, which translates to a $e^{0.415}-1 = 51.4\%$ increase in daily active game players in the TWFE model and a $e^{0.346}-1 = 41.3\%$ increase in the IW model.

Inspired by Bassanini and Scarpetta (2002) and Levin et al. (2002), we also test a model that allows for a linear time trend difference between the treatment and control groups (i.e., group-specific time trends), instead of imposing an identical time fixed effect between the two groups. The results from the TWFE and IW estimators with group-specific time trends are shown in Figure A1 in Supporting Information Appendix A. Again, we find that the estimates of β_l's are insignificant for all periods before the treatment, supporting the parallel trends assumption. In addition, the coefficient estimates of β_l's after the treatment are positive and significant for all periods, and the effect sizes are comparable with those in Figure 5. Together, these models provide evidence that there is indeed a positive and enduring effect on boosting daily active players immediately following the treatment of opening a game for user innovation.

5.2 | The Average Treatment Effect (ATE)

In addition to the event study, we also provide an estimate of the ATE of adopting SW on active product use. There are two ways of calculating an aggregate-level ATE when the treatment is staggered. First, assuming that the treatment effect is homogeneous, the ATE can be estimated in a static DiD design with a TWFE estimator (Liu et al. 2023), specified as follows:

$$\log(q_{it}) = \alpha + \beta_1 D_{it} + u_i + v_t + \epsilon_{it}, \tag{2}$$

where $D_{it} = Treated_i * Post_{it}$. The parameter of interest, β_1, captures the treatment effect on the treated group (the average

TABLE 5 | Average treatment effect of adopting Stream Workshop.

Dependent variable	(1) Log(q_{it})	(2) Log(q_{it})	(3) Log(q_{it})	(4) Log(q_{it})
Sample	Full sample		PSM sample	
Model	Static DiD	CSDiD	Static DiD	CSDiD
Treated$_i$ × *Post*$_{it}$	0.594***	0.415***	0.613***	0.410***
	(0.0932)	(0.127)	(0.0941)	(0.131)
Constant	1.794***	—	2.291***	—
	(0.00428)		(0.0362)	
Observations	488,422	488,422	56,870	56,870
Number of games	13,353	13,353	876	876
R^2	0.888	—	0.916	—
Clustered SE	Yes	Yes	Yes	Yes

Note: Standard errors (SE) in parentheses.
Abbreviations: DiD, difference-in-differences; PSM, propensity score matching.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

treatment effect on the treated). We caution that in this specification, we will not be able to recover a causal parameter because each game's developer self-selects into the treatment condition. However, when combined with a matched sample, earlier work shows that the bias is reasonably small under certain conditions (Abadie and Imbens 2006, p. 252).

Second, when the treatment effect is heterogeneous, one can first run the dynamic, event study specification with treatment leads and lags as we defined in Equation (1), and then take weighted average of the treatment effects of different cohorts and periods—referred to by some as *group-time ATE*—which can be recovered using outcome regression (OR), inverse probability weighting (IPW), or doubly robust (DR) estimands (Callaway and Sant'Anna 2021).

We present the results of both methods—the static estimate of ATE (static DiD) and the group-time average dynamic estimate (CSDiD, the DiD estimator developed by Callaway and Sant'Anna)—in Table 5. In the latter, the group-time ATE is obtained using the DR DiD estimator based on stabilized IPW and ordinary least squares (Sant'Anna and Zhao 2020).[10] For each method, we present the results with the full sample as well as with the PSM-matched sample. All models consistently show a positive and significant effect of adopting the Workshop on daily active game players. Because the use of the dynamic, event study specification requires less stringent assumptions, we deem the group-time average dynamic estimate with the PSM sample (in Column 4) the preferred model. The estimation from Column (4) suggests that after adopting SW, on average, the number of daily active players of a game will increase by $e^{0.410} - 1 = 50.7\%$. Considering that the average of q_{it} is 863.3 for treated games in our sample, this translates to an increase of $863.3\% \times 50.7\% = 437.7$ in the number of daily active players.

5.3 | Robustness Tests

The treatment effect of adopting user innovation that we identified through the DiD analyses could be contaminated by several confounding factors. First, to the extent that mods may have been made available for some games on other online platforms, our estimates may suffer from omitted variable bias. To address this issue, we collected information on games for which mods existed on *Nexus*, the largest game modding community. After scraping data from Nexus, we find that in the control group (12,906 games in total), 737 games have mods on Nexus (and 12,169 games do not). In the treatment group (447 games in total), there are 82 games with mods on Nexus (and 365 games without). We then run a DiD analysis using a sample of games that have no mods on Nexus. The results are presented in Table B1 in Supporting Information Appendix B. We find the results are consistent with our main DiD analysis using the full sample, with similar effect size estimates. We further explore the heterogeneous treatment effect by adding an interaction term between the treatment variable and a binary indicator of whether a game has mods on Nexus. The positive but insignificant coefficient of the interaction term, as shown in Supporting Information Table B2, suggests that the treatment effect of adopting SW does not differ significantly between games with Nexus mods and those without.

Second, a game developer may publish an official toolkit around the time it adopts SW. To separate the effect of SW adoption from the release of toolkits by a game developer, we manually collected information on game toolkits from *Moby*, a third-party website that provides a list of games with official modding tools and another of games with official maps/level editors, respectively. We matched the games on the two lists with the games in our sample and identified 10 matched games in the treated group and 21 matched games in the control group. We then removed these 31 games from our data sample and reran the DiD analyses using games that never released any official modding toolkits or editors. The results are presented in Table C1 in Supporting Information Appendix C. While the treatment effect of adopting the SW from the CSDiD estimator appears slightly lower, all models consistently show a positive effect of adopting SW on attracting active game players.

Third, it is possible that a game's adoption of SW coincides with its release of a DLC. To rule out the confounding factor of DLCs, we performed a battery of additional tests. First, we ran a

DiD analysis by adding the cumulative number of DLCs released by the game developer as a control variable. The results are presented in Table D1 in Supporting Information Appendix D, and they show that our findings are robust to the inclusion of DLCs as a control. Second, we created a dummy variable, $RecentDLC_{it}$, that equals 1 if a game has released a new DLC in the past 2 months and 0 otherwise. The results are shown in Supporting Information Table D2. We find that the recent release of a DLC has contributed significantly to the increase in active game players. More importantly, the inclusion of this variable does not change our main findings. To further test the heterogeneous treatment effect among games with DLCs and those without, we test a model by interacting the treatment with a binary variable $HasDLC_i$, which equals 1 if a game has released any DLCs and 0 if not. The results, presented in Supporting Information Table D3, show that with games that have DLCs, the adoption of the SW generated considerably greater benefits, suggesting a strong complementary effect between DLCs and user innovations.

Finally, to probe the possibility that our findings are driven by the COVID shock, we perform a DiD analysis and an event study using only pre-COVID periods. That is, we exclude observations after February 2020, the start of the COVID lockdown. The results using this restricted sample, presented in Supporting Information Table E1 of Supporting Information Appendix E, are consistent with the main analyses, with the estimated treatment effect slightly higher. The event study results, presented in Supporting Information Figure E1, are also similar. Together, they show that our findings are robust to COVID-related shocks.

6 | Effect of User Innovation at the Workshop Item Level

6.1 | A Dynamic Panel Model

Beyond estimating a treatment effect of adopting user innovation (the extensive margin), we are also interested in the extent to which an additional workshop item helps boost daily active users of the product (the intensive margin). For this investigation, we employ a dynamic panel model specification assuming that each period's number of active players is correlated to the players of the game in the prior period and the workshop items that had been developed for the game till the end of the previous period. Additionally, each game's cumulative number of DLCs is assumed to impact the active players of the same period. Considering that the population of active players in month t includes the set of new game purchasers in the month, we also include the price of the game in month t as a predictor. We use this model as it can accommodate the effects of predetermined regressors and handle unobserved heterogeneity across games. The model is specified as

$$q_{it} = \alpha_1 + \beta_1 q_{it-1} + \gamma p_{it} + \theta N_{it-1} + \lambda DLC_{it} + \zeta_i + \varepsilon_{it}. \tag{3}$$

Here i indexes the games, and t indexes the months. q is the number of daily average active players, p is the game price, DLC is the cumulative number of released DLC packages, and N is the cumulative number of workshop items created for the game. ζ_i represents unobserved game-level heterogeneity, which is a set of fixed effects. To capture the potential recency effects of user-created workshop items, we also estimate a slightly different model specification:

$$\begin{aligned} q_{it} = \alpha_1 + \beta_1 q_{it-1} + \gamma p_{it} + \theta_1 n_{it-1} + \theta_2 N_{it-2} + \lambda DLC_{it} \\ + \zeta_i + \varepsilon_{it}, \end{aligned} \tag{4}$$

where N_{it-1} is decomposed into two parts—the number of new workshop items created in the most recent month, $t-1$, and the number of accumulated workshop items till the end of month $t-2$. That is,

$$N_{it-1} = N_{it-2} + n_{it-1}$$

with n being the number of newly created workshop items in a month. It should be noted that only a fraction of the games eventually adopted SW, and we only include postadoption observations in this analysis. Because of this, the number of active players is not as skewed, and therefore, we do not take the log of this variable in this analysis to allow for a more intuitive interpretation of the marginal effects.

In Equation (4) (and similarly in Equation 3), unobserved heterogeneity can be eliminated by taking the first difference:

$$\begin{aligned} \Delta q_{it} = \beta_1 \Delta q_{it-1} + \gamma \Delta p_{it} + \theta_1 \Delta n_{it-1} + \theta_2 \Delta N_{it-2} + \lambda \Delta DLC_{it} \\ + \Delta \varepsilon_{it}. \end{aligned}$$

The most efficient Instrumental Variable (IV) estimator for the model is to use the stack of lagged independent variables as instruments (Arellano and Bond 1991). For example, because Δq_{it-k} is uncorrelated with the error term for $k \geq 2$, they can be stacked as instruments Z_{it} with moment condition $E(\Delta\varepsilon_{it} Z_{it}) = 0$, where

$$Z_{it} = \begin{pmatrix} \Delta q_{it-2} \\ \Delta q_{it-3} \\ \vdots \\ \Delta q_{it-T} \end{pmatrix}.$$

Similarly, instruments for Δp_{it}, Δn_{it-1}, ΔN_{it-2}, and ΔDLC_{it} are Δp_{it-k}, Δn_{it-k}, ΔN_{it-1-k}, and ΔDLC_{it-k} for $k \geq 2$, respectively. By utilizing moment conditions, we can recover parameters by a robust two-step generalized method of moments.

6.1.1 | Controls for the Effect of Competition

As a robustness check, we further incorporate the effect of competition between similar games into our specification by controlling for the characteristics of a game's competitors. First, we use the game-level time-invariant characteristics to segment the video game market into multiple local markets, with the assumption that each game competes with a set of competitors on price within its local market at any point in time. The game-level time-invariant characteristics we used to define the local markets are a game's genre, its category, and the game's developer and publisher employment sizes. We then derive a couple of control variables based on the local markets we identified. Particularly, we use the average price of competing games, $\bar{p}_{-it}$, and the number of competing games in the same period, m_{it}, to capture the competition effect. Because data on developer and publisher employment size are only available for a fraction of all the games in our sample, the use of these two additional variables leads to a smaller sample of 240 games. In all subsequent analyses, we present results using both the full sample of adopters (as the main analyses) and the reduced sample of adopters with the competition effect (as robustness).

6.1.2 | Instruments for Workshop Items

In the dynamic panel model, it is likely that the lagged number of workshop items is endogenous due to its correlation with unobservable game characteristics. To address the endogeneity of the number of workshop items, we employ the hourly wage of video game designers in the same month as an additional instrument. The time series data was collected from the U.S. Bureau of Labor Statistics (BLS). According to the definition of Standard Occupational Classification (SOC) by BLS, video game designers belong to the occupation group of *Web and Digital Interface Designers* with an occupational code of *15-1255*.[11] We retrieve this wage data from BLS[12] and then deflate the wages using the annual Consumer Price Index. We use this variable as an instrument because it is a direct measure of the opportunity costs of user–innovators when they spend time creating free game mods instead of working on paid jobs. As a higher wage level lures innovators away toward paid jobs, they will allocate less time to the development of game mods, leading to a reduced supply of mods. In addition, because we only use the wages after the game's release (since mods can only be created after the game is released) as the instrument, the instrument can only affect the number of active game players through the supply of workshop items, but not through the unobserved quality of the game (because the development of the game precedes its release).

For robustness checks, we also experimented with using the wage levels of a closely related occupation, *software developer* (with an SOC code of *15-1252*), as the instrument, and obtained completely consistent results. For brevity, all results presented henceforth use the wages of *Web and Digital Interface Designers* as the instrument for workshop items.

It is worth noting that, since the main objective of the dynamic panel analysis is to identify the intensive margin of a workshop item's effect on attracting/retaining active game players, we are primarily concerned with the endogeneity associated with user innovation supply by game players, rather than that related to self-selection of SW adoption by game developers. Therefore, the use of this IV (wage) does not address all sources of endogeneity.

6.1.3 | Results

In Table 6, we report the regression results of Equations (3) and (4), both with and without the instrument for workshop items. For comparison purposes, we report regression results using the full set of adopters—including the ones for which the competitors' average price and numbers are unavailable—as the sample in Columns (1)–(4), and those using the reduced sample with the controls for competition effect in Columns (5)–(8). The coefficient estimates of game price are consistently negative, as expected, because a higher price leads to fewer new game buyers in the period, and new game buyers are usually active players of the period. In addition, results from Columns (5)–(8) show a notable competition effect, as the coefficient estimates for the competitors' average price are consistently positive, and those for the number of competitors are consistently negative.

We find a positive and significant effect of user innovation on the number of active game players, as shown by the coefficient estimates of N_{it-1}. We also note that, by using wage as the additional instrument, the coefficient estimate of workshop items in Column (2) (and 6) is significantly larger than that in Column (1) (and 5), the model specifications without the use of external instruments. This suggests that the endogeneity of the workshop item numbers leads to a bias toward zero, and the model without instruments underestimates its positive effect on the number of active game players. In all model specifications, the Arellano-Bond tests of autocorrelation in the first-differenced errors are significant only for the first order but not for higher orders, indicating that the moment conditions are valid. Furthermore, the Hansen tests for both the set of internal instruments (the lags of independent variables) and the external instrument confirm the validity of over-identification restrictions.

Examining the results from Column (2), in which we use the wage instrument for workshop items, we find that on average, one workshop item (a mod) helps attract 0.375 more active daily players. Considering the sample mean of N is 1411.4, the set of user-created game modifications collectively leads to an increase of 529.3 additional daily active players for an average game that adopts SW. This is equivalent to a 61.3% increase based on an average q_{it} of 863.3 for treated games in our sample. We note the estimated players' increase is similar in magnitude to that obtained from the event study (437.7 for an average game that adopted SW, or 50.7%). Interestingly, results from Column (4), where we decompose the set of workshop items into the most recent and the antecedent ones, reveal that the marginal effect of a workshop item very much depends on its recency: while a newly created game mod (younger than 1 month) helps bring in 1.58 additional daily player, mods that are older than 1 month only attracts 0.30 additional active daily players on average, a fraction of the marginal effect of the former. The pattern is consistent regardless of the use of the additional instrument for workshop items.

6.2 | The Role of User Innovation Quality

To evaluate the role of the quality of user innovation, we incorporate the data of workshop items' quality scores and construct a quality-adjusted measurement of the count of workshop items, and estimate the following model specification:

$$q_{it} = \alpha_1 + \beta_1 q_{it-1} + \gamma p_{it} + \theta N_{it-1} * S_{it-1} + \lambda DLC_{it} + \zeta_i + \varepsilon_{it}. \quad (5)$$

TABLE 6 | Dynamic panel estimates of the effect of workshop items.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	q_{it}				q_{it}			
Sample	**Full sample of adopters**				**Adopters with competition effect**			
q_{it-1}	0.754***	0.741***	0.756***	0.754***	0.672***	0.583***	0.656***	0.575***
	(0.0717)	(0.0626)	(0.0661)	(0.0655)	(0.0813)	(0.0975)	(0.0700)	(0.0968)
p_{it}	−64.49	−63.67	−79.75*	−79.70*	−89.17*	−56.51	−88.55*	−94.89
	(45.93)	(39.21)	(47.38)	(46.75)	(51.42)	(53.15)	(48.66)	(60.56)
N_{it-1}	0.312***	0.375***			0.359***	0.738**		
	(0.115)	(0.137)			(0.127)	(0.368)		
n_{it-1}			1.578**	1.584**			1.918**	11.13***
			(0.677)	(0.674)			(0.850)	(3.033)
N_{it-2}			0.293**	0.300**			0.314***	0.692**
			(0.131)	(0.133)			(0.117)	(0.337)
$\bar{p}_{-it}$					33.37	31.61*	20.59	30.50
					(23.86)	(18.47)	(20.66)	(19.26)
m_{it}					−3.457**	−5.472*	−2.704**	−3.736
					(1.558)	(2.831)	(1.242)	(2.705)
DLC_{it}	−2.475*	−2.523	−3.094**	−3.262*	−1.841	−2.020	−3.700	−3.114
	(1.459)	(1.689)	(1.563)	(1.668)	(3.042)	(3.563)	(3.921)	(4.775)
Observations	21,488	21,488	21,049	21,049	11,955	11,955	11,715	11,715
Number of games	439	439	439	439	240	240	240	240
IV for workshop items	No	Yes	No	Yes	No	Yes	No	Yes
AB test for $AR(1)$	0.0730	0.0721	0.0720	0.0720	0.0762	0.0867	0.0755	0.0698
Hansen test	0.303	0.611	0.274	0.270	0.234	0.329	0.315	0.276
Hansen test (exclude IV for workshop items)		0.617		0.276		0.314		0.263
Hansen test (IV for workshop items)		0.229		0.217		0.670		0.613

Note: Standard errors in parentheses. Only postadoption observations are used in the sample. AB tests for autocorrelation of orders higher than 1 are insignificant in all columns.
Abbreviations: DLC, downloadable content; IV, Instrumental Variable.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Here, S is the mean quality score of the cumulative workshop items. $N_{it-1} * S_{it-1}$ can be considered the total quality provision contributed by the game's players. Because Steam's quality score has a range of (0, 1), items other than those having a perfect quality (with a score of 1) will be discounted, and low-quality workshop items will be discounted more heavily than high-quality ones. To evaluate the recency effects, we also estimate an alternative model specification:

$$q_{it} = \alpha_1 + \beta_1 q_{it-1} + \gamma p_{it} + \theta_1 n_{it-1} * s_{it-1} + \theta_2 N_{it-2} * S_{it-2} + \lambda DLC_{it} + \zeta_i + \varepsilon_{it}, \tag{6}$$

where the total quality provision is further decomposed into two parts:

$$N_{it-1} * S_{it-1} = S_{it-2} * N_{it-2} + n_{it-1} * s_{it-1}$$

with s being the mean quality score of new items created in a month.

The results of Equations (5) and (6) are reported in Table 7. Comparing Tables 6 and 7, we find that the effect of user innovation on product use depends on the quality of a workshop item. For example, comparing the coefficient estimate of $S_{it-1} * N_{it-1}$ in Column (2) of Table 7 and that of N_{it-1} in Column (2) of Table 6, we see that while the marginal effect of an average workshop item is 0.375, the marginal effect of a workshop item of perfect quality (recall that Steam's quality score varies between 0 and 1, so only an item with a perfect quality score is not discounted in the weighted measure) is 0.845, over 125% higher than the former. A similar pattern is also observed when comparing Column (4) of Table 6 and Column (4) of Table 7, where the marginal effect estimate of a perfect-quality item is much higher than that of an average-quality item, which holds true for both the most recent items (7.14 vs. 1.58) and the antecedent items (0.94 vs. 0.30). It is also worth noting that the coefficient estimates of $n_{it-1} * s_{it-1}$ using the wage instrument (in Columns 4 and 8) are significantly larger than those in Columns (3) and (7), suggesting that the endogeneity of workshop items likely produces a downward

TABLE 7 | Dynamic panel estimates of the effect of workshop items, with quality weights.

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	q_{it}				q_{it}			
Sample	Full sample of adopters				Adopters with competition effect			
q_{it-1}	0.741***	0.702***	0.719***	0.693***	0.700***	0.582***	0.697***	0.583***
	(0.0496)	(0.0561)	(0.0529)	(0.0484)	(0.0663)	(0.0953)	(0.0616)	(0.0818)
p_{it}	−76.15	−92.18*	−97.41*	−87.47*	−88.39*	−66.81	−83.44*	−87.29
	(48.08)	(48.71)	(51.98)	(47.08)	(48.71)	(51.17)	(43.72)	(56.11)
$N_{it-1} * S_{it-1}$	0.745***	0.845***			0.835***	1.252*		
	(0.221)	(0.220)			(0.201)	(0.696)		
$n_{it-1} * s_{it-1}$			4.142**	7.140**			2.640	16.58***
			(2.005)	(2.790)			(2.138)	(5.201)
$N_{it-2} * S_{it-2}$			0.693***	0.938***			0.649**	1.175**
			(0.251)	(0.249)			(0.273)	(0.597)
$\bar{p}_{-it}$					16.04	14.33	5.555	13.36
					(19.00)	(21.45)	(16.38)	(22.16)
m_{it}					−2.862***	−2.875**	−1.784**	−2.136*
					(1.111)	(1.420)	(0.838)	(1.276)
DLC_{it}	−1.746	−2.463	−2.388*	−2.151	−2.451	−1.219	−3.829	−2.135
	(1.261)	(1.571)	(1.260)	(1.675)	(3.094)	(3.035)	(3.704)	(3.599)
Observations	21,488	21,488	21,049	21,049	11,955	11,955	11,715	11,715
Number of games	439	439	439	439	240	240	240	240
IV for workshop items	No	Yes	No	Yes	No	Yes	No	Yes
AB test for $AR(1)$	0.0695	0.0694	0.0696	0.0697	0.0727	0.0846	0.0737	0.0757
Hansen test	0.240	0.524	0.385	0.359	0.270	0.293	0.366	0.260
Hansen test (exclude IV for workshop items)		0.533		0.348		0.286		0.251
Hansen test (IV for workshop items)		0.202		0.647		0.427		0.520

Note: Standard errors in parentheses. Only postadoption observations are used in the sample. AB tests for autocorrelation of orders higher than 1 are insignificant in all columns.
Abbreviations: DLC, downloadable content; IV, Instrumental Variable.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

bias, which can be particularly large for recently produced mods.

Although the results from Equations (5) and (6) are informative, the quality-weighted sum of workshop items may not capture the importance of quality accurately, as it assumes that the sum of many low-quality workshop items would achieve the same effect as a high-quality one, which we argue is unlikely to hold in the context of video games. That is, the provision of quality is unlikely to be additive, because low-quality user innovations may be perceived as "bad" that lead to negative gameplay experience and increase player search costs, and therefore have a detrimental effect on player retention. To better illustrate the impact of the quality factor, we further categorize workshop items as low- and high-quality. Particularly, we define low-quality items as the ones with a score between 0 (inclusive) and 0.5 (inclusive), and high-quality items as the ones receiving a score higher than 0.5. We then test the following specifications of

$$q_{it} = \alpha_1 + \beta_1 q_{it-1} + \gamma p_{it} + \theta_l N^{\mathrm{l}}_{it-1} + \theta_h N^{\mathrm{h}}_{it-1} + \lambda DLC_{it} + \zeta_i + \varepsilon_{it}, \tag{7}$$

$$q_{it} = \alpha_1 + \beta_1 q_{it-1} + \gamma p_{it} + \theta_{l1} n^{\mathrm{l}}_{it-1} + \theta_{h1} n^{\mathrm{h}}_{it-1} + \theta_{l2} N^{\mathrm{l}}_{it-2} + \theta_{h2} N^{\mathrm{h}}_{it-2} + \lambda DLC_{it} + \zeta_i + \varepsilon_{it}, \tag{8}$$

where superscript l and h represent low- and high-quality, respectively.

In Table 8, where we report the results from Equations (7) and (8), we observe considerable heterogeneity in the effect of workshop items of different quality. For example, from Column (2), we find that a high-quality item helps attract 0.67 additional active players, a marginal effect greater than the average effect identified in Column (2) of Table 6 (0.375). In contrast, low-quality items hurt the existing player base, leading to a significant user attrition with a marginal effect estimate of −0.31. Again, the pattern—that high-quality workshop items contribute to user acquisition, but low-quality items contribute to user

TABLE 8 | Dynamic panel estimates of the effect of workshop items, with quality tiers.

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	q_{it}				q_{it}			
Sample	Full sample of adopters				Adopters with competition effect			
q_{it-1}	0.729***	0.702***	0.735***	0.692***	0.682***	0.690***	0.675***	0.660***
	(0.0591)	(0.0597)	(0.0541)	(0.0551)	(0.0509)	(0.0512)	(0.0495)	(0.0375)
p_{it}	−88.62*	−88.25*	−85.22*	−85.25*	−88.88*	−85.61*	−94.06*	−92.59*
	(51.70)	(51.88)	(50.68)	(50.76)	(48.24)	(45.88)	(52.56)	(51.28)
N^l_{it-1}	−0.237***	−0.312***			−0.195***	−0.296***		
	(0.0720)	(0.0907)			(0.0474)	(0.0739)		
N^h_{it-1}	0.539***	0.672***			0.709***	0.836***		
	(0.172)	(0.200)			(0.200)	(0.234)		
n^l_{it-1}			−1.095	−1.959			−0.0173	−0.152
			(0.748)	(1.329)			(1.056)	(1.070)
n^h_{it-1}			2.780**	5.791***			5.892***	6.000***
			(1.253)	(1.688)			(1.748)	(2.239)
N^l_{it-2}			−0.245***	−0.295***			−0.131*	−0.121*
			(0.0718)	(0.0937)			(0.0674)	(0.0719)
N^h_{it-2}			0.494**	0.744***			0.813***	0.823***
			(0.195)	(0.212)			(0.165)	(0.224)
$\bar{p}_{-it}$					11.60	15.31	19.29	24.96
					(14.72)	(15.11)	(19.70)	(20.04)
m_{it}					−2.488**	−2.247**	−2.089**	−1.989*
					(1.166)	(1.060)	(1.059)	(1.044)
DLC_{it}	−1.828	−1.479	−1.849	−0.511	−2.533	−1.655	−3.140	−2.588
	(1.508)	(1.529)	(1.621)	(1.786)	(3.439)	(3.044)	(3.872)	(3.682)
Observations	21,488	21,488	21,049	21,049	11,955	11,955	11,715	11,715
Number of games	439	439	439	439	240	240	240	240
IV for workshop items	No	Yes	No	Yes	No	Yes	No	Yes
AB test for *AR*(1)	0.0697	0.0700	0.0704	0.0694	0.0706	0.0708	0.0713	0.0703
Hansen test	0.467	0.485	0.384	0.387	0.419	0.464	0.182	0.217
Hansen test (exclude IV for workshop items)		0.500		0.384		0.496		0.219
Hansen test (IV for workshop items)		0.156		0.384		0.102		0.270

Note: Standard errors in parentheses. Only postadoption observations are used in the sample. AB tests for autocorrelation of orders higher than 1 are insignificant in all columns.
Abbreviations: DLC, downloadable content; IV, Instrumental Variable.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

attrition—is persistent when we decompose the set of workshop items into the most recent and the antecedent ones, as shown in Column (4).

6.3 | The Role of User Innovation Adoption Time

We now evaluate if the timing of adopting user innovation will also affect its effectiveness for a game. For this analysis, we only include games for which we have data on active daily players throughout their lifetime, that is, we remove games released before April 2015 (because *SteamSpy* only started collecting information on active players since April 2015). This results in a sample with 367 games. To simplify the model specification, we divide the lifetime of a game into two stages: the expansion stage, when the number of daily active game players is increasing, and the decline stage, when the number is decreasing. Specifically, for each game, we first identify the month in which the number of daily active players reaches its peak. We then define the periods from the release date of the game up to the peak month (inclusive) as the expansion stage, and the periods after the peak month as the decline stage. Next,

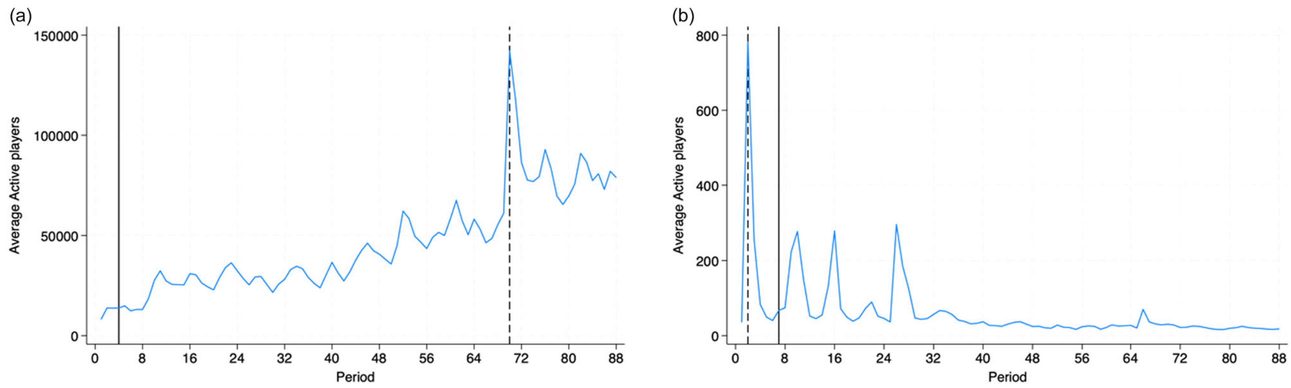

FIGURE 6 | The number of active players over the lifetime of a game. (a) *Rust*: Adoption during the expansion stage. (b) *Windward*: Adoption during the decline stage. *Note:* The dashed line marks the month in which the number of active players reaches its peak. The solid line marks the month of adopting the Steam Workshop. [Color figure can be viewed at wileyonlinelibrary.com]

for each game that adopted SW, we determine whether the adoption took place during its expansion stage or its decline stage. Figure 6 shows the number of daily active players over time for two games, *Rust* and *Windward*, with the former adopting SW during its expansion stage and the latter during its decline stage.

To answer the research question, we run split sample analyses to contrast the two groups that adopted user innovation during different stages in their product life cycle and report the results in Table 9. We first present the results from models without incorporating item quality (in Columns 1–4) and then the ones from models that use quality-weighted item counts (in Columns 5–8). Comparing Column (1) with Column (2), we find that a positive effect of user innovation on attracting active players is only detected when a game adopted SW during the expansion stage of its life cycle; for games that adopted the workshop during their decline stage, the marginal effect is negligible. Therefore, to make the best of user innovation, it is vital for a game developer to strike when the iron is hot and adopt early. During the expansion stage, the growing user base and the creation of new game mods reinforce one another through a positive feedback loop, forming a vicious circle. In contrast, when the game's user base is shrinking, it will be too late to reignite the interest of game players and renew their enthusiasm for user innovation, perhaps due to a diminished network effect and the fact that most of them will have moved on to other games. We also observed that a higher average price of competing games leads to more active players, although the effect is estimated with less precision for games that adopted SW during the expansion stage than for those that adopted SW during the decline stage, probably due to the smaller sample size of the former.

We find this pattern remains the same when we decompose workshop items into the most recent and the antecedent ones (in Columns 3–4), and when we use quality weights to measure item counts (in Columns 5–8). Surprisingly, it appears that not many game developers were aware of this insight: in fact, in our sample of adopters (for which competition variables are available), more developers opened their games for user innovation in their decline stage (146 games) than in their expansion stage (48 games). Note that since SW was introduced in 2011 and all the games in this analysis were released after April 2015, the developers had the option to adopt it at any time following their games' release dates, provided they chose to do so.

It is probable that early adoption of SW leads to a prolonged lifetime of a game, potentially extending its expansion stage.[13] Therefore, a binary indicator of expansion/decline stages may not fully capture how the effect of game mods changes over time. To address this limitation, we test a model in which the binary measure of expansion/decline stages is replaced by a continuous measure of adoption timing. Particularly, we create a variable, $Age\_at\_Adoption_i$, which measures the length of the time interval (in months) between the game's release date and its date of adoption of the SW. We then add an interaction term between the cumulative number of mods (N_{it-1} w/o quality weight or $N_{it-1} \times S_{it-1}$ with quality weight) and $Age\_at\_Adoption_i$ into the model. This interaction term can help us understand the impact of the timing of SW adoption on the effectiveness of user innovation. The results are presented in Table 10. The negative coefficients of $N_{it-1} \times Age\_at\_Adoption_i$ and $N_{it-1} \times S_{it-1} \times Age\_at\_Adoption_i$ suggest that the benefits of user innovations indeed become weaker if the game adopts SW late, consistent with our earlier finding.

7 | Conclusions and Discussion

With user innovation increasingly capturing practitioners' as well as researchers' attention, it is important to evaluate the degree to which producers benefit from enlisting users as coinnovators (Abrate and Menozzi 2021). However, prior literature mainly focused on the sales- or price-related benefits of user innovation, ignoring the dimension related to product stickiness, a strategic advantage that drives growth by improving customer retention, providing account expansion opportunities, and increasing customer lifetime value. We address this limitation with an empirical study of the video game industry, linking the supply of user-created game modifications to the number of daily active players of a game. Not surprisingly, we find a positive effect of adopting user innovation on active product use, with an average increase of 50.7% daily players for the adopters. Furthermore, when we investigate the effect at the workshop item level, we find that the addition of one game

TABLE 9 | Estimates of workshop items with games' adoption stage.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	q_{it}							
Sample	Adopters with competition effect							
Model	w/o quality				w quality			
Adoption stage	**Expansion**	**Decline**	**Expansion**	**Decline**	**Expansion**	**Decline**	**Expansion**	**Decline**
q_{it-1}	0.657***	0.296***	0.581***	0.333***	0.631***	0.294***	0.595***	0.335***
	(0.0228)	(0.0178)	(0.0315)	(0.0481)	(0.0271)	(0.0260)	(0.0342)	(0.0452)
p_{it}	−511.2**	−31.19	−534.7**	−35.51*	−511.0**	−28.46	−481.9**	−35.43*
	(211.2)	(21.93)	(248.1)	(18.63)	(226.4)	(20.50)	(228.2)	(18.19)
N_{it-1}	0.620**	−0.0621						
	(0.248)	(0.0683)						
n_{it-1}			5.330***	1.673				
			(1.503)	(1.460)				
N_{it-2}			0.569**	0.120				
			(0.249)	(0.109)				
$N_{it-1} * S_{it-1}$					0.959***	−0.179		
					(0.258)	(0.237)		
$n_{it-1} * s_{it-1}$							6.340**	8.912
							(2.820)	(6.550)
$N_{it-2} * S_{it-2}$							0.849**	0.535
							(0.358)	(0.464)
$\bar{p}_{-it}$	69.54	29.66*	87.30	28.82**	56.40	26.29*	55.78	26.40***
	(52.96)	(16.63)	(80.22)	(11.98)	(60.74)	(15.10)	(71.01)	(9.388)
m_{it}	−4.073	0.426	−5.563	0.235	0.0902	0.428**	0.210	0.171
	(5.559)	(0.299)	(7.028)	(0.183)	(2.572)	(0.207)	(3.157)	(0.192)
DLC_{it}	−60.15	−88.47	−58.48	−112.2*	−44.80	−85.83	−44.00	−106.2*
	(67.74)	(65.83)	(69.34)	(62.31)	(45.73)	(67.01)	(45.88)	(61.35)
Observations	3074	5372	3026	5226	3074	5372	3026	5226
Number of games	48	146	48	146	48	146	48	146
IV for workshop items	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AB test for $AR(1)$	0.0917	0.0820	0.0867	0.0116	0.0910	0.0919	0.0951	0.0196
Hansen test	0.127	0.451	0.145	0.362	0.327	0.426	0.263	0.332
Hansen test (exclude IV for workshop items)	0.124	0.475	0.172	0.363	0.350	0.458	0.308	0.342
Hansen test (IV for workshop items)	0.314	0.162	0.146	0.297	0.205	0.129	0.130	0.227

Note: Standard errors in parentheses. Only postadoption observations are used in the sample. For brevity, we present results using the sample of adopters with competition effects (194 games). The results using the full set of adopters (with 367 games) are consistent and available upon request. AB tests for autocorrelation of orders higher than 1 are insignificant in all columns.
Abbreviations: DLC, downloadable content; IV, Instrumental Variable; w, with; w/o, without.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

modification is associated with a 0.375 increase in the number of daily active players; aggregated across the repository of game mods, this translates to an average addition of 529.3 daily game players for a game. Interestingly, the workshop item-level analyses also reveal that there exist huge heterogeneities in the effect of user innovation: Not only does the effect vary in relation to the user innovation's recency and quality, but it also depends on the stage in the product life cycle in which a producer chooses to open its product for external innovation.

Our research makes a number of novel contributions to the stream of literature on user innovation (Franke and von Hippel 2003; Gambardella et al. 2017; von Hippel and Katz 2002). For example, the findings pertaining to the quality of user innovation help shed light on a longstanding puzzle that

TABLE 10 | Estimates of workshop items with game age at adoption.

Sample	Adopters with competition effect	
	(1)	(2)
Model	w/o quality	w quality
Dependent variable	q_{it}	
q_{it-1}	0.579***	0.589***
	(0.0236)	(0.0270)
p_{it}	−289.3**	−290.3**
	(140.0)	(138.5)
N_{it-1}	1.456***	
	(0.450)	
$N_{it-1} \times Age\_at\_Adoption_i$	−0.0286***	
	(0.00963)	
$N_{it-1} \times S_{it-1}$		3.280***
		(1.055)
$N_{it-1} \times S_{it-1} \times Age\_at\_Adoption_i$		−0.0814**
		(0.0335)
$\bar{p}_{-it}$	123.2*	121.1*
	(63.84)	(62.12)
m_{it}	0.0445	1.295
	(0.980)	(1.362)
DLC_{it}	−82.12	−71.72
	(97.82)	(85.07)
Observations	8446	8446
Number of games	194	194
IV for workshop items	Yes	Yes
AB test for $AR(1)$	0.0930	0.0931
Hansen test	0.292	0.325
Hansen test (exclude IV for workshop items)	0.309	0.354
Hansen test (IV for workshop items)	0.169	0.119

Note: Standard errors in parentheses. Only postadoption observations are used in the sample. For brevity, we present results using the sample of adopters with competition effects (194 games). The results using the full set of adopters (with 367 games) are consistent and available upon request. AB tests for autocorrelation of orders higher than 1 are insignificant in all columns.
Abbreviations: DLC, downloadable content; IV, Instrumental Variable; w, with; w/o, without.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

has perplexed researchers: If producers stand to gain tremendous benefits from user innovation, why do not we see more firms adopting this model? Our study provides the first piece of evidence that, if not managed properly, the adoption of user innovation can backfire and hurt user experience. This is likely to happen when most of the complementary goods produced by users are of inferior quality, which will lead to user attrition in the same way that a flood of low-quality games led to the crash of the video game market in the early 1980s (K. Boudreau and Hagiu 2009). Therefore, the low adoption rate of user innovation may reflect rational behavior on the part of producers out of their legitimate concerns.

Another contribution of this study is the in-depth insights into the longitudinal properties of user innovation. Here, we show that user innovations have a recency effect: they are of the greatest interest to product users in the first few months immediately after their introduction. Over time, as their novelty fades, their marginal effect on attracting active product users starts to attenuate. Therefore, to maintain a steady user base over time, a producer must incentivize the lead users of its product to innovate constantly. In addition, the time of opening a product for user innovation is of strategic importance: the benefits of user innovation are much greater when the size of the user network is increasing, which creates a virtuous cycle of positive reinforcement between user growth and the production of user innovation. In this regard, many video game producers were ignorant; they adopted user innovation too late when the user base was already shrinking.

Our study can be extended in several ways. One promising area of study is other potential downsides of opening a product for user innovation, such as the burden of upfront investments in developing and distributing toolkits, or the loss of control of the product, especially related to the conflict over intellectual property rights between users and producers (Postigo 2008). Future studies can also explore better measurements of the benefits associated with user innovation, such as customer lifetime value or the extension of product life, instead of placing the emphasis solely on sales or willingness to pay. We hope this study will stimulate the interest of researchers to pursue these potentially fruitful directions.

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author, Y. Wang, upon reasonable request.

Endnotes

[1] See https://userpilot.com/blog/increase-product-stickiness-saas/.

[2] See https://massivelyop.com/2016/04/30/massively-ops-guide-to-mmo-business-models/.

[3] DLC is additional digital content provided by the developer that a player can install on top of an existing video game. DLC can range from cosmetic content, such as skins, to new in-game content, such as characters, levels, modes, and larger expansions that may contain a mix of such content as a continuation of the base game.

[4] See https://blog.osum.com/steam-market-share/.

[5] For more details, see https://store.steampowered.com/about/communitymods/.

[6] For more details, see https://partner.steamgames.com/doc/features/workshop.

[7]Microtransactions are a business model where users can purchase virtual goods with micropayments within a game. Microtransactions are often used in free-to-play games to provide a revenue source for the developers.

[8]This is because the treatment effect could vary across different posttreatment periods (Sun and Abraham 2021). Therefore, the coefficients of lags in Equation (1) can help us capture the dynamics.

[9]This happens due to the comparison between treated units throughout the period. When imposing the third restriction instead of allowing the heterogeneity of treatment effect, such a comparison eliminates the evolution of treatment effect throughout time and places a negative weight.

[10]We used the Stata package *csdid* with the option *method(dripw)* to perform the estimation.

[11]See https://www.onetcodeconnector.org/ccreport/15-1255.01.

[12]See https://www.bls.gov/oes/current/oes151255.html.

[13]Indeed, our preliminary analysis shows that compared to games that adopted SW in the decline stage, games that adopted SW in their expansion stage, on average, enjoy an expansion stage that is prolonged by 27%—28%.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.
appendices final.