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Abstract

Many digital platforms rely on the contributions of volunteer communities for collaborative value creation and ultimately competitive advantage. Thus, (unpaid) contributors are a valuable resource for the platform, but control over their activities is limited and lock-in to any particular platform is uncertain, especially if there are competing platforms. We explore how contributor behavior depends on a platform's competitive position and argue that contributor behavior is driven by two mechanisms: First, a higher level of platform dominance reduces issues of contributor coordination affecting the size of the active community, the extensive margin of value creation. Second, a platform's competitive position is also related to contributor motivation through the non-pecuniary benefits contributors derive, which affects how much individuals contribute, the intensive margin of value creation. We study two competing game wiki platforms using game updates as a source of exogenous variation and find that a platform's more dominant position is associated with higher overall levels of contributor activity, which is primarily driven by the extensive margin of value creation. This creates higher social benefits, which in turn leads to increased activity at the intensive margin. We find that most of this effect comes from high-productivity contributors on a more dominant platform.

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Platform Competition and Online Communities: Evidence from Game Wikis

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Abstract

Many digital platforms rely on the contributions of volunteer communities for collaborative value creation and ultimately competitive advantage. Thus, (unpaid) contributors are a valuable resource for the platform, but control over their activities is limited and lock-in to any particular platform is uncertain, especially if there are competing platforms. We explore how contributor behavior depends on a platform's competitive position and argue that contributor behavior is driven by two mechanisms: First, a higher level of platform dominance reduces issues of *contributor coordination* affecting the size of the active community, the extensive margin of value creation. Second, a platform's competitive position is also related to *contributor motivation* through the non-pecuniary benefits contributors derive, which affects how much individuals contribute, the intensive margin of value creation. We study two competing game wiki platforms using game updates as a source of exogenous variation and find that a platform's more dominant position is associated with higher overall levels of contributor activity, which is primarily driven by the extensive margin of value creation. This creates higher social benefits, which in turn leads to increased activity at the intensive margin. We find that most of this effect comes from high-productivity contributors on a more dominant platform.

1 Introduction

Multi-sided platforms connect and facilitate interactions between two or more distinct groups via an indirect network or ecosystem (Jacobides et al., 2018; McIntyre & Srinivasan, 2017). They rely on suppliers of complementary goods or services – i.e. complementors – to attract and create value for consumers (Kretschmer et al., 2021; Parker & van Alstyne, 2005), and the attraction and sustained support of both groups is a crucial determinant of its profitability and competitive performance (Rietveld & Eggers, 2018).

Prior work on platform competition highlights the role of network effects and economies of scale in adoption (Cennamo & Santalo, 2013). As a platform's attractiveness to both

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consumers and complementors depends on the presence of the respective other group, platforms are often said to compete "for the market", with one or few dominant players emerging over time (Eisenmann et al., 2006). Indeed, the notion that prior success drives future success is well-established (Cennamo & Santalo, 2013; Corts & Lederman, 2009; Kretschmer & Claussen, 2016; Clements & Ohashi, 2005; Shankar & Bayus, 2003; Zhou, 2017), suggesting that size can not only be an outcome, but also a driver of competitive advantage. This advantage can be attenuated when a smaller platform has higher quality (Zhu & Iansiti, 2012) or when multi-homing is prevalent (Cennamo et al., 2018). More recent contributions focus on the role and performance of complementors as a driver of a platform's value proposition to consumers (e.g. Boudreau, 2012; Boudreau & Jeppesen, 2015; Claussen et al., 2013; Rietveld et al., 2019; Rietveld & Eggers, 2018). However, our understanding of how *between*-platform competition relates to *within*-ecosystem value creation processes is still limited.

These value creation processes are often organized around online communities of volunteer contributors who freely provide their knowledge and skills (Fershtman & Gandal, 2011; Lerner & Tirole, 2002; von Hippel & von Krogh, 2003).[1] For the platform, such communities of unpaid complementors can be a valuable resource as output is created at low cost and high quality (Burtch et al., 2020; Shah & Nagle, 2020). However, the voluntary nature of contributions limits the platform's ability to control the scope and extent of activities (Altman et al., 2019; Nickerson et al., 2017). Moreover, platforms frequently face competition from similar platforms (Nagaraj & Piezunka, 2020), creating challenges of contributor lock-in (Farrell & Klemperer, 2007). This raises the question of the extent to which online communities – while potentially valuable – can actually grant a platform an advantage in terms of value creation when facing a competitor.

We explore how value creation processes in online communities are affected by the presence of a competing platform. Specifically, we ask if and to what extent a more dominant platform has an advantage by posing the following questions: First, *how does the activity and productivity of a platform's volunteer contributors depend on its competitive position?* And second, *which mechanisms tie macro-level platform competition to outcomes at the micro-level of contributors?*

We expect two key mechanisms to tie a platform's competitive position to the activity and productivity of its contributors: First, we consider *contributor coordination*, which affects the size of the active community; the *extensive margin* of value creation. Naturally, community size will correspond to higher total levels of activity. However, beyond this size effect, we

[1] Examples include Wikipedia, arguably the world's largest repository of general knowledge, and GitHub, where contributors continuously develop novel and useful open-source software.

also consider *contributor motivation*, which determines how active each community member is; the *intensive margin* of value creation. This depends on a contributor's ability to derive non-pecuniary benefits, which may be heterogeneous across different contributor types.

We study two competing platforms hosting video game wikis, *Fandom* and *Gamepedia*. Similar to Wikipedia, volunteer contributors gather information and write articles about the various contents of different video games. We leverage detailed contribution-level data to track the process of value creation in these online communities over time. Each platform hosts multiple wikis, each covering a different game and populated by different online communities. Hence, some games are covered on one platform, others on both. This creates considerable heterogeneity in community sizes across these domains, which we use to operationalize a platform's competitive position. We exploit game updates as an exogenous impulse to contributor activity to establish the direction of the relationship with the platform's competitive position – we are interested in how activity varies by competitive position, and not vice versa.

Our study provides four key insights: 1) A better competitive position in a domain is related to higher aggregate levels of contributor activity, suggesting that a dominant platform indeed has an advantage in the process of subsequent value creation. 2) Community size, the extensive margin, explains this relationship to a large extent, but not fully. 3) There is a weak positive relationship between a platform's competitive position and activity at the intensive margin, i.e. each contributor contributes more on a more dominant platform. However, this relationship is likely related to higher social benefits derived from being part of a larger community (extensive margin). 4) Contributor heterogeneity matters: The activity of high-productivity contributors (top 10% in an online community) is positively related to a platform's competitive position, even after controlling for changes at the extensive margin. This suggests that this small subset of highly valuable community members is an important driver of platform competitive advantage.

2 Theoretical Background

2.1 Online Communities and User-Generated Content

Platforms organized around online communities commonly rely on volunteer contributions to generate value (Kane & Ransbotham, 2016; Nagaraj & Piezunka, 2020; Shah & Nagle, 2020). Given its voluntary nature, however, firms have limited control over the types of activities contributors undertake (Altman et al., 2019; Nickerson et al., 2017). Consequently, work on contributors' motivation (Fershtman & Gandal, 2011; Lerner & Tirole, 2002; von Krogh et al.,

2012) has identified a wide range of non-pecuniary benefits they can derive.

Contributors may have a need for a particular solution themselves (Osterloh & Rota, 2007; Shah, 2006), they may participate in online communities to learn more about the content (Handley et al., 2006) or to work on a particular skill (Brabham, 2010; Lakhani & von Hippel, 2003). Others may simply participate as a hobby (Jeppesen & Frederiksen, 2006; Shah, 2006) or because they enjoy the process (Lakhani & Wolf, 2005) or autonomy associated with open source environments (Belenzon & Schankerman, 2015; Roberts et al., 2006).

Conversely, participation may be driven by the impact their contributions have on others (Lerner & Tirole, 2002). As such, contributors consider on the use-value (Roberts et al., 2006; Shah, 2006) and accessibility (Fershtman & Gandal, 2007; Subramaniam et al., 2009) of the content they create and the audience they reach (Boudreau & Jeppesen, 2015; Qiu & Kumar, 2017; Goes et al., 2014; Huberman et al., 2009). This this can lead to a positive feedback loop of consumption and content creation (Kane & Ransbotham, 2016).

Social benefits can also be an important source of motivation (Gallus, 2017; von Hippel & von Krogh, 2003). Contributors may enjoy collaborating with peers (Brabham, 2010; Zhang & Zhu, 2011). They grow attached to the community (Ren et al., 2007, 2012) and develop a sense of a common identity and commitment (Bateman et al., 2011; Chan & Li, 2010; Ma & Agarwal, 2007; von Hippel & von Krogh, 2003). Consequently, contributors' embeddedness in a network of peers can be an important driver of activity (Gandal & Stettner, 2016; Shriver et al., 2013; Wasko & Faraj, 2005). Contributing can entail status-related benefits (Ariely et al., 2009; Roberts et al., 2006; Toubia & Stephen, 2013) and increase peer reputation (Archak, 2010; Belenzon & Schankerman, 2015). Therefore, community-based awards and status-hierarchies can drive activity (Anderson et al., 2013; Burtch et al., 2020; Goes et al., 2016; Restivo & Van De Rijt, 2012).

While these sources of motivation are important *micro*-level antecedents to voluntary content creation, we know much less about how volunteer contributors are affected by the *macro*-level construct of platform competition, despite recent calls for more research here (Lerner & Tirole, 2002; von Krogh et al., 2012). Most prior work in this area has been theoretical and analyzed the competition between open-source and commercial alternatives (Athey & Ellison, 2014; Casadesus-Masanell & Ghemawat, 2006; Llanes & de Elejalde, 2013; Sacks, 2015). In addition, Nagaraj & Piezunka (2020) empirically study how the level of contributor activity changed after the entry of a dominant, commercial alternative. They find that on OpenStreetMaps, a community-driven platform, contributions by new members decreased after the entry of Google

Maps, while established ones increased their contributions. We complement their findings by analyzing the impact of platform competitive position on contributor activity in the context of two entirely community-driven alternatives.

2.2 Platform Competitive Position and Contributor Activity

We explore the relationship between a platform's competitive position relative to its competitor(s) and the activity of its contributors. Given the importance of network effects on platforms (Eisenmann et al., 2006; Katz & Shapiro, 1994), we define a platform's competitive position as its ability to attract contributors. Hence, the larger a platform's community of contributors vis-à-vis its competitors', the better its competitive position.

We argue that the competitive position affects two distinct dimensions of contributor activity and content creation: First, it will affect the number of contributors that are active at any given point in time, i.e. the *extensive margin* of content creation. Second, it will also affect each active contributor's level of activity, or the *intensive margin* of content creation. Both dimensions together will determine the *aggregate* level of contributor activity.

2.2.1 Contributor Coordination and the Extensive Margin of Content Creation

The coordination problem in platform competition is an important aspect in determining adoption decisions of users (Farrell & Klemperer, 2007; Katz & Shapiro, 1985; Farrell & Saloner, 1985). The idea is that, in the presence of network effects, the value for the individual user is maximized if all adopt the same platform (Schilling, 2003; Zhu & Iansiti, 2012), leading to winner-take-all phenomena (Eisenmann et al., 2006). Conversely, if users fail to coordinate on a single platform, the community of potential users is splintered across multiple disconnected networks, leading to an overall decrease in welfare and adoption (Kretschmer, 2008; Simcoe & Watson, 2019).[2]

Coordination is a non-trivial problem. As they have to anticipate the decision of other adopters, users cannot perfectly predict the value they will receive from joining one of multiple competing platforms (Halaburda & Yehezkel, 2016, 2019). Instead, they base their adoption decisions on ex-ante expectations or *beliefs* about which alternative is chosen by the majority of others, hence constituting the value-maximizing choice (Caillaud & Jullien, 2001, 2003). In turn, beliefs are formed based on the platforms' past ability to attract users (Argenziano &

[2] With heterogeneous consumer preferences and/or product differentiation, the coexistence of multiple alternatives may be optimal (Farrell & Saloner, 1986). However, in our empirical context, the competing platforms are largely homogeneous.

Gilboa, 2012; Biglaiser & Crémer, 2016). Prospective adopters expect the alternative that has been more successful in the past to be the utility-maximizing alternative for them as well.[3]

We expect similar dynamics in the competition between community-driven platforms, where both direct and indirect network effects drive the value for contributors. First, contributors generate content collaboratively, implying direct network effects. The size of the platform-hosted online community will drive (expected) utility from social benefits (Zhang & Zhu, 2011). Second, the number of people consuming the generated content are an important motivator for contributors (Boudreau & Jeppesen, 2015; Huberman et al., 2009), highlighting the role of indirect network effects. Third, contributors may start out as only *consuming* the content before transitioning into a *contributing* role (Kane & Ransbotham, 2016; Nagaraj & Piezunka, 2020), giving a platform in a better competitive position an additional advantage over its competitor(s). A dominant platform is thus likely to retain its dominant position in terms of the number of contributors, so that a better competitive position should be positively related to the number of active contributors. Therefore, a more dominant platform will likely have an advantage in terms of the *extensive margin* of content creation.

2.2.2 Contributor Motivation and the Intensive Margin of Content Creation

We now consider the link between a platform's competitive position and the *intensive margin* of content creation, i.e. the level of activity of each contributor on a platform. At the individual level, this link becomes a question of contributor motivation, i.e. if and how the competitive position is related to the (non-pecuniary) benefits they can derive.

First, the competitive position is likely related to the social benefits a contributor can derive. We expect a more dominant platform to have a larger number of active contributors (the *extensive margin* of content creation) compared to its less successful rival(s). Not only is community size a predictor of individual activity (Zhang & Zhu, 2011), but it could influence social benefits in multiple ways. Being part of a large, thriving community can promote a feeling of attachment and identity, driving individual's contributions (Bateman et al., 2011; Ren et al., 2007, 2012). It may also enhance the quality of collaboration, as having diversity in contributors facilitates task division (Arazy et al., 2011; Ransbotham & Kane, 2011). Moreover, existing content can spark follow-on contributions (Aaltonen & Seiler, 2016; Gorbatai, 2014; Olivera et al., 2008), so that the possibility to build on others' work enhances participation. Conversely, a larger community may also *decrease* the quality of collaboration: A larger number

[3] This is one of the primary sources of incumbency advantage in platform markets (Biglaiser et al., 2019).

of contributors may lead to conflict and increased coordination requirements (Arazy et al., 2011; Kittur et al., 2007; Kittur & Kraut, 2008), stifling the collaborative process.

Second, status-related motivation (Belenzon & Schankerman, 2015; Roberts et al., 2006) may also be related to a platform's competitive position. On the one hand, if a contributor occupies a position of high status in the community, it is a reasonable assumption that her reputational benefits increase with community size (*big fish in a big pond*). On the other hand, reaching such a position may be harder in a larger community (*big fish in a small pond*), which would suggest that the marginal reputational benefit of contributing is higher on a less successful platform. This may be especially relevant if contribution opportunities are limited (Guo et al., 2020), creating competition among contributors within a *community* (Boudreau & Jeppesen, 2015). This ambiguity in the effect of the competitive position also suggests that the potential to derive reputational benefits is subject to heterogeneity across different contributor types, namely those who already occupy a position of high status and those who do not.

Third, the competitive position should affect the motivation of *contributors* if it is associated with a larger number of users who *consume* the generated content. Indeed, the activity and productivity of contributors increases if they can reach a larger audience (Boudreau & Jeppesen, 2015; Subramaniam et al., 2009). If contributors care about the impact of their efforts (Lerner & Tirole, 2002), reaching a larger audience will lead to a greater feeling of accomplishment and ego-gratification (Huberman et al., 2009), driving participation.

Finally, competition itself may be motivating. Facing a strong competitor can increase identification with the community (Hogg & Terry, 2000), which may incentivize effort provision. Contributors may also want to save their community from vanishing and preserve prior investments, especially if they contributed heavily in the past (Nagaraj & Piezunka, 2020).

In sum, the relationship between a platform's competitive position and the *intensive margin* of content creation is ambiguous and may be linked to community size as well as subject to heterogeneity across contributors.

2.2.3 Heterogeneity across Contributor Types

Contributions to online communities typically follow a "power-law" distribution (Rullani & Haefliger, 2013) where most content is produced by a small set of dedicated contributors (Gorbatai, 2014; Shah, 2006). These high-productivity contributors possess expertise in the process of collective content production and are often involved in the coordination activities in the online community (Dahlander & O'Mahony, 2011). Less productive contributors operate at the periphery and only contribute occasionally (Kriplean et al., 2008) and in specific areas (Shah, 2006). Consequently, the two groups may be subject to different motivations (Gorbatai, 2014; Kriplean et al., 2008; Panciera et al., 2009).

First, status-related benefits are especially motivating for high-productivity contributors. They create the majority of content, which creates a greater sense of ”ownership” (Halfaker et al., 2009). In addition, engaging in higher-level coordination activities (Dahlander & O'Mahony, 2011) instills them with a sense of responsibility over the quality of the generated content, especially when they derive a sense of accomplishment through the consumption by the public (Boudreau & Jeppesen, 2015). In contrast, less productive contributors tend to build on already existing content created by others (Aaltonen & Seiler, 2016; Olivera et al., 2008). Hence, high-productivity contributors may rely less on a large network of collaborating peers than less-productive contributors do.

This difference in motivational sources has implications for the role of a platform's competitive position. First, as less productive contributors rely more on the presence of collaborators, we expect that the mechanisms that tie the competitive position to individual activity for them are closely tied to community size. On a dominant platform they encounter a large network of peers providing them with ample opportunity to build on the work of others. This may also increase their feeling of being part of a community. Second, while we would expect this type of social benefit to also motivate high-productivity contributors, they tend to be also driven by status-related benefits beyond community size effects. Indeed, a larger community may imply that they have to exert more effort coordinating the process of content creation, shifting their own activities from creating content to maintenance of existing content. This may demotivate less productive contributors, who are put off by excessive quality control (Halfaker et al., 2013). Overall, the role of a platform's competitive position remains ambiguous for both contributor types, and their motivational sources likely differ.

3 Data and Methods

3.1 Empirical Setting

We study a platform's competitive position and contributor activity in the context of video game wikis. Similar to Wikipedia, contributors gather information about different video games – such as playable characters or levels – and compile them into publicly accessible articles.[4] Our

[4]Figure A2 in the Appendix shows the article ”Monsters” from the ”Fortnite” wiki on Gamepedia.

dataset contains information about the two most popular wiki-hosting platforms, Fandom[5] and Gamepedia.[6,7] While Gamepedia only covers video games, Fandom hosts wikis about nearly all forms of entertainment media. Gamepedia hosts more than 2000 game wiki communities, while Fandom has more than 385,000 wikis across all media types. Gamepedia and Fandom provide the digital infrastructure for the myriad of specialized, distinct wikis, which are started and maintained by users. They also provide support in the form of standardized guidelines and staff who actively participate in the communities by either contributing knowledge directly or by providing maintenance (e.g. restoring articles affected by vandalism). The two platforms resemble Wikipedia[8] in the way they are structured and designed. Both use the MediaWiki engine, the software used by Wikipedia. However, while Wikipedia is a unified repository for general knowledge, Gamepedia and Fandom host multiple disconnected wikis, each with specific information about a clearly defined domain, i.e. the game it covers. Further, although the content is licensed under Creative Commons, both platforms rely on advertising as their primary source of revenue.

Video game wikis are well-suited to study our research questions for multiple reasons: First, we observe two platforms who offer virtually the same service and have to compete for contributors and the value they create. Second, the two platforms consist of multiple disconnected wikis, each covering a different video game, and each maintained by a different community. While some games are covered by only one of the two platforms, the majority is covered by both. As a result, the platforms are in competition for potential contributors in some domains, but not all, and there exists considerable heterogeneity in each platform's competitive position. Third, the creators of the games we cover in our analysis regularly release content updates, providing an exogenous impulse to contributor activity, which we exploit in our identification strategy.

3.2 Data

Our primary source of information are contribution history pages,[9] which are publicly accessible for all articles on both platforms. They provide useful information at the contribution level, including exact time stamps, which lets us track how articles and wikis evolved over time. In

[5] `www.fandom.com`

[6] `www.gamepedia.com`

[7] Note that Fandom acquired Gamepedia in early 2019. While there have been consolidation efforts ever since, this does not impact our analysis as we our data collection concluded beforehand.

[8] While Gamepedia clearly is playing on Wikipedia's name recognition, so was Fandom, which is also known as Wikia and primarily used this name before 2016.

[9] Figure A3 in the Appendix shows the contribution history for the article "Monsters" from the wiki about the game "Fortnite" on Gamepedia.

addition, they contain information about the contributor. This includes the name of registered contributors and an IP address associated with contributions by unregistered ones. The platforms also employ staff who actively contribute to the wikis. They can be identified via a list of special contributor types available for each wiki. Moreover, some contributions are made by bot accounts, mainly for scripted changes that affect a large number of articles. Typically, such contributions are cosmetic in nature and can be identified via comments attached to them. The comments also provide additional insights. Most prominently, they identify contributions used to revert prior ones, e.g. in the case of vandalism. Finally, history pages contain information about the number of characters (or bytes) added to or removed from an article. In all, this information lets us track how the content in each wiki developed over time, and how the activity of contributors evolved both at the wiki and the individual level.

We access two additional sources of information. First, for each individual contribution the state of the article at a particular point in time can be accessed. As a result, we can track how the written content of an article evolved. Second, the history page lets us access another page containing a detailed comparison of the state of the article before and after an individual contribution.[10] This includes an overview of those parts of the article that have been added, removed, or altered, providing additional information how its content changed.

Using web-scraping techniques we collected data for more than 2.3 million distinct contributions, made by 234,318 contributors active in 30 wiki communities, covering 20 different games across the two platforms. We limit our analysis to 13 games covered by 23 wiki communities,[11] because we rely on content updates being released repeatedly in our identification strategy and consequently removed games for which this is not the case. We construct a daily panel at both the wiki and individual level, tracking several measures of activity and other characteristics, and use this structure both for the construction of our key variables as well as the majority of our analysis.

The data have two important limitations: First, while we collected very detailed information about the behavior of *contributors*, we cannot observe readers who merely *consume* the created content there, i.e. we observe only one side of the platform. Second, as we gathered information from the platforms separately, we cannot unambiguously identify contributors who are active on both platforms at the same time, i.e. multi-homers, or who switched from one to the other at some point in time. This may impact the relationship between competition and platform

[10] Figure A4 in the Appendix shows such a difference between revisions for the article ”Monsters” from the wiki about the game ”Fortnite” on Gamepedia.

[11] Table A5 in the Appendix contains the games used here, as well as the information which platform contains a wiki about each game.

activity. For instance, multi-homing contributors may simply add the same content to both platforms, thus weakening the effect of competition (Hagiu, 2009) and biasing the effects we estimate downwards. We address this concern in two ways. To identify potential multi-homers or switchers, we locate contributors who appear on both platforms at least once. For unregistered contributors we only know their IP address, which lets us identify them unambiguously. For registered contributors, we identify them based on similarity in their names[12] instead. Of course, this approach cannot capture contributors using different names and IP addresses on the two platforms, therefore potentially producing some false negatives. Still, following this approach, we find that a mere 0.65% of all contributors have been active on both platforms at least once. To complement this approach, we also use information from the aforementioned differences between two stages of an article. Here, we aim to detect contributions that add the same content to articles on both platforms, or copy it from one to the other.[13] We do not find any widespread evidence of this.

3.3 Measuring Competitive Position

To measure the competitive position, we exploit the fact that Gamepedia and Fandom host several disconnected wiki communities, each collecting information about different games. We observe each platform's success in attracting contributors across these different domains. For three out of 13 domains (games), only one of the two platforms covered the game. For the other ten games, contributors are distributed across the respective wiki communities on the two platforms, and we observe considerable heterogeneity in contributor activity and community size, both within each platform and across games as well as across platforms and within each game. Hence, for some games Fandom attracts and motivates contributors more successfully than Gamepedia or vice versa, and for others the two are level with one another.

For our measure of a platform's competitive position within a domain we use information about the size of its community covering the respective game relative to the other platform. The intuition is straightforward: If a platform hosts a larger community than its competitor, it has been more successful in attracting contributors and is in a better competitive position in that respective domain at that time. We first construct a daily panel of wikis on the two platforms. Second, for each day and wiki, we count the number of unique contributors who have made at

[12] We use the Python package "FuzzyWuzzy" to calculate the similarity score between two strings based on the Levenshtein distance.

[13] Specifically, we checked this using a three-step process. First, we matched articles about the same topic within a game across the two platforms based on their title. Then, for each identified pair of articles, we used information about their written content at each point in time, to evaluate their similarity over time. Finally, we flagged instances of high similarity, which is indicative of copying.

least one contribution to it within the preceding 30 days. This generates a rolling measure of community size, which we denote by N. We then calculate platform i's competitive position in domain g on day t as

$$\mathrm{CP}_{igt} = \frac{N_{igt}}{N_{igt} + N_{jgt}},$$

with subscript j indicating the other platform. This captures a platform's share ($0 \leq \mathrm{CP}_{igt} \leq 1$) of total contributors over time, with larger values indicating a more dominant competitive position in a domain. If $\mathrm{CP}_{igt} = 1$, platform i is the exclusive host of the entire (active) community covering game g.[14]

Figure 1 illustrates the heterogeneity across different domains. Each panel shows the development of the platforms' competitive position in the coverage of a certain game over time.[15] In some domains, we observe a clear dominant player over the whole study period. For example, in the coverage of "For Honor" Fandom has a larger community than Gamepedia throughout. We observe the opposite for "Hearthstone" or "Paladins", while for "Fortnite" or "Overwatch", we observe more balanced competitive positions. The competitive position can also fluctuate significantly over time. Hence, neither of the two platforms is dominant across the board, and the competitive position fluctuates even within domains.

=== Figure 1 here ===

3.4 Identification Strategy

Identifying the effect of a platform's competitive position on the activity of its contributors – and not vice versa – is an empirical challenge. In our setting, platform success depends on having a large, active community of contributors, and so does its competitive position. Therefore, the causal link between the two likely works both ways, so that simply regressing one on the other would produce upward-biased estimates.

Absent random shocks to competitive position, we exploit updates to a game's content as an exogenous impulse to contributor activity. The intuition is as follows: The decision to release such an update is made by the game's creators and is unlikely to depend on the activity of contributors to game wikis or on the competitive position of the platforms hosting these communities (*exogeneity*). In addition, such updates trigger changes to a game's content, and often introduce new features such as characters, levels or game modes. As a result, contributors

[14] As a robustness check, we run our main analyses using a measure of the competitive position based on contributor activity in the preceding 30 days. This lets us control for community size (N_{igt}) directly. The results are robust to this alternative operationalization, and details are presented in Appendix A.2.

[15] We do not show the three games that are exclusively covered on one of the two platforms.

have to gather new information, write new articles, or revise existing ones to accommodate these changes (*impulse*).

We use these exogenous updates in a quasi-experimental approach: We first hand-collected the release dates for all updates for the games in our sample. Game creators typically provide detailed information about the associated changes and new feature introductions. The majority of updates are "patches" that remove glitches or improve technical performance. As these do not change its contents, they should not induce activity to the wiki communities, and we do not use them in our analysis. For the remaining updates we evaluate contributor activity in a narrow time window around the release date of each. Specifically, we use the four days before and the five days after and including this day. If release dates are close and would result in overlapping nine-day windows, we removed these updates. We use a total of 443 distinct updates across all games. Our research design resembles a regression discontinuity in time framework (RDiT, see Hausman & Rapson (2018)):[16] Observations just after the release of an update are considered *treated*, while those just before serve as *control*. As we observe multiple updates over time and across games, we estimate an average treatment effect (ATE) on different outcomes of interest. To explore the role of a platform's competitive position, we estimate heterogeneous treatment effects along this dimension. In sum, the idea behind our approach is that contributors to all wiki communities will increase their activity just after the release of an update, i.e. we expect a positive ATE, but the effect size will depend on the competitive position. Hence, we estimate conditional average treatment effects (CATE).

Our design is illustrated in Figure 2. We measure the competitive position at the fourth day before the release of an update and hold it constant over the entire nine-day window. This assumes that its perception by contributors does not change in those nine days. As a result, the competitive position around each update is thus not affected by the (expected) increase in contributor activity, mitigating the reverse causality issue.

=== Figure 2 here ===

Note that we estimate short-run effects: We ask how contributors react when presented with a certain work load, and how this relates to the current competitive environment. As such, we eschew exploring the competition-activity-link in the long run in favor of a cleaner identification of short-run effects.

[16] Our approach is similar to an event study design.

3.5 Samples and Variables

We argued that activity in wiki communities can be decomposed into the extensive margin, i.e. how many members contribute, and the intensive margin, i.e. how much each member contributes to a wiki. Further, highly productive contributors may exhibit different contribution patterns than others. We thus investigate contributor behavior at two levels. At the wiki level, we study the effect of platform competitive position on aggregate contributor activity as well as on the extensive and intensive margins separately. We then go to the contributor level to dig deeper into the intensive margin as well as to study heterogeneity across contributor types.

3.5.1 Wiki-level analysis

In a first step, we are interested in the *aggregate effects* of the competitive position, i.e. how it relates to the total level of activity in a wiki community. Here, we use the total number of contributions made to that wiki on a given day as dependent variable.[17] Next, we evaluate the effects at the *extensive margin*, i.e. how many members are contributing. Consequently, we use the number of *active contributors* who made at least one contribution to a wiki on a given day as dependent variable. Finally, to study effects at the *intensive margin*, we use the average number of contributions per active contributor in a wiki on a given day. As we are interested in the behavior of unpaid contributors, we disregard revisions made by platform staff and bot accounts in the construction of our dependent variables.

We use several control variables and fixed effects to account for potential confounding factors. First, there may be differences in members' contribution behavior and the way they react to updates depending on how well-maintained a wiki already is. Therefore, we control for its size by using the number of existing articles at the beginning (i.e. measured at $t = -4$) of each nine-day window. On the one hand, in doing so we account for unobserved factors related to the age of the wiki. One the other hand, prior evidence suggests that existing content promotes follow-on contributions (Aaltonen & Seiler, 2016), which may confound the relationship we want to study if not controlled for. Second, while we disregard contributions made by platform staff in the construction of our dependent variables, we do add their daily number as a control throughout the analysis. These contributions are a direct way for the platform to engage in content creation

[17]Note that this measure does not distinguish between different types of activity, i.e. next to additions to a wiki's content it also contains revisions that undo prior contributions, as well as very minor ones, such as fixing a typo or adding punctuation marks. As an alternative measure for activity, we also run all analyses using a measure of content growth instead. Specifically, we use information about how many characters are added (or removed) with a certain contribution, which we aggregate to the wiki-day-level. As a result, it is a measure of how much content is actually being added. Results are comparable and presented in Appendix A.1.

on the wikis. Therefore, they may be linked to its competitive position in a domain. In addition, these contributions are likely to affect the behavior of unpaid contributors, either by laying the foundation for follow-on contributions, or by actually crowding-out their activity, making it necessary to control for them.

We also add three sets of fixed effects.[18] First, we include dummies for each day of the week. For example, if updates are released just before the weekend for some games, a weekend effect may confound our results if not accounted for. Second, we include dummies for each of the 23 wikis used in our analysis to account for time-invariant differences. Most prominently, some wikis enjoy the official endorsement of the game creator, which may drive differences in each platform's competitive position within that domain. By including this set of dummies we explore within-wiki variation only. In addition, as each wiki is specific to a platform, this set of dummies accounts for unobserved characteristics here as well. Third, we include dummies for each of the 443 game updates. On the one hand, this accounts for time-varying game-specific unobservables, e.g. the size of its player base at the time of the release of an update. As such, it also accounts for the total number of contributors to wiki communities across both platforms covering that game. By including this set of dummies we disentangle our measure of the competitive position from a mere size effect. On the other hand, the updates may differ in the amount of changes and new features they introduce to the game, which may affect our estimation of the ATEs. By including this set of dummies we essentially equalize the treatment intensity across updates, and we explore variation that exclusively stems from differences in contributor behavior just before and after each update's release date. The econometric model we are using in this part of the analysis is given by:

$$Y_{igt} = \beta_0 + \beta_1 \cdot \text{Post}_{gt} + \beta_2 \cdot \text{CP}_{ig\tau} + \beta_3 \cdot \text{Post}_{gt} \cdot \text{CP}_{ig\tau} + \text{Controls} + \text{Fixed Effects} + \epsilon, \quad (1)$$

with Y_{igt} denoting the respective outcome for platform i's wiki covering game g on day t and Post_{gt} being a dummy indicating observations just after the release of an update for g. The term $\text{CP}_{ig\tau}$ refers to platform i's competitive position in the coverage of game g during the update time window τ. Lastly, ϵ serves as the econometric error term in our model. As described above, we estimate the average treatment effect of game updates and are particularly interested in heterogeneity along $\text{CP}_{ig\tau}$. This can be retrieved via $\hat{\beta}_1 + \hat{\beta}_3 \cdot \text{CP}_{ig\tau}$.

We use the natural logarithm[19] of all our outcome and control variables to evaluate percentage changes. This lets us assess the economic significance of our effects, and evaluating

[18]While we present results with this set of fixed effects, they are robust to a wide range of alternative specifications.

[19]We add one to each variable to not lose observations exhibiting a value of zero.

(semi-)elasticities lets us compare coefficients across different models and samples.

3.5.2 Contributor-level analysis

To uncover more details about the effects at the intensive margin, we move the unit of analysis and use a daily panel of wiki-level contributors instead. We use a subset of all contributors, namely those who exhibit a minimum of 30 lifetime contributions to the respective wiki and that have been active over a period of at least 30 days. The vast majority of contributors in our data make only single contribution, and exploring their contribution patterns would offer little insight. Instead, we explore how competition relates to the motivational factors for *existing* and regular contributors. Again, we exclude platform staff and bot accounts. Note that we can only use 21 wikis and 441 patches here because two wiki communities[20] do not exhibit any contributors who satisfy our inclusion criterion during any of the relevant update time windows. In total, our sample consists of 1213 contributors across all wiki communities on the two platforms.

Similar to our wiki-level analysis we use the daily number of contributions a community member makes to the wiki as dependent variable and several control variables and fixed effects. We add the same wiki-level controls as before, namely the size of a wiki at the release of an update and the number of contributions made by platform staff on a day. Moreover, we add two contributor-level controls. First, as contributors' behavior may be linked to her experience, we control for the total number of contributions she has made to the wiki up until the previous day. Second, for each contributor and day we calculate how many *other contributors* are active at the same time. We do this as changes at the intensive margin may be caused by changes at the extensive margin if the social benefits a contributor receives depend on the number of potential collaborators. As a result, depending on how the competitive position affects the extensive margin, there may be spill-over effects on the intensive margin. By controlling for the number of potential collaborators we essentially mute this indirect channel.

We also include game update and weekday fixed effects, and add contributor fixed effects to account for unobserved heterogeneity. Simultaneously, this controls for unobserved wiki and platform characteristics. In addition, this means that we are exploring within-contributor variation only, letting us interpret our results as changes in their behavior. The econometric model then is

$$Y_{kigt} = \beta_0 + \beta_1 \cdot \mathrm{Post}_{gt} + \beta_2 \cdot \mathrm{CP}_{ig\tau} + \beta_3 \cdot \mathrm{Post}_{gt} \cdot \mathrm{CP}_{ig\tau} + \mathrm{Controls} + \mathrm{Fixed\ Effects} + \epsilon, \quad (2)$$

[20]"For Honor" and "Rocket League" on Gamepedia.

with the only difference being that the outcome variables, denoted by Y_{kigt}, are specific to contributor k who is active in the wiki covering game g on platform i. The estimated treatment effect is also retrieved via the term $\hat{\beta}_1 + \hat{\beta}_3 \cdot \mathrm{CP}_{ig\tau}$. As before, we use the natural logarithm[21] of all outcome and control variables to obtain (semi-)elasticities.

Lastly, we explore heterogeneity in the competition-activity link across different types of contributors. Specifically, we ask whether or not highly-productive contributors (HPC) exhibit different contribution patterns. We identify them based on the number of prior contributions they have made to a wiki up until the previous day and construct a dummy equal one if they belong to the 10% of contributors.[22] We add this dummy to our model as part of a three-way interaction with our *Post*-dummy and our measure of the competitive position.

4 Results

We first provide descriptive statistics for our key variables both at the wiki and the contributor level. Second, we present and discuss our results about the aggregate effects of a platform's competitive position in a domain on the activity of its contributors. Third, we separate these into changes at the extensive and intensive margin. Fourth, we further analyze the intensive margin by looking at different contributor types. Finally, we run additional analyses to further test the underlying mechanisms. We run OLS regressions throughout.[23]

4.1 Descriptive Statistics

4.1.1 Wiki Level

Table 1 contains summary statistics for our wiki-level variables.[24] We present the absolute values to give some intuition about our setting and data. The 443 nine-day update windows and 23 wikis we use result in a total of 6999 observations. On average and per day, wiki communities have 5.34 active contributors and 20.92 contributions, with each active community member contributing 5.2 times. Also note that our sample contains values that are considerably higher than that, e.g. the maximum value for the daily contributions is 362, even after excluding outliers.[25] We also ran all our estimations including these outliers as well as excluding more

[21] We add one to each variable to not lose observations exhibiting a value of zero.

[22] Using the top 5% or 25% does not change the conclusions drawn from our analysis. However, the effect gets stronger yet less-precisely estimated the more restrictively we identify high-productivity contributors.

[23] Note that in the cases where our outcome of interest is a count variable (e.g. daily contributions) our results are robust to running Poisson regressions instead.

[24] Table A6 in the Appendix contains the correlation matrix for our wiki-level variables.

[25] For observations just before and just after the release of an update we excluded observations that exceed the respective 99th percentile of the number of contributions to a wiki on a day.

with identical results. Further, as we count the release date of an update as part of this group in our research design, 56% of all observations are treated in our sample. Also, the variable measuring a platform's competitive position in a domain is 0.56 on average. While for games covered on both platforms the this measure adds up to one for the two wikis (i.e. an average of 0.5 per domain), this it not the case for the three exclusive games, so that the average is above 0.5. The distribution of values is shown in Figure 3a, with some bunching at the lower and upper ends, suggesting that observations exhibiting a clear dominant player are more frequent compared to cases of neck-on-neck competitors. On average, a wiki features 1273.12 existing articles at the beginning of a time window, and platform staff contributes 1.85 times per day.

=== Table 1 here ===

=== Figure 3 here ===

4.1.2 Contributor Level

Contributor-level summary statistics are in Table 2.[26] At this level of analysis we can only use 441 updates and 21 wikis, giving a total of 1213 contributors and a total sample size of 234,361 observations. On average, a community member exhibits a daily number of 0.39 contributions to a wiki. Values in the data follow a "long tail" distribution, with the maximum being 508. Again, excluding outliers from the analysis does not affect our results. As before, 56% of all observations are treated in our sample. Here, the mean of the variable measuring the competitive position is 0.88, so that better-positioned wikis are over-represented. Figure 3b shows that this is indeed the case, with pronounced bunching at the top end of the distribution. This alone accounts for around 60% of all observations and is the result of our inclusion criterion of contributors, which excludes those who do not exhibit a certain amount of lifetime contributions to a wiki, and that are active only over a very limited time period. Clearly, in domains where platforms are lagging behind, such contributors are not prevalent. 11% of observations are made by contributors we identified as highly productive. Further, each day, the average community member exhibits 279.67 prior contributions, again following a pronounced long-tail distribution. Lastly, the number of potential collaborators, i.e. other active contributors, per day is 20.17, on average. Concerning our wiki-level constructs here, on average, its size in terms of the number of existing articles at the beginning of an update window is 1996.73, thus slightly higher than in the sample at the wiki level (also driven by the skewed distribution of the competitive position), while the value for staff contributions is slightly lower at 1.20.

[26]Table A7 in the Appendix contains the correlation matrix for our contributor-level variables.

=== Table 2 here ===

4.2 Regression Analysis

4.2.1 Updates as an Impulse to Contributor Activity

An important requirement for our identification strategy to work as intended is that updates act as an impulse to contributor activity.[27] To evaluate this, we first estimate their ATEs without exploring heterogeneous effects.

=== Table 3 here ===

=== Figure 4 here ===

Wiki-level estimation results are presented in Models 1 and 2 of Table 3. Using the number of contributions as the dependent variable (Model 1), the estimated coefficient for the Post-dummy is positive and statistically significant ($\hat{\beta} = 0.2675$, $p < 0.001$), so that activity in a wiki is indeed higher just after the release of an update compared to just before. Specifically, the number of contributions is 30.67% higher for treated observations[28] on average. We estimate the same model using separate dummies for each day of the update window instead in Model 2 and plot the estimated coefficients in Figures 4a. The pattern we observe is in line with our expectations: Using $t = -4$ as our baseline, activity levels just before an update are not statistically distinguishable from one another, but we observe a sharp increase on the day of an update's release. This increase fades away over the next days, reverting to its original levels. These results provide evidence that updates indeed work as an impulse to contributor activity at the wiki-level.

We run a similar set of regressions at the contributor level. As we include contributor fixed effects throughout, this analysis evaluates to what extent updates induce each contributor to increase their efforts. Estimation results are presented in Models 3 to 6 Table 3, and we again find that updates act as expected. We find that daily contributions are 2.82% higher just after an update compared to just before (Model 3, $\hat{\beta} = 0.0282$, $p < 0.001$), on average. Again, we use separate dummies for each day (Model 4 of Table 3), and plot the coefficients in Figure 4b. The pattern is very similar to the wiki-level analysis, and in line with expectations. At the same time, we find that the effects at the contributor level are considerably lower than at the wiki level, suggesting that the intensive margin only explains a small fraction of the

[27] To test the validity of our identification strategy we ran a pre-trend analysis, which is provided in section A.3 in the Appendix.

[28] Effect sizes are obtained via $\exp(\hat{\beta}_2) - 1$, with $\hat{\beta}_2$ being the estimated coefficient for the Post dummy.

observed total variation. In addition, when we add the number of active other contributors to our model to control for increases at the extensive margin, effect sizes are even smaller. Specifically, daily contributions now are only 1.78% higher just after the release of an update (Model 5, $\hat{\beta} = 0.0178$, $p < 0.001$). In addition to the effect here being considerably smaller than at the wiki level generally, this suggests that each contributor's activity and productivity is tied to the number of contemporaneous active collaborators.

4.2.2 Aggregate Effects of Platform Competitive Position

We now turn to our analysis of the role a platform's competitive position in a domain at the wiki level. Recall that we are interested in the interaction between the competitive position at the beginning of an update time window and the Post-dummy, thus exploring heterogeneity in the treatment effect of updates. At this stage, we investigate total activity at the wiki level, i.e. we do not yet look at disaggregated effects at the intensive and extensive margins.

=== Table 4 here ===

=== Figure 5 here ===

Model 1 of Table 4 reports the results using the number of daily contributions as outcome variable. The estimated coefficient for the Post-dummy is statistically indistinguishable from zero. However, its interaction with a platform's competitive position is positive and statistically significant ($\hat{\beta} = 0.4617$, $p < 0.001$). The coefficients for the average treatment effect at different levels of CP are plotted in Figure 5a. The effect of updates is stronger the better a platform's competitive position. Specifically, at the low end of the spectrum there is no increase in activity following an update. Thus, in domains where a platform is in a weak position compared to its rival, contributors do not exert effort to compile information about the changes brought about by an update. However, at the other end of the spectrum, i.e. in domains where a platform is the single host of all contributors (CP = 1), we find that effects are strongest with 46.66% more contributions made just after the release of an update compared to just before.[29] Finally, in domains where the two platforms are even (CP = 0.5), we still find positive, but weaker effects, with daily contributions being 26.4% higher.

[29]Effect sizes for different levels of the competitive position are calculated as $\exp(\hat{\beta}_2 + \text{CP} \times \hat{\beta}_3) - 1$, with $\hat{\beta}_2$ being the estimated coefficient for the Post dummy, and $\hat{\beta}_3$ for the interaction term with CP.

4.2.3 Effects at the Extensive Margin

In our analysis of how a platform's competitive position is linked to the extensive margin of contribution activity, we are using the number of daily active contributors as dependent variable. We present the results in Model 2 of Table 4. Again, the estimated coefficient for the Post dummy is statistically indistinguishable from zero, but we estimate a statistically significant positive coefficient for the interaction term with CP ($\hat{\beta} = 0.2273$, $p < 0.01$). We plot the coefficient for different levels of CP in Figure 5b. Again, there is no difference between treated and untreated observations at the low end of the spectrum, but at the opposite end (CP = 1) the number of active contributors rises by 24.47% just after the release of an update. In domains where both platforms are on an equal footing (CP = 0.5), 11.1% more contributors are active. Again, the better the competitive position, the more contributors come together to collect and compile information about the changes introduced by an update. Thus, a more dominant platform has an advantage in terms of the extensive margin of activity. This also implies that the aggregate effects can be attributed to changes at the extensive margin to some degree.

4.2.4 Effects at the Intensive Margin

We now explore the effects at the intensive margin, both at the wiki and the contributor level. For the latter we use a reduced sample of contributors who exhibit a certain number of lifetime contributions to the wiki they are active in as well as a certain period of activity.

Wiki Level We use the daily number of contributions per active community member as dependent variable, and present results in Model 3 of Table 4. We obtain a positive and slightly statistically significant coefficient for the Post dummy ($\hat{\beta} = 0.1099$, $p < 0.1$), however the interaction with the platform's competitive position is statistically indistinguishable from zero. We again plot the estimated coefficients at different levels of the competitive position in Figures 5c. Each contributor increases their contributions by 11.61% just after the release of an update, regardless of the platform's competitive position in that domain.

Contributor Level We now turn to our contributor-level analysis for a more detailed look at the intensive margin. We use a daily panel of contributors with contributor fixed-effects to evaluate changes in behavior. We use daily contributions at the individual level as dependent variable and present results in Table 5.

=== Table 5 here ===

=== Figure 6 here ===

In Model 1, similar to our wiki-level analysis of the aggregate effects, the estimated coefficient for the Post dummy is statistically insignificant, but we estimate a positive significant coefficient for its interaction with a platform's competitive position ($\hat{\beta} = 0.0224$, $p < 0.05$). We again plot the coefficients at different levels of CP in Figures 6a. Similar to previous findings, we do not observe statistically significant effects for low values of CP. Note, however, that the estimates in this region are very imprecise, which may be due to the low number of observations (recall the distribution of observations in Figure 3b). Still, we find the strongest effects at the opposite end of the spectrum (CP = 1) with community members inceasing their contributions by 3.15% just after the release of an update. In domains where platforms are level, we observe 2% more contributions. This contrasts our wiki-level results on the effects at the intensive margin and suggests that activity increases induced by an update do depend on the competitive position. However, effect sizes are considerably weaker than both the aggregate effects as well as the effects at the extensive margins.

As described earlier, effects at the intensive margin may be tied to changes at the extensive margin, for instance if greater social benefits for each contributor are tied to a larger network of potential collaborators. Indeed, we find that a better competitive position is tied to increases a the extensive margin, i.e. more contributors coming together to compile information about the content changes associated with an update. Therefore, in a next step we check if we find effects at the intensive margin that go beyond those induced by changes at the extensive margin. To this end, we include the daily number of active other contributors as a control and present results in Model 2 of Table 5. The estimated coefficient for the interaction between the Post dummy and CP is now statistically indistinguishable from zero. We plot the estimated coefficient for different levels of CP in Figure 6b, confirming that a platform's competitive position and the treatment effect of updates appear unrelated after controlling for the extensive margin. At the same time, we obtain a positive and highly statistically significant coefficient for the daily number of active others on a community member's daily contributions ($\hat{\beta} = 0.0267$, $p < 0.001$). Thus, the (slight) increase at the intensive margin we identified in Model 1 of Table 5 appears to be related to an increased number of potential collaborators, and that there exist no overall association between a platform's competitive position and effects at the intensive margin above and beyond this channel.

4.2.5 High-Productivity Contributors

We now turn to differences across contributor types. Specifically, highly productive contributors, i.e. the top 10% in terms of prior contributions, may exhibit different activity patterns as they may enjoy non-pecuniary benefits that are not tied to a higher number of potential collaborators. Consequently, we allow the heterogeneity in the ATE of updates along the competitive position to vary by contributor type. As such, we include a three-way interaction of the Post dummy, a platform's competitive position in a domain, and a dummy indicating high-productivity contributors (HPC) in our empirical model.[30]

=== Figure 7 here ===

We present the results in Models 3 and 4 of Table 5. In Model 3 we do not yet control for the number of active other contributors and estimate a positive and statistically significant coefficient for our three-way interaction ($\hat{\beta}$ = 0.1075, p < 0.01). At the same time, all other estimated coefficients that include the Post dummy are statistically indistinguishable from zero. This suggests that a positive treatment effect of updates only exists for high-productivity contributors, and that it is stronger the better a platform's competitive position. In Model 4 we add our control for the number of other active contributors, yielding practically identical results: Again, the estimated coefficient for our three-way interaction is positive, statistically significant, and it is of the same magnitude as before ($\hat{\beta}$ = 0.1082, p < 0.01). Based on this specification, we plot the estimated coefficient of the Post dummy for different levels of CP, and for the two different contributor types in Figure 7, illustrating three important findings: First, we observe a positive relationship between a platform's competitive position and the strength of the treatment effect of updates for highly productive contributors only, but not for others. Second, we do not observe increased efforts to compile information about the changes associated with an update for either group when the competitive position is very low. Third, these relationship persist after controlling for changes at the extensive margin, suggesting that high-productivity contributors are not only driven by the presence of potential collaborators.

4.3 Further Analyses

4.3.1 Reverts and Maintenance

We now provide further tests about the mechanisms underlying our results. Recall that the relationship between a platform's competitive position and contributors' non-pecuniary benefits

[30] As the identification of HPC is based on prior contributions, we do not include this measure in the same regressions.

are at the core of our argumentation. At the same time, however, we note that a better competitive position may also entail the need for increased engagement in coordination and quality control if it is associated with a larger number of contributors. As a result, part of the patterns we observe may not be connected to content creation, but rather its maintenance.

We test this at the contributor level using two different outcome variables: First, one tool to ensure high-quality content on a wiki is to simply undo contributions by others, for instance if they contain false information or constitute vandalism. As this is a built-in feature of both platforms, *reverts* are automatically flagged in the comments attached to each contribution. Using this information, we identify 3.5% of all contributions as reverts. Second, aside from flat-out undoing contributions by others, community members can engage in more subtle quality-control, for example by correcting spelling or grammar errors contained in articles, or by changing its format. Here, neither new content is created, nor existing content is altered extensively. To identify such *maintenance* contributions, we use insights from the pages detailing the exact differences between two stages of an article.[31] Here, we evaluate whether or not its informational content is altered, which we consider to be the case if at least one of the two following conditions is met: On the one hand, relevant information in video games often comes in digits, e.g. how much damage a certain weapon inflicts, or how much health points certain enemies possess. Therefore, we consider it a change in an articles' informational content if at least a single digit is altered with a contribution. On the other hand, we consider this to be the case if the article text is changed significantly. Here, we evaluate the overlap in the character strings[32] in the altered sections of the articles before and after the contribution, and consider values below 90% to constitute a meaningful change in its informational content. We then flag a contribution as maintenance if *neither* of the two conditions is met, i.e. the informational content is *not* altered. This lets us identify 29.34% of all contributions as maintenance.

We present the results in Table 6. First, we observe that daily reverts do not seem to be driving our results at all, neither for contributors in general (Models 1 and 2), nor when looking at different types of contributors (Models 3 and 4). Across the board, we do not find any evidence for an increase in reverts following an update. Second, we observe a more nuanced picture when analyzing daily maintenance contributions, finding higher levels just following the release of an update compared to just before (Model 5, $\hat{\beta} = 0.0077$, $p < 0.05$). This effect, however, disappears when we control for the number of active other contributors (Model 6).

[31] Recall that both platforms provide a detailed overview of the parts of an article that are altered with each contribution. Figure A4 in the Appendix provides an example of such a page.

[32] We again use the Python package "FuzzyWuzzy" to calculate this similarity score.

This is in line with what we would expect: The more active contributors, the more coordination and quality control is needed. Next, when we explore heterogeneity across contributor types, we find that only high-productivity contributors increase their maintenance activities just after the release of an update (Model 7, $\hat{\beta} = 0.0495$, $p < 0.01$), and this effect persists when controlling for the number of active others (Model 8, $\hat{\beta} = 0.0497$, $p < 0.01$), with the effect practically being of the same size and statistical significance. High-productivity contributors seem to engage in maintenance activity regardless of the activity of others. Hence, it indeed appears to be driving part of high-productivity contributors' increase in activity laid out in section 4.2.5, but not completely as effect sizes here are considerably smaller.

4.3.2 Exclusivity

Next, we test if domains where a platform hosts an exclusive wiki (CP = 1) present a special case as facing weak or not facing any competition might be qualitatively distinct. To capture this, we run two additional sets of regressions, both at the wiki and the contributor level.

=== Table 7 here ===

In a first step, instead of our CP measure between 0 and 1, we use a dummy variable indicating an exclusive wiki and explore heterogeneity in the ATE of updates along this distinction in Table 7. In Model 1 we analyze aggregate effects at the wiki level and we find a positive and significant interaction effect between the Post and Exclusivity dummy ($\hat{\beta} = 0.2410$, $p < 0.1$). However, the size of the effect is considerably smaller and less precisely estimated than in our previous analysis. In Model 2 we use the number of active contributors as dependent variable, thus evaluating the extensive margin of activity. Here, we estimate a positive, statistically significant coefficient for the interaction between the Post and Exclusivity dummy ($\hat{\beta} = 0.2357$, $p < 0.05$), suggesting a larger treatment effect for exclusively hosted wikis.

We turn to the contributor level in Models 3 and 4. First, we do not allow for heterogeneity across different types in Model 3. Controlling for changes at the extensive margin, and consistent with our previous findings, we do not find evidence for heterogeneity in the treatment effect of updates in terms of daily contributions. In Model 4 we allow for heterogeneity across different types and find that the estimated coefficient for the three-way interaction between the Post, Exclusivity, and HPC dummies is positive and statistically significant ($\hat{\beta} = 0.0652$, $p < 0.05$), suggesting that high-productivity contributors indeed exhibit larger treatment effects on exclusively hosted wikis. This suggests that some results at the contributor level are partly driven by exclusivity, especially when looking at heterogeneity across different types.

=== Table 8 here ===

In a final step, we run a set of regressions using the same dependent variables, but only including the non-exclusive wikis in Table 8. At the wiki level (Models 1 and 2) we still find a positive interaction between the Post dummy and CP for daily contributions and active contributors, with the latter exhibiting slightly smaller effect sizes than in our full analysis. Hence, our main results are not predominantly driven by exclusively hosted wikis.

This is different at the contributor level. First, Model 3 is in line with our analysis in section 4.2.4 in that we do not find evidence for a relationship between the strength of the treatment effect and a platform's competitive position. Second, and in contrast, Model 4 shows an absence of such a relationship for high-productivity contributors as well. On the one hand, this contradicts our findings discussed in section 4.2.5. On the other hand, we found a heterogeneous treatment effects for high-productivity contributors in exclusively hosted wikis, suggesting that our previous results on this group of contributors are indeed mainly driven by exclusive wikis.

4.4 Relative Importance of the Extensive and Intensive Margins

We showed that there are considerable differences in the estimated treatment effects by a platform's competitive position. We also found that these differences are driven by changes both at the extensive and intensive margins of content creation. However, their relative importance in explaining aggregate changes following an update is not clear. To assess if changes in overall contributions are mainly driven by a higher number of active users or by each active user increasing their efforts, we run a series of simulations. We proceed as follows: To begin, and for ease of exposition, we define four levels of the competitive position: *Laggard* (CP ≤ 0.33), *Neck-on-Neck* ($0.33 <$ CP ≤ 0.67), *Leader* ($0.67 <$ CP < 1), and *Exclusive* (CP $= 1$). For each, we separately calculate the percentage change in total contributions initiated by the release of an update. We obtain its level in the *Pre*-period by simply multiplying the average number of active users in a wiki and per day (i.e. the extensive margin), denoted by $\bar{n}_{\text{Pre}}$, with the average level of contributions by each active contributor (i.e. the intensive margin), $\bar{y}_{\text{Pre}}$. Further, for the intensive margin we obtain separate averages for highly productive contributors (HPCs) and others separately, and we weigh each by its share of total contributions. The calculated outcome is then given by:

$$Y_{\text{Pre}} = \bar{n}_{\text{Pre}} \cdot (s_{\text{Pre}}^{\text{HPC}} \cdot \bar{y}_{\text{Pre}}^{\text{HPC}} + (1 - s_{\text{Pre}}^{\text{HPC}}) \cdot \bar{y}_{\text{Pre}}^{\text{Non-HPC}}), \tag{3}$$

with $s_{\text{Pre}}^{\text{HPC}}$ denoting the share of contributions attributable to HPCs.

Next, to predict the contribution levels in the *Post*-period we use our estimates for the conditional average treatment effects (CATE) for the relevant outcomes.[33] The idea is that they give us the percentage change in an outcome of interest between the *Pre*- and *Post*-periods. Based on this and for each level of a platform's competitive position, we calculate the predicted number of active users in the *Post*-period as $\hat{n}_{\text{Post}} = \bar{n}_{\text{Pre}} \cdot (1 + \widehat{\Delta n})$, with $\widehat{\Delta n}$ denoting the estimated CATE.[34] Analogously, we calculate the predicted change at the intensive margin (again separately for HPCs and Non-HPCs) as $\widehat{Y}_{\text{Post}} = \bar{y}_{\text{Pre}} \cdot (1 + \widehat{\Delta y})$. Together, this lets us predict the total number contributionsin the *Post*-period as

$$\widehat{Y}_{\text{Post}} = \hat{n}_{\text{Post}} \cdot (s^{\text{HPC}}_{\text{Post}} \cdot \widehat{Y}^{\text{HPC}}_{\text{Post}} + (1 - s^{\text{HPC}}_{\text{Post}}) \cdot \widehat{Y}^{\text{Non-HPC}}_{\text{Post}}). \tag{4}$$

Finally, with (1) we can calculate the percentage change in contributions between the *Pre*- and *Post*-periods as

$$\widehat{\Delta Y} = \frac{\widehat{Y}_{\text{Post}} - Y_{\text{Pre}}}{Y_{\text{Pre}}}. \tag{5}$$

The advantage of this simple approach is that all parameters used are either true sample means or easily computed based on estimated coefficients.[35] Moreover, these simple equations let us simulate different scenarios easily.

Specifically, to tease out the relative importance of extensive and intensive margins in the content creation process, we simulate five scenarios: First, and as a baseline ("Full" scenario), we calculate the full prediction according to (3). Second, we simulate a situation in which there are no changes at the intensive margin between the *Pre*- and *Post*-periods by setting parameters $\widehat{\Delta y}_{\text{HPC}}$ and $\widehat{\Delta y}_{\text{Non-HPC}}$ to zero. The idea is to predict the change in total contributions to a wiki if only the number of active contributors changes. We call this scenario "Extensive Margin". Third, we simulate a situation in which changes only occur at the intensive margin by setting parameter $\widehat{\Delta n}$ to zero, predicting total contributions if the number of active contributors stays the same, but each adjusts their efforts. We call this scenario "Intensive Margin". Lastly, we run two additional simulations in which we distinguish between changes at the intensive margin for HPCs and Non-HPCs. Again, in both we set parameter $\widehat{\Delta n}$ to zero. In addition, in scenario "Intensive Margin (Non-HPC)" parameter $\widehat{\Delta y}_{\text{HPC}}$ is set to zero, and in in scenario "Intensive

[33] Recall that the CATE can be calculated as $\exp(\hat{\beta}_2 + \text{CP} \times \hat{\beta}_3) - 1$, with $\hat{\beta}_2$ being the estimated coefficient for the Post dummy, and $\hat{\beta}_3$ for the interaction term with CP.

[34] For example, the average number of active contributors in the *Pre*-period and for the *Neck-on-Neck* position is 4.69. From our regression Model 2 of Table 4 we retrieve the estimated CATE as 0.1109. The predicted number of active contributors in the *Post*-period is then calculated as $4.69 \times 1.1109 = 5.21$.

[35] We provide an overview of all used parameters in Table A8 in the Appendix.

Margin (HPC)" parameter $\widehat{\Delta y}_{\text{Non-HPC}}$ is set to zero. In both, we predict the total contributions if the number of active contributors stays the same, and only one type of contributor adjusts their effort.

=== Figure 8 here ===

We present the predicted changes in the number of contributions for each scenario and at different levels of the competitive position in Figure 8.[36] Under the "Full" scenario, the change from *before* to *after* is larger the better the competitive position. We see similar patterns for the scenarios "Extensive Margin", "Intensive Margin", and "Intensive Margin (HPC)". "Intensive Margin (Non-HPC)" is the only scenario in which this is not the case. Next, while the general relationship between the competitive position and predicted changes is similar across these scenarios, we document differences the relative importance of the extensive and intensive margins. Most notably, we observe that the percentage increases attributable to the extensive margin are considerable higher than those at the intensive margin (for HPCs). We take from this that – when it comes to activity measured as daily contributions – a more dominant platform is at an advantage mainly because of the higher number of contributors. In addition, the intensive margin also explains a meaningful increase in wiki-level contributions. However, this channel is driven by a small subset of high-productivity contributors, and its influence is not as strong as the extensive margin.

5 Discussion and Conclusion

We analyze competition between two platforms organized around online communities of volunteer contributors. In particular, we ask if and through which channels a dominant platform may have an advantage in the process of value creation in such a setting. To that end, we investigate how the activity of a platform's community of volunteers depends on its competitive position, and which mechanisms may tie macro-level platform competition to outcomes at the micro-level of contributors. We argued that the competitive position will be related to the number of active contributors a platform has at any point in time (*contributor coordination*) and each contributor's activity (*contributor motivation*), thus impacting both the extensive and intensive margins of value creation.

[36] Note that, despite the additive setup, the changes under "Intensive Margin" and "Extensive Margin" do not perfectly add up to the changes under "Full" due to the weighting by the share of HPCs (s^{HPC}) which differs between the *Pre* and *Post* periods.

We study the behavior of contributors to two competing digital platforms hosting video game wikis. Exploiting variation in their competitive positions within different domains (i.e. different games being covered), and using game updates as a source of exogenous variation, we provide four key insights: First, a better competitive position in a domain is related to higher total levels of contributor activity. As such, we provide evidence for the notion that a more dominant platform indeed has an advantage in the process of subsequent value creation.

Second, a better competitive position is related to a higher number of active contributors. Therefore, the increased levels of activity we observe are partly driven by the extensive margin of value creation, and we conclude that this element of community size provides a significant advantage for a more dominant platform. This finding is in line with expectations and insights from previous studies on how dominance in platform (and other network) markets affects subsequent adoption decision by alleviating coordination issues (Argenziano & Gilboa, 2012; Biglaiser & Crémer, 2016; Eisenmann et al., 2006). At the same time, it is important to note the effect sizes at the extensive margin alone cannot explain the aggregate increases in activity and productivity levels in their entirety, suggesting further underlying drivers.

Third, we find a subtle, but positive relationship between a platform's competitive position and contributor activity at the intensive margin of value creation. This suggests that non-pecuniary benefits to contributors are higher on a dominant platform, leading to higher effort provision. However, compared to the effects at the extensive margin, effect sizes are considerable smaller. As such, contributor motivation seems to be a less important factor than contributor coordination when it comes to a dominant platform's advantage in the process of value creation. In addition, part of our findings suggest that the advantage at the intensive margin is the result of higher social benefits connected to a larger online community, such as more peers to collaborate with and to build on. This highlights the dual role of a leading platform's size advantage: Not only is it connected to simply more contributors creating value, but it also creates positive motivational spill-overs to the intensive margin of value creation. This is in line with work documenting a positive link between contributor activity and community size (Zhang & Zhu, 2011; Aaltonen & Seiler, 2016), but in contrast to work that finds stifling effects connected to conflict and within-community coordination needs (Arazy et al., 2011; Kittur et al., 2007; Kittur & Kraut, 2008) or degradation of reputational benefits (Boudreau & Jeppesen, 2015; Guo et al., 2020).

Lastly, we find that heterogeneity across different types of contributors matters for the intensive margin of value creation. When looking at the different effects for high-productivity contributors and others, we find that the former exhibit considerably higher activity levels on a leading platform, while there is no such relationship for the latter. In addition, effect sizes for high-productivity users are considerable. This suggests that this relatively small subset of community members accounts for a high share of value creation, and that they are an important aspect of a dominant platform's competitive advantage. Moreover, we also show that this relationship is not driven by community size, suggesting that high-productivity contributors draw from motivational sources other than social benefits, such as a sense of ownership or commitment to the platform, both of which may rather be functions of their past effort provision than the activity of their peers. While the fact that this group accounts for a majority of value created is in line with previous findings (Gorbatai, 2014; Rullani & Haefliger, 2013; Shah, 2006), we highlight that they do so especially if "their" platform's competitive position is strong. In addition, their increased activity on a dominant platform is partly driven by content maintenance rather than content creation. This suggests that they not only give their platform an advantage in terms of the scale of the content, but also its quality. On the flip side, we also find that a larger community entails higher levels of maintenance[37], potentially suggesting that high-productivity contributors may shift their attention away from content creation to some extent on a leading platform.

We contribute to two literature streams. First, we contribute to the literature on platform competition (Cennamo & Santalo, 2013; Eisenmann et al., 2006; Halaburda & Yehezkel, 2016). A bulk of the existing literature has looked at aspects of increasing returns to scale in adoption under network effects (Katz & Shapiro, 1985; Schilling, 2003) and its limits (Zhu & Iansiti, 2012), with studies on the inner workings of platform ecosystems only recently emerging (Kretschmer et al., 2021; McIntyre & Srinivasan, 2017). We add to both conversations by investigating how between-platform competition may relate to within-ecosystem value creation processes. Similar to Boudreau & Jeppesen (2015), we investigate a case where complementors are free of pecuniary motivations, creating managerial dilemmas for the platform (Shah & Nagle, 2020; Nickerson et al., 2017) and calling into question whether such online communities can be the source of a competitive advantage. In particular, we find that scale still matters, as a larger community entails higher levels of value creation. At the same time, size only tells part of the story as the *type* of unpaid complementor also matters, with highly-productive ones contributing to both the amount and quality of value created to a large extent. Therefore, we first contribute to this literature by providing empirical evidence for the connection between-platform dynamics

[37] This relationship is distinct from the relationship with a platform's competitive advantage.

and within-ecosystem processes in the context of community-driven value creation. Second, we contribute by providing insights about the extent to which (direct) network effects play a role in our context. While we do find evidence that a larger community (i.e. contributor network) positively relates to the activity of each contributor, this effect is very subtle. In addition, it does not seem to be a driving force for the small subset of high-productivity contributors who account for a large share of value creation.

Second, we provide novel insights about motivational sources and underlying drivers of volunteer contributions to online communities (Jeppesen & Frederiksen, 2006; Lakhani & Wolf, 2005; Shah, 2006; Shah & Nagle, 2020). Heeding calls for more research in this area (Lerner & Tirole, 2002; von Krogh et al., 2012), we highlight and provide empirical evidence for some mechanisms linking the external and macro-level factor of platform competition to micro-level contributor behavior. Previous work largely produced insights and propositions derived from theoretical models (Athey & Ellison, 2014; Casadesus-Masanell & Ghemawat, 2006; Llanes & de Elejalde, 2013; Sacks, 2015). An exception is the study by Nagaraj & Piezunka (2020), who find that facing a dominant competitor deprives a platform of new contributors, but leads to an increase in the activity of already existing ones. While the underlying drivers are similar to what we document in our study, there are some key differences. Nagaraj & Piezunka (2020) (as well as previous theoretical studies) study competition with a dominant, *commercial* alternative, while we study two competing *community*-driven platforms. This difference may explain a key divergence in our findings: In their study, established members increase their efforts when facing strong competition, i.e. being in a *weaker* competitive position. In contrast, we find that high-productivity users are more active in areas of a *stronger* competitive position. Accordingly, we regard our findings to be complementary to theirs. In all, we provide (further) empirical evidence on the relationship between competition and contribution behavior on the one hand, and by analyzing more "open-ended" competition between community-driven alternatives on the other.

Our study has some limitations that point towards some potential future research avenues. First, note that our research design generates results for the short-run only. Specifically, we investigate how contributors react to a work load (in the form of game updates) presented to them, conditional on the competitive position in that domain at that point in time. Therefore, we cannot speak to long-run dynamics between contributor activity and competition. Future research could investigate precisely these potentially self-reinforcing dynamics. Second, we only observe the contributing side of our platforms, but not wiki readership. This is an important boundary condition as part of the mechanisms we describe are related to audience effects. As a result, we (implicitly) assume that community size and readership are positively related. While we consider this assumption reasonable, future research could look at the interplay of both sides of the platforms, which would also provide interesting insights about the interplay between direct and indirect network effects and its role for platform competition. Thirdly, the subjects we study are "gamers". As such, they may exhibit some idiosyncrasies which may limit the extent to which our findings generalize to other settings, such as open-source software development.

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Figures

Figure 1 Development of the competitive position in different domains

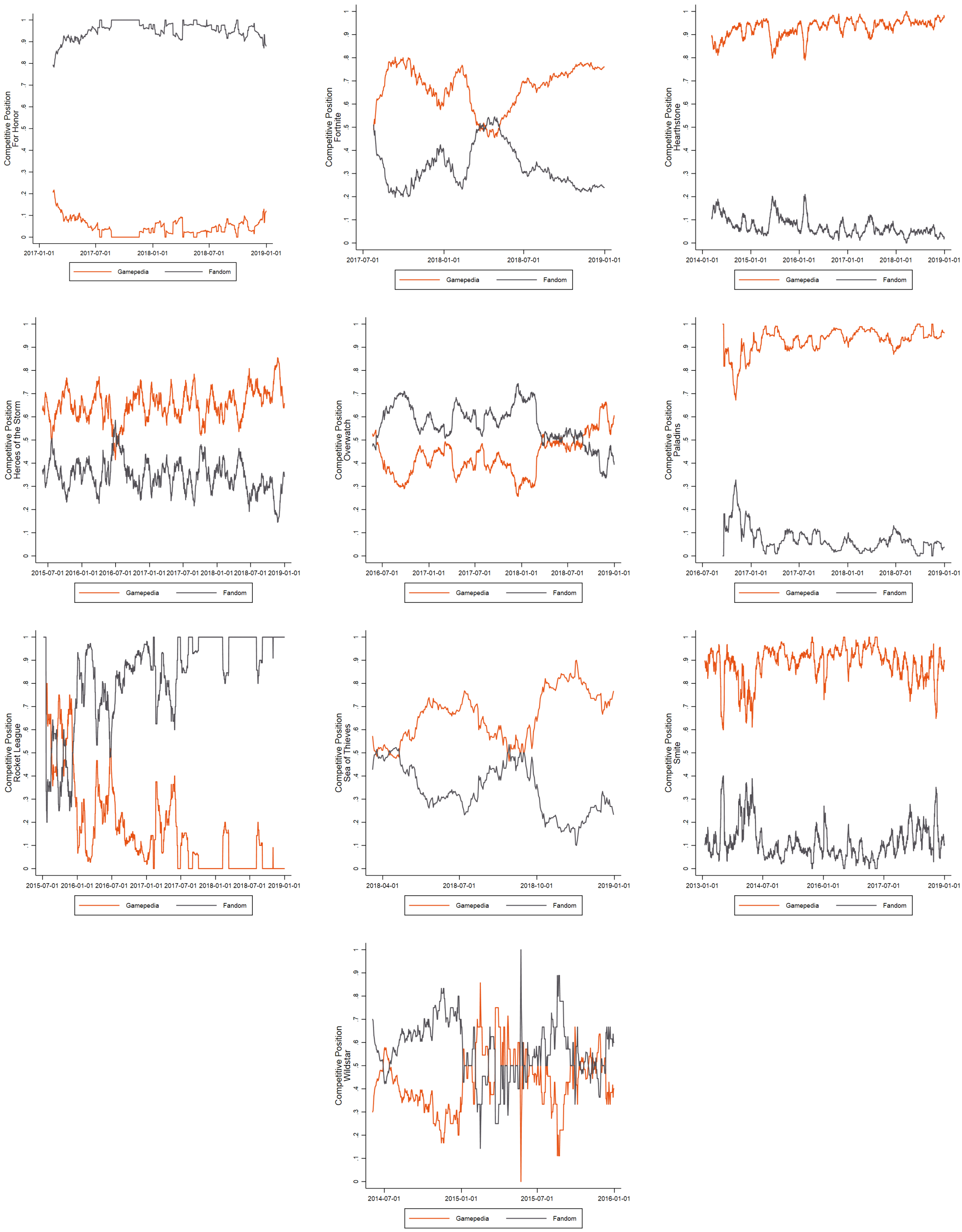


Figure 2 Heterogeneous treatment effects in the RDiT framework

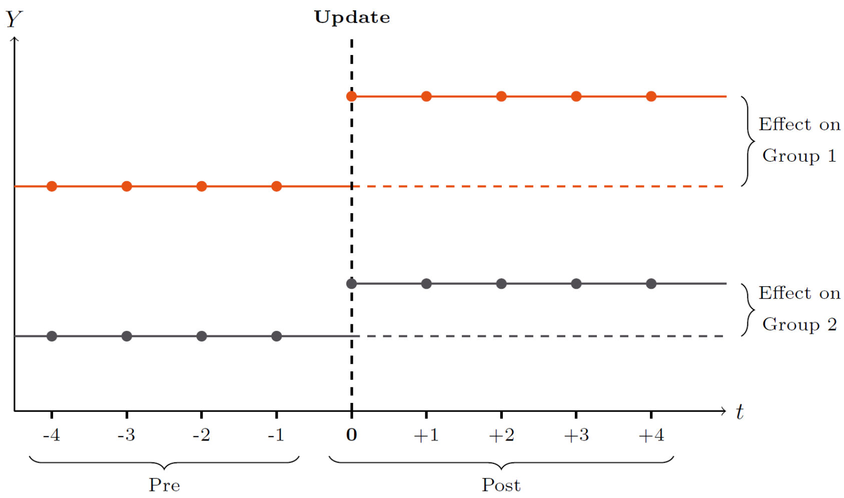
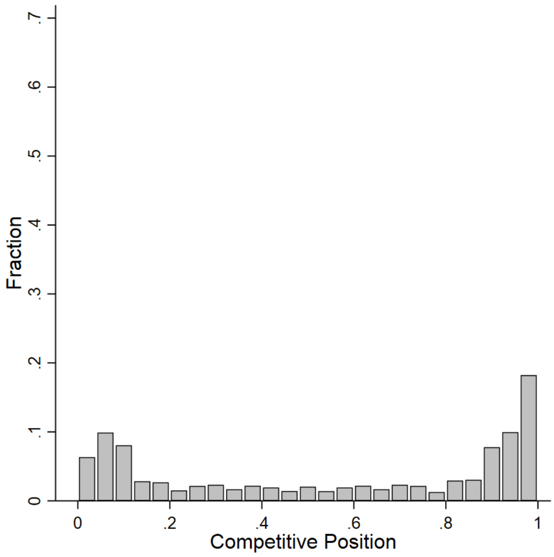


Figure 3 Distribution of Competitive Position Levels

(a) Wiki Level



(b) Contributor Level

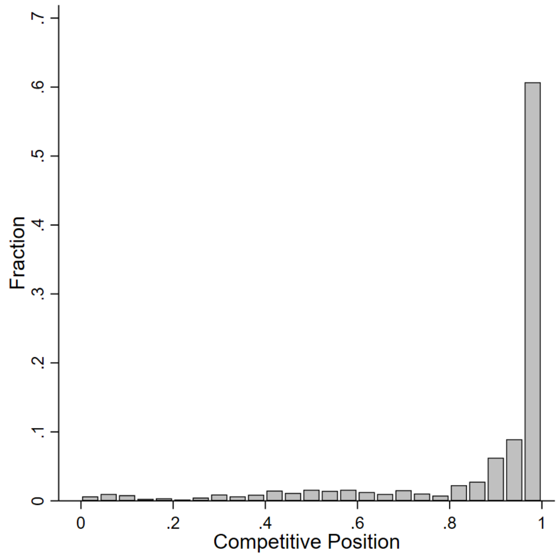


Figure 4 Updates as an Impulse to Contributor Activity

(a) Wiki Level **(b)** Contributor Level

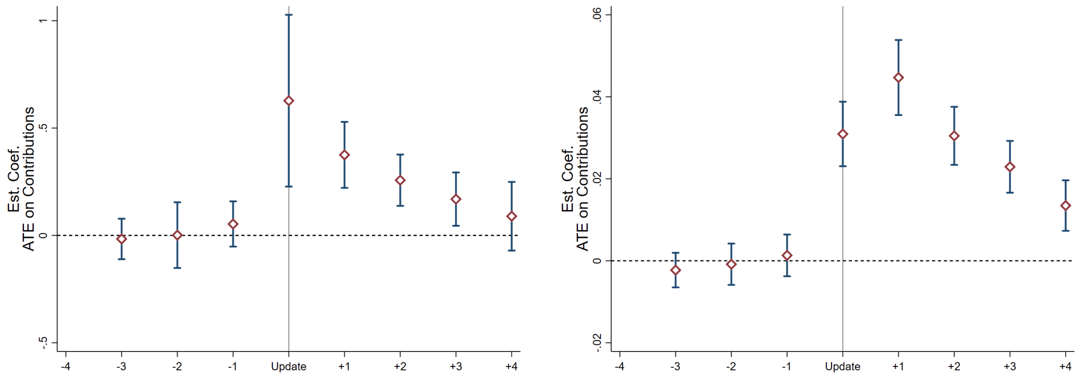


Figure 5 Wiki-Level Effects

(a) Contributions **(b)** Active Contributors **(c)** Contribs. per Contributor

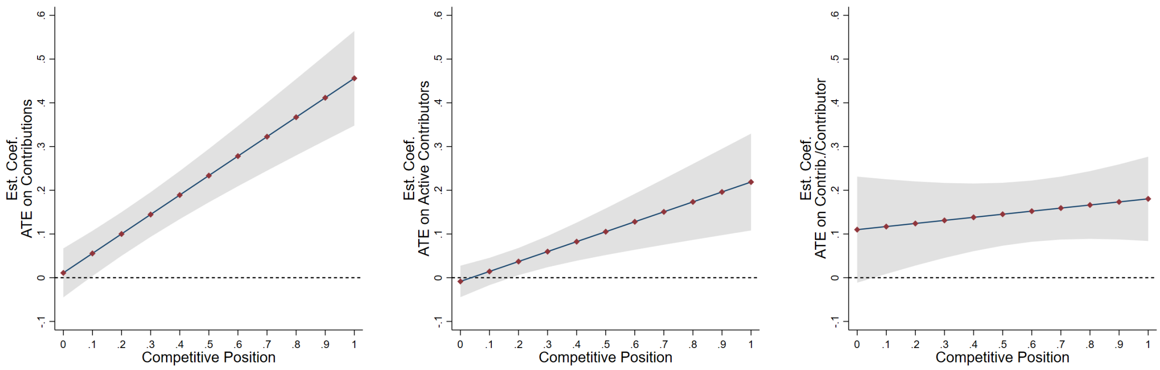


Figure 6 Contributor-Level Effects

(a) No control **(b)** Extensive margin control

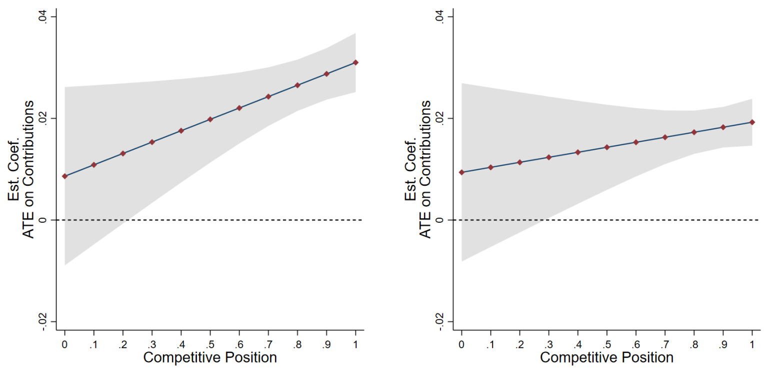


Figure 7 Heterogeneity across contributor types

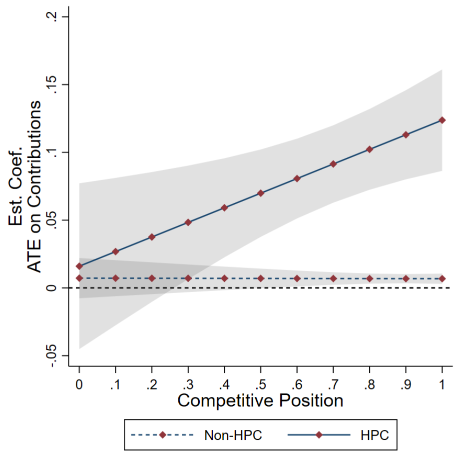
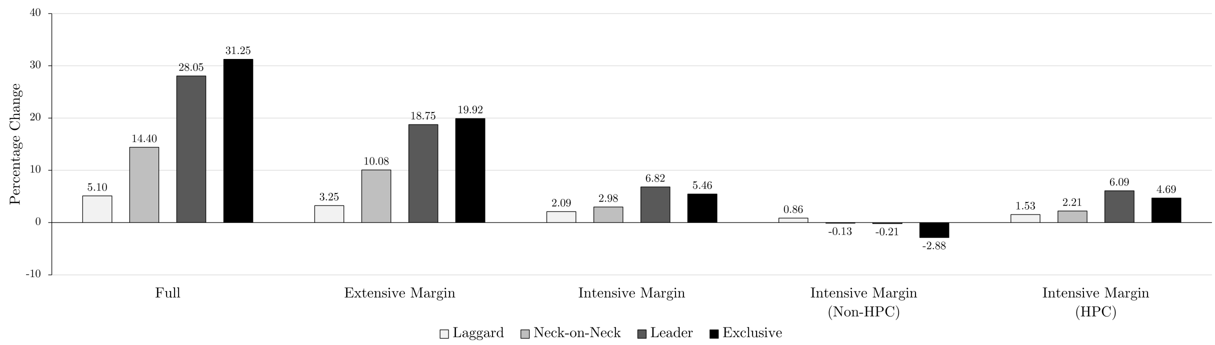


Figure 8 Simulation: Predicted Changes in Contributions



Tables

Table 1 Descriptive Statistics: Wiki Level

		Absolutes				Logarithms			
	Obs.	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.
Contributions	6,999	20.92	41.53	0	362	1.84	1.62	0	5.89
Active Contributors	6,999	5.34	10.40	0	113	1.19	1.06	0	4.74
Contrib. / Contributor	4,800	5.20	10.86	1	312	1.46	0.71	0.69	5.75
Post	6,999	0.56	0.50	0	1				
Competitive Position	6,979	0.56	0.38	0	1				
Wiki Size	6,999	1273.12	1089.60	10	5772	6.67	1.16	2.40	8.66
Staff Contributions	6,999	1.85	13.22	0	244	0.18	0.71	0	5.50

Table 2 Descriptive Statistics: Contributor Level

		Absolutes				Logarithms			
	Obs.	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.
Contributions	234,361	0.39	4.69	0	508	0.08	0.40	0	6.23
Post	234,361	0.56	0.50	0	1				
Competitive Position	233,402	0.88	0.23	0	1				
High-Productivity Contributor	234,361	0.11	0.31	0	1				
Prior Contributions	234,361	279.67	1,131.66	0	31,004	4.37	1.39	0	10.34
Wiki Size	234,361	1,996.73	1,126.38	19	5,772	7.41	0.68	3.00	8.66
Staff Contributions	234,361	1.20	9.00	0	254	0.19	0.64	0	5.54
Active Other Contributors	234,361	20.17	26.18	0	213	2.37	1.22	0	5.36

Table 3 Updates as an Impulse to Contributor Activity

	Contributions					
	Wiki Level		Contributor Level			
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.2675***		0.0282***		0.0178***	
	(0.0586)		(0.0025)		(0.0020)	
-4		Baseline		Baseline		Baseline
-3		−0.0164		−0.0023		−0.0011
		(0.0481)		(0.0022)		(0.0022)
-2		0.0014		−0.0008		−0.0003
		(0.0781)		(0.0026)		(0.0026)
-1		0.0533		0.0013		0.0005
		(0.0537)		(0.0026)		(0.0026)
Update		0.6276**		0.0309***		0.0224***
		(0.2041)		(0.0040)		(0.0037)
+1		0.3751***		0.0447***		0.0307***
		(0.0784)		(0.0047)		(0.0040)
+2		0.2572***		0.0305***		0.0194***
		(0.0609)		(0.0036)		(0.0033)
+3		0.1691*		0.0229***		0.0149***
		(0.0634)		(0.0032)		(0.0029)
+4		0.0894		0.0135***		0.0070*
		(0.0816)		(0.0031)		(0.0030)
Active Others					0.0273***	0.0252***
					(0.0028)	(0.0028)
Wiki Size	0.0411	0.0411	−0.0217	−0.0214	−0.0260	−0.0255
	(0.0990)	(0.0992)	(0.0416)	(0.0416)	(0.0429)	(0.0428)
Staff Contrib.	0.0210	0.0183	0.0080*	0.0073*	0.0051+	0.0049
	(0.0279)	(0.0295)	(0.0031)	(0.0031)	(0.0031)	(0.0031)
Prior Contrib.			−0.0091	−0.0091	−0.0089	−0.0089
			(0.0068)	(0.0068)	(0.0068)	(0.0068)
Constant	1.4089*	1.3853+	0.2601	0.2586	0.2331	0.2341
	(0.6638)	(0.6765)	(0.3087)	(0.3084)	(0.3188)	(0.3178)
Update FE	Y	Y	Y	Y	Y	Y
Wiki FE	Y	Y				
Contributor FE			Y	Y	Y	Y
Day of Week FE	Y	Y	Y	Y	Y	Y
Observations	6,999	6,999	234,361	234,361	234,361	234,361
Adj. R^2	0.6792	0.6847	0.2619	0.2622	0.2627	0.2629
Within-R^2	0.0193	0.0369	0.00207	0.00253	0.00319	0.00345

Robust standard errors in parentheses
Standard errors clustered at the level of the panel unit
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 4 Wiki Level Results

	(1) Contrib.	(2) Active Contributors	(3) Contrib./ Contributor
Post	0.0019	−0.0084	0.1099^{+}
	(0.0267)	(0.0183)	(0.0619)
Post × Competitive Position	0.4647***	0.2273**	0.0704
	(0.0588)	(0.0641)	(0.0843)
Competitive Position	1.2651***	0.8283***	0.1843
	(0.1227)	(0.0634)	(0.1915)
Wiki Size	0.0018	−0.0770***	0.1590
	(0.0531)	(0.0161)	(0.1217)
Staff Contrib.	0.0240	0.0225	−0.0030
	(0.0251)	(0.0158)	(0.0168)
Constant	0.9713**	1.1555***	0.1314
	(0.3014)	(0.1047)	(0.7964)
Update FE	Y	Y	Y
Wiki FE	Y	Y	Y
Day of Week FE	Y	Y	Y
Observations	6,979	6,979	4,798
Adj. R^2	0.6903	0.8283	0.1549
Within-R^2	0.0563	0.0720	0.0173

Robust standard errors in parentheses
Standard errors clustered at the level of the wiki
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 5 Contributor-Level Results

	Contributions			
	(1)	(2)	(3)	(4)
Post	0.0086	0.0094	0.0063	0.0072
	(0.0090)	(0.0090)	(0.0076)	(0.0076)
Post × CP	0.0224*	0.0099	0.0131	−0.0004
	(0.0101)	(0.0099)	(0.0082)	(0.0082)
Post × HPC			0.0091	0.0088
			(0.0318)	(0.0317)
Post × CP × HPC			0.1075**	0.1082**
			(0.0410)	(0.0407)
Active Others		0.0267***		0.0287***
		(0.0027)		(0.0028)
Competitive Position (CP)	0.0421	0.0176	0.0379	0.0121
	(0.0506)	(0.0502)	(0.0525)	(0.0524)
HPC			−0.1048	−0.1022
			(0.0699)	(0.0706)
Prior Contrib.	−0.0087	−0.0086		
	(0.0068)	(0.0068)		
Wiki Size	−0.0259	−0.0281	−0.0289	−0.0312
	(0.0424)	(0.0433)	(0.0541)	(0.0548)
Staff Contrib	0.0079*	0.0051+	0.0081**	0.0051+
	(0.0031)	(0.0031)	(0.0031)	(0.0031)
Constant	0.2528	0.2330	0.2544	0.2327
	(0.3162)	(0.3227)	(0.3981)	(0.4036)
Update FE	Y	Y	Y	Y
Contributor FE	Y	Y	Y	Y
Day of Week FE	Y	Y	Y	Y
Observations	233,402	233,402	233,637	233,637
Adj. R^2	0.2628	0.2636	0.2619	0.2628
Within-R^2	0.00215	0.00320	0.00479	0.00596

Robust standard errors in parentheses
Standard errors clustered at the level of the contributor
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 6 Additional Analysis: Reverts and Maintenance

	Reverts				Maintenance			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	−0.0020	−0.0019	−0.0012	−0.0011	0.0019	0.0021	0.0025	0.0028
	(0.0015)	(0.0015)	(0.0014)	(0.0014)	(0.0030)	(0.0030)	(0.0022)	(0.0023)
Post × CP	0.0026	0.0009	0.0014	−0.0003	0.0077*	0.0033	0.0027	−0.0022
	(0.0016)	(0.0017)	(0.0014)	(0.0015)	(0.0035)	(0.0034)	(0.0025)	(0.0025)
Post × HPC			−0.0048	−0.0049			−0.0059	−0.0060
			(0.0053)	(0.0053)			(0.0140)	(0.0140)
Post × CP × HPC			0.0087	0.0088			0.0495**	0.0497**
			(0.0070)	(0.0070)			(0.0188)	(0.0187)
Active Others		0.0037***		0.0037***		0.0096***		0.0103***
		(0.0008)		(0.0008)		(0.0013)		(0.0013)
Competitive Position (CP)	0.0251	0.0217	0.0171	0.0138	0.0139	0.0051	0.0113	0.0020
	(0.0153)	(0.0149)	(0.0140)	(0.0137)	(0.0181)	(0.0183)	(0.0180)	(0.0182)
HPC			−0.0234	−0.0231			−0.0375	−0.0366
			(0.0171)	(0.0172)			(0.0254)	(0.0256)
CP × HPC			0.0386+	0.0382+			0.0087	0.0076
			(0.0221)	(0.0222)			(0.0328)	(0.0330)
Wiki Size	−0.0052	−0.0055	−0.0031	−0.0034	0.0071	0.0063	0.0063	0.0054
	(0.0068)	(0.0069)	(0.0099)	(0.0100)	(0.0120)	(0.0124)	(0.0165)	(0.0168)
Staff Contrib.	−0.0002	−0.0005	−0.0002	−0.0005	0.0026+	0.0016	0.0029+	0.0018
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0016)	(0.0016)	(0.0016)	(0.0016)
Prior Contrib.	0.0029*	0.0029*			−0.0019	−0.0019		
	(0.0014)	(0.0014)			(0.0029)	(0.0029)		
Constant	0.0122	0.0095	0.0158	0.0130	−0.0370	−0.0440	−0.0328	−0.0407
	(0.0515)	(0.0523)	(0.0723)	(0.0729)	(0.0936)	(0.0955)	(0.1232)	(0.1251)
Update FE	Y	Y	Y	Y	Y	Y	Y	Y
Contributor FE	Y	Y	Y	Y	Y	Y	Y	Y
Day of Week FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	233,402	233,402	233,637	233,637	233,402	233,402	233,637	233,637
Adjusted R-squared	0.2971	0.2974	0.2971	0.2974	0.1906	0.1910	0.1891	0.1896
Within-R2	0.000576	0.000898	0.000959	0.00127	0.000782	0.00131	0.00217	0.00277

Robust standard errors in parentheses
Standard errors clustered at the level of the user
*** $p<0.001$, ** $p<0.01$, * $p<0.05$, + $p<0.1$

Table 7 Additional Analysis: Exclusive vs. Competing

	Wiki Level		Contributor Level	
	(1)	(2)	(3)	(4)
	Contrib.	Active Contributors	Contrib.	
Post	0.2273***	0.0822**	0.0152***	0.0071*
	(0.0570)	(0.0235)	(0.0035)	(0.0030)
Post × Exclusive	0.2410+	0.2357*	0.0047	−0.0006
	(0.1191)	(0.0933)	(0.0048)	(0.0036)
Post × HPC				0.0659**
				(0.0201)
Post × Exclusive × HPC				0.0652*
				(0.0299)
Active Others			0.0268***	0.0287***
			(0.0028)	(0.0028)
Exclusive	0.4271*	0.1343	0.0110	0.0122
	(0.1950)	(0.1054)	(0.0340)	(0.0363)
HPC				−0.0879*
				(0.0411)
Exclusive × HPC				−0.0534
				(0.0586)
Wiki Size	0.0255	−0.0597	−0.0258	−0.0296
	(0.0880)	(0.0369)	(0.0430)	(0.0489)
Staff Contrib.	0.0191	0.0185	0.0051	0.0050
	(0.0263)	(0.0147)	(0.0031)	(0.0031)
Prior Contrib.			−0.0089	
			(0.0068)	
Constant	1.4564*	1.4844***	0.2265	0.2246
	(0.5804)	(0.2516)	(0.3233)	(0.3678)
Update FE	Y	Y	Y	Y
Wiki FE	Y	Y		
Contributor FE			Y	Y
Day of Week FE	Y	Y	Y	Y
Observations	6,999	6,999	234,361	234,596
Adj. R^2	0.6809	0.8208	0.2627	0.2620
Within-R^2	0.0247	0.0294	0.00320	0.00599

Robust standard errors in parentheses
Standard errors clustered at the level of the panel unit.
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 8 Additional Analysis: Exclusives Excluded

	Wiki Level		Contributor Level	
	(1)	(2)	(3)	(4)
	Contrib.	Active Contributors	Contrib.	
Post	−0.0072	−0.0042	0.0085	0.0039
	(0.0255)	(0.0197)	(0.0099)	(0.0084)
Post × CP	0.4612***	0.1619**	0.0068	0.0019
	(0.0569)	(0.0543)	(0.0133)	(0.0107)
Post × HPC				0.0302
				(0.0326)
Post × CP × HPC				0.0535
				(0.0574)
Active Others			0.0149***	0.0161***
			(0.0034)	(0.0035)
Competitive Position (CP)	1.4755***	1.0277***	0.0651	0.0507
	(0.1528)	(0.0712)	(0.0678)	(0.0677)
HPC				−0.1303+
				(0.0782)
CP × HPC				0.0678
				(0.1144)
Wiki Size	0.0263	−0.0638**	−0.0284	−0.0284
	(0.0540)	(0.0173)	(0.0432)	(0.0565)
Staff Contrib.	0.0152	0.0121	0.0029	0.0026
	(0.0245)	(0.0121)	(0.0043)	(0.0043)
Prior Contrib.			−0.0035	
			(0.0095)	
Constant	0.5861+	0.8482***	0.2319	0.2358
	(0.3114)	(0.1147)	(0.3141)	(0.4048)
Update FE	Y	Y	Y	Y
Wiki FE	Y	Y		
Contributor FE			Y	Y
Day of Week FE	Y	Y	Y	Y
Observations	5,991	5,991	101,369	101,466
Adj. R^2	0.6312	0.7568	0.2128	0.2119
Within-R^2	0.0452	0.0590	0.000854	0.00236

Robust standard errors in parentheses

Standard errors clustered at the level of the panel unit.

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

Appendix

A.1 Alternative Measure of Contributor Activity

In our main analyses we use the number of daily contributions as dependent variable to evaluate contributor activity. However, this measure does not distinguish between different types of activity. Next to adding to the content in a wiki it also contains reverts that undo previous contributions, as well as very minor changes, such as fixing a typo or adding punctuation. Therefore, here we re-run part of our analysis using content growth an alternative measure as a robustness check. Specifically, we use information about how many characters are added (or removed) with a contribution, which we aggregate to the wiki or contributor level (depending on the analysis). As such, it is a measure of how much content is actually added on a day.

Results are reported in Table A1. In Model 1, we evaluate the aggregate wiki-level effects. Consistent with our main analysis (section 4.2.2) the estimated coefficient of the interaction between the Post dummy and the competitive position is positive and statistically significant ($\hat{\beta} = 0.7138$, $p < 0.01$). In fact, the effect is slightly stronger compared to our main analysis.

Next, we move to the analysis of the effects at the intensive margin. First, in Model 2 we re-run out wiki-level analysis using content growth per active contributor as dependent variable. Again, the results are consistent with our main analysis (section 4.2.4) in that the estimated coefficient of the interaction term is statistically indistinguishable from zero. Second, we re-run the analysis at the contributor level in Model 3 (controlling for changes at the extensive margin). Again, results are consistent with our main analysis in that we do not find significant effects. Third, we check for further heterogeneity across different contributor types in Model 4. Here, too, results are consistent with our main analysis (section 4.2.5): The three-way interaction between the Post dummy, the dummy indicating an HPC, and the competitive position is positive ans statistically significant, while all other interaction terms including the Post dummy are statistically insignificant. Again, the estimated effect is stronger when compared to our main analysis. In all, we take this as evidence that our main analysis is robust to this alternative measure of contributor activity.

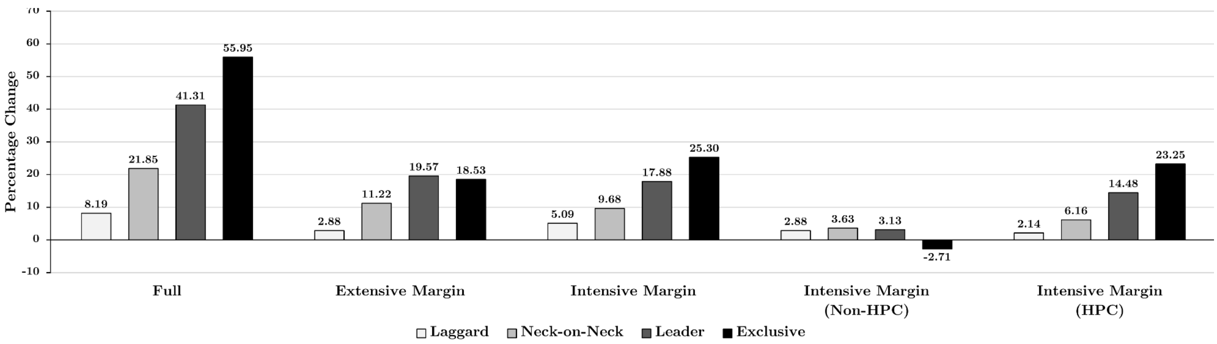
Lastly, we performed the same simulation exercise as in section 4.4. The predicted changes in content growth by competitive position and across different scenarios are shown in Figure A1. While we can confirm the positive association between activity increases and the competitive position here, a slightly different picture emerges about the relative importance of the extensive and intensive margins. Specifically, here the percentage changes for the extensive margin are largely on par with the changes for the HPC changes at the intensive margin. While the extensive margin is clearly dominant when looking at the contributions, both channels appear equally important when looking at the amount of content that is added to the wiki.

Table A1 Robustness: Alternative Measure of Contributor Activity

	Wiki Level		Contributor Level	
	(1) Content Growth	(2) Growth/ Contributor	(3) Content Growth	(4)
Post	0.0565	0.1660	0.0371	0.0392^{+}
	(0.0956)	(0.1957)	(0.0266)	(0.0225)
Post × CP	0.7138^{**}	0.2384	0.0182	−0.0166
	(0.1886)	(0.2401)	(0.0291)	(0.0242)
Post × HPC				−0.0235
				(0.1183)
Post × CP × HPC				0.3446^{*}
				(0.1388)
Active Others			0.0756^{***}	0.0805^{***}
			(0.0076)	(0.0076)
Competitive Position (CP)	3.7586^{***}	0.6744	0.0668	0.0501
	(0.5257)	(0.6793)	(0.1421)	(0.1419)
CP × HPC			−0.0375	−0.0464
			(0.2530)	(0.2547)
Wiki Size	−0.1377	0.0918	−0.0908	−0.1016
	(0.1025)	(0.1878)	(0.1296)	(0.1687)
Staff Contrib.	0.1947^{*}	0.1979^{***}	0.0164^{+}	0.0169^{+}
	(0.0724)	(0.0483)	(0.0087)	(0.0086)
HPC				−0.3133
				(0.2152)
Prior Contrib.			−0.0257	
			(0.0187)	
Constant	3.1733^{***}	4.1380^{*}	0.7299	0.7427
	(0.7924)	(1.5392)	(0.9684)	(1.2442)
Update FE	Y	Y	Y	Y
Wiki FE	Y	Y		
Contributor FE			Y	Y
Day of Week FE	Y	Y	Y	Y
Observations	6,487	4,319	230,882	231,076
Adj. R^2	0.5948	0.1242	0.2191	0.2195
Within-R^2	0.0406	0.0108	0.00290	0.00541

Robust standard errors in parentheses
Standard errors clustered at the level of the panel unit
*** $p<0.001$, ** $p<0.01$, * $p<0.05$, + $p<0.1$

Figure A1 Simulation: Predicted Changes in Content Growth



A.2 Alternative Measure of the Competitive Position

In our main analysis our measure for a platform's competitive position within a domain is calculated based on its respective community size. Here, we provide a robustness test using the level of contributor *activity* as the basis of its construction instead. This approach then enables us to control for community *size* directly, providing support to the notion that the patterns we uncover are distinct from a pure size effect.

Specifically, for each wiki and day, we take the total number of contributions made over the preceding 30 days, creating a rolling measure of community activity, denoted by M Platform i's competitive position in domain g on day t is then given by

$$\mathrm{CP}_{igt} = \frac{M_{igt}}{M_{igt} + M_{jgt}},$$

with subscript j indicating the respective other platform. As before, this measure is bound between zero and one, with higher values indicating a better competitive position. Intuitively, it measures how the total level of activity in a domain is distributed across the two platforms. We then add our previously used rolling measure of community size (N_{igt} from section 3.3) as a control variable. Again, we run two sets of regressions, bot at the wiki and contributor level. The results are presented in Table A2.

Across the board, the estimated coefficients for the interaction between the Post dummy and the competitive position are consistent with those obtained in our main analyses, not only qualitatively but also in terms of effect sizes. At the wiki level (Models 1 and 2 of Table A2) they are virtually the same as in our original analysis (Models 1 and 2 of Table 4)). In addition, we find that community size is positively related to our wiki-level dependent variables, too, suggesting that there exists a size effect that is distinct from their relationship with the competitive position.

At the contributor level, results are largely consistent as well. One key difference here is that the positive relationship between the competitive position and activity increases at the intensive margin (Models 3 of Table A2) persists after controlling for the number of other active contributors. However, when exploring heterogeneity across different types (Models 4 of Table A2) results confirm that this positive relationship appears entirely driven by high-productivity contributors. In addition, here the estimated coefficients for the triple interaction is very much consistent with those obtained in our main analyses (Model 4 of Table 5).

Together, this robustness checks provides two key insights: First, it adds support to the notion that our operationalization of the competitive position based on community size in combination with our game update fixed effects provides estimates for a relationship that is distinct from a mere size effect. Second, and in line with previous studies (e.g. Zhang & Zhu, 2011) we do however find evidence for the existence of a distinct size effect at the wiki level.

Table A2 Robustness: Alternative Measure of the Competitive Position

	Wiki Level		Contributor Level	
	(1)	(2)	(3)	(4)
	Contrib.	Active Contributors	Contrib.	
Post	0.0148	−0.0080	0.0044	0.0032
	(0.0283)	(0.0191)	(0.0073)	(0.0061)
Post × CP (Activity)	0.4388***	0.2266**	0.0161*	0.0046
	(0.0595)	(0.0603)	(0.0080)	(0.0065)
Post × HPC				0.0028
				(0.0292)
Post × CP (Activity) × HPC				0.1163**
				(0.0377)
Active Others			0.0257***	0.0278***
			(0.0027)	(0.0027)
CP (Activity)	0.5757***	0.1353**	0.0828*	0.0691*
	(0.0548)	(0.0424)	(0.0337)	(0.0283)
HPC				−0.1509*
				(0.0698)
CP (Activity) × HPC				0.0540
				(0.0792)
Community Size	0.2881***	0.2228***	−0.0096	−0.0141
	(0.0186)	(0.0185)	(0.0180)	(0.0171)
Wiki Size	−0.1241**	−0.0922***	−0.0579	−0.0596
	(0.0328)	(0.0174)	(0.0479)	(0.0655)
Staff Contrib	0.0067	0.0160	0.0043	0.0043
	(0.0252)	(0.0160)	(0.0031)	(0.0031)
Prior Contrib.			−0.0087	
			(0.0068)	
Constant	1.3204***	0.8789***	0.4475	0.4651
	(0.2250)	(0.1556)	(0.3748)	(0.4971)
Update FE	Y	Y	Y	Y
Wiki FE	Y	Y		
Contributor FE			Y	Y
Day of Week FE	Y	Y	Y	Y
Observations	6,999	6,999	234,361	234,596
Adj. R^2	0.7104	0.8293	0.2630	0.2625
Within-R^2	0.0704	0.0753	0.00360	0.00670

Robust standard errors in parentheses
Standard errors clustered at the level of the panel unit.
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

A.3 Pre-Trend Analysis

In our empirical analysis, game updates serve as a key element in identifying the relationship between a platform's competitive position and our outcomes of interest. As layed out in section 3.4, we specifically analyze to what extent the increase in the outcome, which is induced by the update, depends on the competitive position at the beginning of each nine-day time window. An identifying assumption here is that the observed patterns in the outcomes do not also vary by he competitive position, which we analyze here.

Specifically, we construct separate dummies indicating each day in the update time windows. Here, the four days preceding their releases ($t = -4$ to $t = -1$) are the *pre*-period, and the remaining five days ($t = 0$ to $t = +4$) are the *post*-period or our *treated* observations. To now test the parallel trends assumption, we run a set of regressions with different dependent variables both at the wiki and contributor level, that includes this set of individual day-dummies as well as their interaction with a platform's competitive position in that domain. The assumption is violated if the estimated coefficients for the interaction terms in the pre-period are statistically different from zero, suggesting that patterns in the outcome vary regardless of the impulse initiated by the update.

Table A3 contains the results. As is the case in our main analysis (i.e. Table 3) the first day of each time window ($t = -4$) serves as the reference point. At the wiki-level, both when using the daily number of contributions (Model 1) all estimated coefficients for the interaction between a day dummy and the competitive position are statistically indistinguishable from zero in the *pre*-period, suggesting that the parallel trends assumption is not violated. However, when looking at the number of daily active contributors (Model 2), we do obtain a slightly negative and statistically significant estimate for the second day in a time window (i.e. CP $\times -3$, $\hat{\beta} = -0.0959$, $p < 0.05$). At the contributor level, the parallel trends assumption is not violated either (Model 3). In all, despite the single significant estimated coefficient, we are not concerned that the obtained pre-trends invalidate our identification strategy.

Table A3 Pre-Trends

	Wiki Level		Contributor Level
	(1)	(2)	(3)
	Contrib.	Active Contributors	Contrib.
-4	Baseline	Baseline	Baseline
-3	0.0470	0.0270	−0.0070
	(0.0437)	(0.0246)	(0.0092)
-2	0.0951	0.0325	−0.0015
	(0.0689)	(0.0325)	(0.0114)
-1	0.0019	0.0063	−0.0102
	(0.0843)	(0.0390)	(0.0107)
Update	0.0036	0.0017	0.0302
	(0.0917)	(0.0356)	(0.0217)
+1	0.0541	0.0305	0.0056
	(0.0932)	(0.0471)	(0.0123)
+2	0.1091	0.0247	0.0044
	(0.0761)	(0.0364)	(0.0111)
+3	0.1031	0.0095	0.0067
	(0.0799)	(0.0410)	(0.0125)
+4	0.1202^{+}	0.0413	−0.0098
	(0.0581))	(0.0276)	(0.0121)
CP	1.4207^{***}	0.8771^{***}	0.0393
	(0.1067)	(0.0699)	(0.0517)
CP × -4	Baseline	Baseline	Baseline
CP × -3	−0.1140	-0.0959^{*}	0.0056
	(0.1068)	(0.0408)	(0.0097)
CP × -2	−0.1829	−0.0728	0.0003
	(0.1470)	(0.0487)	(0.0119)
CP × -1	0.0360	−0.0148	0.0124
	(0.1199)	(0.3141)	(0.0115)
CP × Update	0.9859^{**}	0.2425^{***}	0.0004
	(0.3184)	(0.0638)	(0.0234)
CP × +1	0.5129^{**}	0.2637^{*}	0.0439^{**}
	(0.1378)	(0.0993)	(0.0145)
CP × +2	0.2366	0.2031^{*}	0.0296^{*}
	(0.1501)	(0.0910)	(0.0124)
CP × +3	0.1222	0.1538	0.0186
	(0.1656)	(0.0994)	(0.0140)
CP × +4	−0.0377	0.0178	0.0268^{*}
	(0.2053)	(0.1008)	(0.0131)
Wiki Size	−0.0187	-0.0767^{***}	−0.0256
	(0.0545)	(0.0161)	(0.0423)
Staff Contrib.	0.0283	0.0230	0.0071^{*}
	(0.0242)	(0.0153)	(0.0031)
Prior Contrib.			−0.0087
			(0.0068)
Constant	1.1215^{**}	1.1300^{***}	0.2538
	(0.3354)	(0.1109)	(0.3142)
Update FE	Y	Y	Y
Wiki FE	Y	Y	
Contributor FE			Y
Day of Week FE	Y	Y	Y
Observations	6,979	6,979	233,402
Adj. R^2	0.7130	0.8294	0.2631
Within-R^2	0.0834	0.0800	0.00265

Robust standard errors in parentheses
Standard errors clustered at the level of the panel unit
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

A.4 Placebo Tests

Our identification strategy relies on game updates to act as an impulse to contributor activity. While in section 4.2.1 we show that the activity patterns around their releases are in line with our expectations, there may still be the concern that these patterns actually are a random artifact in our data. To address this, we perform placebo tests as an additional robustness check. In particular, we proceed as follows: First, for each game in our sample we make a number of random draws of dates that correspond to the number of updates[38] and the date range we use in our main analyses. Second, around each of these dates we construct a nine-day window consisting of the four days before and five days after and including the date. According to our approach laid out in section 3.4 we then regard the latter as *treated* observations, and the former as *control*. Third, from these windows we construct our placebo samples (at the wiki and contributor levels) which consist of all created random time windows. Lastly, we use these samples to rerun parts of our main analyses.

The results are presented in Table A4. Models 1 and 2 contain the results at the wiki level. In each, both the Post-dummy and its interaction with a platform's competitive position in a domain are statistically insignificant. Models 3 and 4 contain the results at the contributor level. Again, the Post-dummy, it's interaction with the competitive position, as well as their three-way interaction with the dummy indicating high-productivity contributors (in Models 6 and 7) are statistically indistinguishable from zero. Together, these placebo tests provide evidence for the notion that the activity patterns around update releases in our main analyses are not random artifacts, underpinning the validity of our identification strategy.

[38]For instance, for the game "Overwatch" we use 34 updates. In accordance, we draw 34 dates at random.

Table A4 Placebo Tests

	Wiki Level		Contributor Level	
	(1)	(2)	(3)	(4)
	Contrib.	Active Contributors	Contrib.	
Post	0.0033	-0.0157	0.0011	-0.0092
	(0.0141)	(0.0222)	(0.0111)	(0.0110)
Post × CP	-0.0223	0.0285	-0.0015	0.0098
	(0.0282)	(0.0285)	(0.0119)	(0.0116)
Post × HPC				0.0815
				(0.0543)
Post × CP × HPC				-0.0882
				(0.0574)
Active Others			0.0021	0.0031
			(0.0037)	(0.0039)
CP	1.0180^{***}	0.7789^{***}	0.3688	0.3193
	(0.0548)	(0.0424)	(0.0337)	(0.0283)
HPC				-0.2757^{*}
				(0.1241)
CP × HPC				0.3474^{*}
				(0.1349)
Wiki Size	0.1109^{**}	-0.0570^{*}	0.0669	0.0537
	(0.0311)	(0.0219)	(0.0983)	(0.0996)
Staff Contrib	-0.0047	0.0238^{+}	0.0003	0.0001
	(0.0229)	(0.0135)	(0.0029)	(0.0029)
Prior Contrib.			0.0198^{*}	
			(0.0098)	
Constant	0.2716	1.0826^{***}	-0.8481	-0.6225
	(0.1847)	(0.1391)	(0.8851)	(0.8803)
Update FE	Y	Y	Y	Y
Wiki FE	Y	Y		
Contributor FE			Y	Y
Day of Week FE	Y	Y	Y	Y
Observations	7,119	7,119	251,161	251,381
Adj. R^2	0.6286	0.8305	0.3190	0.3162
Within-R^2	0.0125	0.0341	0.00528	0.00483

Robust standard errors in parentheses
Standard errors clustered at the level of the panel unit.
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

A.5 Additional Figures and Tables

Figure A2 Article about "Monsters" from the Fortnite Wiki on Gamepedia

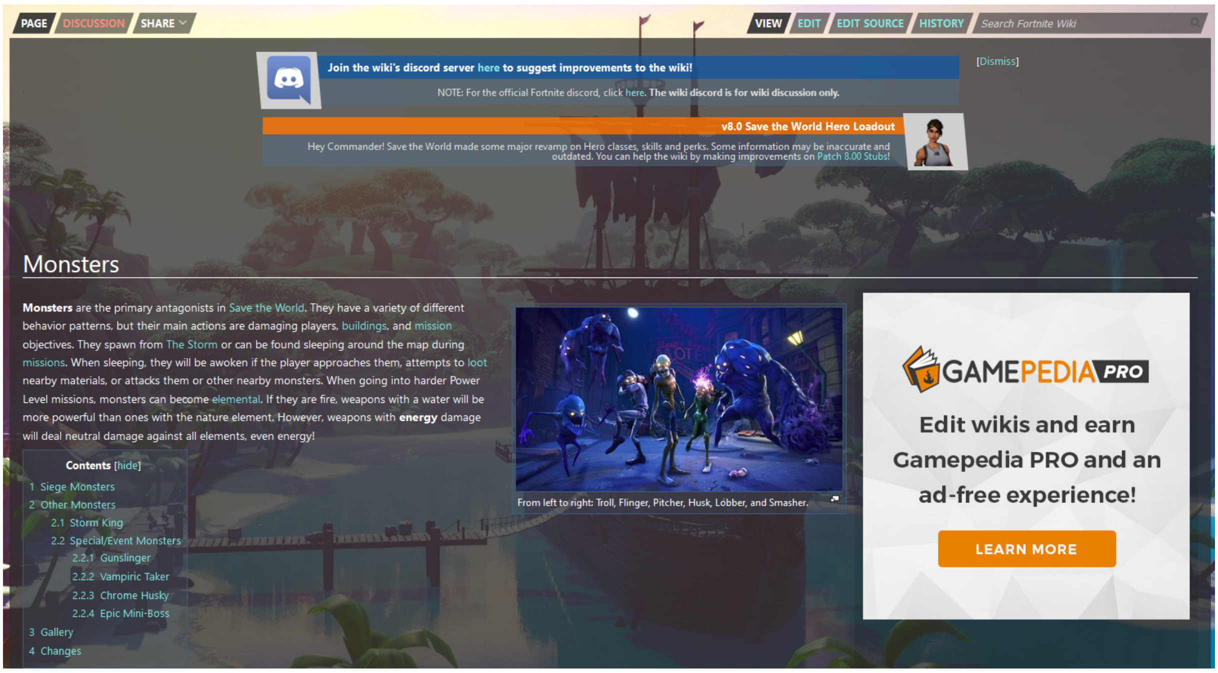


Figure A3 Contribution History for the "Monsters" Article from the Fortnite Wiki on Gamepedia

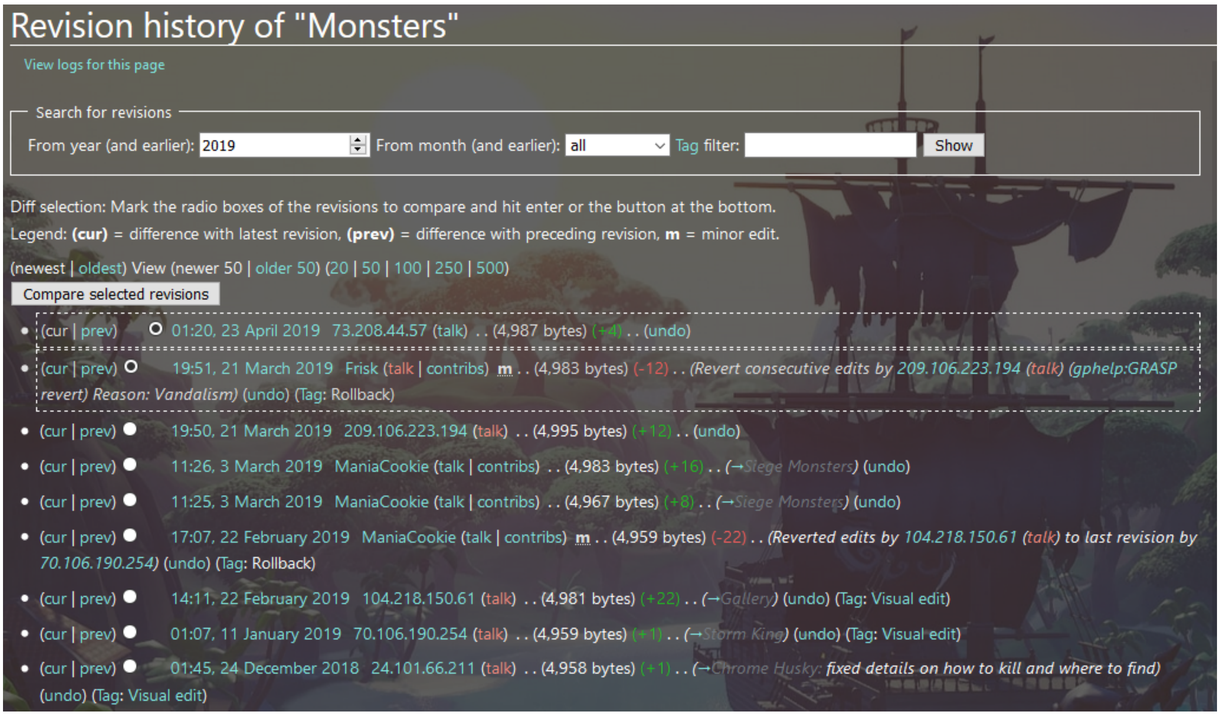


Figure A4 Difference between Revisions for the ”Monsters” Article from the Fortnite Wiki on Gamepedia

Table A5 Overview of Games and Wikis

	Gamepedia	Fandom
Ark: Survival Evolved	×	
For Honor	×	×
Fortnite	×	×
Hearthstone	×	×
Heroes of the Storm	×	×
Overwatch	×	×
Paladins	×	×
Rocket League	×	×
Sea of Thieves	×	×
Smite	×	×
Unturned		×
Warframe		×
Wildstar	×	×

Table A6 Correlation Matrix (Wiki Level)

		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
[1]	Contributions	1.0000								
[2]	Content Growth	0.8934	1.0000							
[3]	Active Contributors	0.9199	0.8058	1.0000						
[4]	Contrib. / Contributor	0.6185	0.4961	0.0432	1.0000					
[5]	Growth / Contributor	0.3921	0.9117	0.0706	0.5580	1.0000				
[6]	Post	0.0849	0.0780	0.0561	0.1224	0.0965	1.0000			
[7]	Competitive Position	0.6703	0.6569	0.6784	0.0572	0.0907	-0.0057	1.0000		
[8]	Wiki Size	0.0980	0.0817	0.1380	-0.0427	-0.0049	0.0682	-0.0217	1.0000	
[9]	Staff Contributions	0.3483	0.3355	0.3548	0.0490	0.0731	-0.0025	0.3744	0.0808	1.0000

Table A7 Correlation Matrix (Contributor Level)

		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
[1]	Contributions	1.0000								
[2]	Content Added	0.9138	1.0000							
[3]	Post	0.0384	0.0388	1.0000						
[4]	Competitive Position	-0.0134	-0.0202	-0.0003	1.0000					
[5]	High-Productivity Contributor	0.2255	0.1823	0.0001	-0.0517	1.0000				
[6]	Prior Contributions	0.2075	0.1683	0.0004	-0.1102	0.6483	1.0000			
[7]	Wiki Size	-0.0572	-0.0555	-0.0019	0.3901	-0.0303	0.0784	1.0000		
[8]	Staff Contributions	0.0316	0.0300	0.0710	-0.0124	-0.0006	-0.0125	-0.0000	1.0000	
[9]	Active Other Contributors	0.0534	0.0423	0.1616	0.4953	-0.0410	-0.1169	0.2857	0.1632	1.0000

Table A8 Relative Importance of Extensive and Intensive Margins: Simulation Parameters

	$\bar{n}_{\text{before}}$	$\bar{y}^{\text{HPC}}_{\text{before}}$	$\bar{y}^{\text{Non-HPC}}_{\text{before}}$	$s^{\text{HPC}}_{\text{before}}$	$s^{\text{HPC}}_{\text{after}}$	$\widehat{\Delta n}$	$\widehat{\Delta y}_{\text{HPC}}$	$\widehat{\Delta y}_{\text{Non-HPC}}$
				Contributions				
Laggard	1.03	10.96	8.91	0.28	0.30	0.03[a]	0.04[b]	0.01[b]
Neck-on-Neck	4.69	9.44	5.85	0.31	0.29	0.11[a]	0.08[b]	0.01[b]
Leader	5.01	16.51	5.88	0.33	0.32	0.20[a]	0.12[b]	0.02[b]
Exclusive	13.52	6.89	3.84	0.51	0.45	0.24[a]	0.15[b]	0.02[b]
				Content Growth[d]				
Laggard	1.03	740.62	775.71	0.28	0.30	0.03[a]	0.08[c]	0.04[c]
Neck-on-Neck	4.69	1735.49	1851.11	0.31	0.29	0.11[a]	0.22[c]	0.04[c]
Leader	5.01	3908.38	2899.74	0.33	0.32	0.20[a]	0.37[c]	0.06[c]
Exclusive	13.52	594.74	272.44	0.51	0.45	0.24[a]	0.46[c]	0.06[c]

[a] based on the estimated coefficients presented in Model 2 of Table 4.
[b] based on the estimated coefficients presented in Model 3 of Table 5.
[c] based on the estimated coefficients presented in Model 4 of Table A1.
[d] robustness check using content growth as alternative outcome of interest