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RESEARCH ARTICLE

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How Do Star Contributors Influence the Quality and Popularity of Artifacts in Online Collaboration Communities?

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Abstract

Online collaboration communities (OCCs) enable geographically distributed individuals, groups, and organizations to self-organize and contribute to community-owned artifacts. The significance of these artifacts has been underscored by recent advancements in large language models, which leverage community content for training sophisticated models across diverse domains, including productivity, healthcare, and education. This study investigates star contributors—individuals making disproportionately large contributions to focal OCC artifacts. Drawing on theories of collective action and strategic interactions, we hypothesize a curvilinear relationship between star contributors' contributions and both artifact quality and popularity. Utilizing data from over 21,000 open-source software projects between 2015 and 2019, we find: (1) an inverted U-shaped relationship between the number of star contributors and artifact quality, (2) an inverted U-shaped relationship between the number of star contributors and artifact popularity, (3) that a higher proportion of star contributors' contributions enhances artifact quality but not popularity, and (4) that environmental dynamism moderates the relationship between the number of star contributors and both artifact quality and popularity. This research advances the conceptualization of star contributors, offering a more nuanced understanding aligned with the fluid boundaries of OCCs compared to traditional core-periphery models. A key implication is that while star contributors positively impact artifact quality and popularity, an excessive proportion of their contributions negatively affects artifact quality.

Keywords: Online Collaboration Communities, Peer Production, Core, Periphery, Star Contributors, Hierarchical Linear Modeling, Open Source Software

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1 Introduction

Online collaboration communities (OCCs) enable geographically distributed individuals, groups, and organizations to self-organize and openly contribute towards a common goal, unbound by the contractual obligations typical of traditional organizations. OCCs are prevalent across different domains, including open-source software development (e.g., GitHub), knowledge management (e.g., Wikipedia), social networking (e.g., Reddit), and question-and-answer platforms (e.g., Stack Overflow, Quora), where they facilitate the creation of shared artifacts (Forte & Lampe, 2013). OCCs also have significant economic and generative implications, as evidenced by Microsoft's acquisition of GitHub for $7.5 billion in 2018 and the utilization of OCC-generated data in the development of recent large language models such as ChatGPT and Google Bard (Brown et al., 2020).

The sustenance and success of an OCC depend on contributions from a diverse group of non-contracted individual contributors (Butler, 2001; Chengalur-

Smith et al., 2010; Mindel et al., 2018). Prior research has explored several factors that influence contribution to OCCs, such as intrinsic and extrinsic motivation factors (Wasko & Faraj, 2005; Wasko et al., 2009), quality and deficiency signals emitted by the artifact (Setia et al., 2020), and economic and health-related shocks (Kummer et al., 2020; Malgonde et al., 2023). A common theme in this body of work is the classification of contributors based on access rights (Lin & Chen, 2018; Lin & Wang, 2020; Setia et al., 2012): core contributors, who own artifacts, hold power over design decisions, and/or manage processes related to the artifact, and peripheral contributors, whose contributions are evaluated by core members before assimilation.

However, this traditional conceptualization of core and peripheral contributors presents four major limitations in the context of OCCs. First, empirical evidence suggests that contributors without core status may make disproportionately large contributions to an artifact (Kuk, 2006; Mindel et al., 2018). Second, OCC artifacts are characterized by fluidity, with a constant inflow and outflow of resources such as skills and ideas. Consequently, a contributor's level of contribution may vary significantly over the artifact's lifespan (Faraj et al., 2016). Third, a contributor's activity across the platform may differ from their contribution behavior to a specific artifact; for example, a contributor might only participate in discussions related to Python programming. Finally, as contributors increase their level of contribution, they gain influence, resulting in the development of lateral authority (Dahlander & O'Mahony, 2011) due to the flat hierarchical structures prevalent in OCCs.

These limitations highlight the need for a more nuanced understanding of contributor roles in OCCs. Rullani and Haefliger (2013) suggest that, unlike the core-periphery distinction based on access rights, a categorization based on contributions provides a clearer differentiation. In response to the limitations of the traditional core-periphery model, we conceptualize[1] star contributors as individual contributors making a disproportionate number of recent contributions to a focal OCC artifact, relative to the average contributor. This approach allows us to identify contributors whose presence can significantly impact key outcomes in collaborative work settings (Call et al., 2021; Taylor & Bendickson, 2021). The concept of "stars" has gained traction within information systems research (Bockstedt et al., 2022; Foerderer et al., 2023), primarily in the context of non-collaborative online communities such as innovation contest platforms, with a focus on platform-wide identification of star contributors.

This paper investigates three related but distinct questions: (1) How do the number of star contributors impact OCC artifact quality and popularity? (2) How does the relative proportion of star contributors' contributions impact OCC artifact quality and popularity? (3) How does the environmental dynamism, defined as the rate of change in the OCC content, moderate the effect of star contributors on OCC artifacts' quality and popularity?

These questions are important and timely for three reasons. First, OCCs are crucial for knowledge management, enabling organizations to incorporate diverse perspectives and facilitate open innovation (Ahuja, 2000; Kankanhalli et al., 2017). However, the fluidity of OCCs, characterized by the constant inflow and outflow of resources such as contributors' skills (Faraj et al., 2011), necessitates an understanding of how different categories of contributors, particularly star contributors, influence artifact success. Second, prior work has documented unequitable participation in OCCs (Mindel et al., 2018). For example, Kuk (2006, p. 1031) observed that "much of the OSS development is realized by a small percentage of individuals despite the fact that there are tens of thousands of developers available." This highlights the need for managerial guidance on the role of star contributors in the success of OCC artifacts. Finally, we analyze the impact of star contributors on two key measures of OCC artifact success from the literature: (1) quality, which entails making improvements to the artifact such as fixing defects (Jarczyk et al., 2018; Setia et al., 2012), and (2) popularity (Weng & Soh, 2023), which reflects the level of platform users' interest in the artifact. These measures are important indicators of the technical, social, sustenance, generativity, and use of OCC artifacts (Butler, 2001; Chengalur-Smith et al., 2010; Mindel et al., 2018; Setia et al., 2020).

OCC artifact quality refers to the evolving state of the artifact and is measured by the number of outstanding errors, issues, edits, and fixes to issues raised by the community. In OCCs, community members contribute to identifying quality-related issues and/or provide contributions to address quality-related issues. OCC artifact popularity is the artifact's status within the OCC and is measured based on the number of community members interested in the artifact. Interest may be measured along multiple dimensions, such as contribution, tracking (community members track the progress and activities related to the artifact), and marketing (the artifact is highly discussed within the community).

To investigate the role of star contributors in OCC artifact success, we analyzed longitudinal data from GitHub, a popular open source software platform, spanning the period between 2015 and 2019. Our results suggest (1) a

[1] Our conceptualization of star contributors aligns with prior conceptualization of core-periphery contributors, where star contributors align with core and non-star contributors align with peripheral contributors.

curvilinear (inverted U-shaped) relationship between the number of star contributors and OCC artifact quality, (2) a curvilinear (inverted U-shaped) relationship between the number of star contributors and OCC artifact popularity, and (3) a moderating effect by the relative proportion of star contributors' contributions and the level of environmental dynamism in an OCC artifact development.

This study makes two major contributions. First, it advances a novel conceptualization of star contributors in OCCs that addresses the rigidity of the extant conceptualization of core-periphery. Specifically, unlike the core-periphery distinction using access rights, our contributions-based categorization provides a "clear core-periphery distinction" (Rullani & Haefliger, 2013, p. 942) by internalizing the fluid characteristic of OCCs. Further, whereas the core-periphery approach generally assumes a fixed proportion (usually based on the 80-20 rule) of contribution between core and peripheral contributors, our approach relaxes this assumption and considers a more dynamic proportion of contribution for star and non-star contributors. Second, while existing literature has examined the impact of peripheral contributors (Setia et al., 2012), emphasized the role of core contributors (Colazo & Fang, 2010; Jiang et al., 2019; Moqri et al., 2018), and acknowledged the general importance of contributions to OCC sustenance (Butler, 2001; Chengalur-Smith et al., 2010; Mindel et al., 2018), this study specifically addresses the gap in understanding the effect of star contributors' contributions on OCC artifact quality and popularity. Notably, this is one of the first studies to examine the role of star contributors in the context of OCCs, a non-traditional organizational form.

2 Theoretical Background

Three areas of research are relevant to our study: (1) online collaboration communities, (2) categories of contributors to OCCs, and (3) star performers in collaborative work.

2.1 Online Collaboration Communities

Online collaboration communities are communities of innovation (Safadi et al., 2021) where geographically distributed individuals (contributors) coordinate and collaborate to create artifacts—such as products or services—of economic and social value that are often freely available for consumption. OCCs span multiple domains, including open source software, question-and-answer, and knowledge systems, among others. The success and sustenance of OCCs are dependent on member contributions (Butler, 2001; Chengalur-Smith et al., 2010; Mindel et al., 2018), which can take various forms depending on the nature, goals, and protocols of the OCC. For instance, edits, comments, and commits to open source software projects are considered contributions (Daniel et al., 2013; Kummer et al., 2020; Malgonde et al., 2023; Setia et al., 2020; Setia et al., 2012), whereas asking or responding to a question is considered a contribution in question-and-answer OCCs (Safadi et al., 2021; Xu et al., 2020). Furthermore, the notion of artifact changes with the OCC domain (Kane & Ransbotham, 2016; Levine & Prietula, 2014). For example, in a question-and-answer OCC, the artifact typically comprises the comments and answers associated with a focal question (Safadi et al., 2021), while in open source software, the artifact represents the focal project along with its associated issues, code commits, and comments (Malgonde et al., 2023).

Much of the research on OCCs has examined why contributors contribute and the effect of their contributions on OCC outcomes. Studies investigating contribution behavior highlight consumption and motivation as key factors (Kane & Ransbotham, 2016; Lakhani & Von Hippel, 2003). Kane and Ransbotham (2016) describe a recursive relationship where individuals first consume the artifact, identify a gap following consumption, and then contribute to address that gap. Contributors may be driven by intrinsic motivations, such as gaining a sense of community, deriving satisfaction from their passion for the OCC, or experiencing joy from working on its challenges (Lakhani & Von Hippel, 2003). Extrinsic motivations also play a role; contributors may seek favorable outcomes such as enhanced status and reputation within the community (Levina & Arriaga, 2014) or offline gains in the labor market (Huang & Zhang, 2016; Xu et al., 2020). Beyond intrinsic and extrinsic motivations, prior work identifies external factors, such as unemployment or health-related shocks, that affect contribution dynamics (Kummer et al., 2020; Malgonde et al., 2023). Research examining OCC outcomes has considered various technical and social outcomes for artifacts, such as take-off (Setia et al., 2020), copies for consumption (Jiang et al., 2017), artifact quality (Setia et al., 2012), and popularity (Weng & Soh, 2023).

Finally, prior work has recognized the influence of the environmental dynamism of OCC artifacts on outcomes (Jones et al., 2004; Levina & Arriaga, 2014). Environmental dynamism refers to the extent to which an artifact's development necessitates rapid and continuous updates. OCC artifacts exhibiting high environmental dynamism require consistent and rapid contributions to meet the need for frequent updates (Baskerville et al., 2003). For example, operating systems and web browsers' need for software patches on security vulnerabilities, and fast-paced policy-related discussions on the use of generative technology on Stack Overflow (Overflow, 2023). Conversely, OCC artifacts with low environmental dynamism are characterized by slower evolution, prioritizing organic stability over rapid changes. Examples include embedded systems software (e.g., in devices and appliances) and firmware. Table 1 summarizes key studies from prior work.

Table 1. Related Work

Paper	OCC context	Key variables	Contributors' classification	Star contributor conceptualization	Key findings
Lin and Wang (2020)	Online encyclopedia (Wikipedia)	• Article quality • Number of core members • Content revised by occasional participants	• Core member (cumulative edits above 80% *across* platform) • Occasional participants	• Based on contribution frequency (cumulative edits above 80% *across* platform) • Static classification	• Contributions by core participants positively impact article quality.
Safadi et al. (2021)	Technical question and Answer platform (Stack Overflow)	• Valued knowledge contributions • Social embeddedness • Epistemic marginality	• Embedded contributors (central to community network) • Marginal contributors (peripheral in the community network)	• Based on location within the community network • Dynamic classification	• High socially embedded and epistemically marginal participants contribute valued knowledge. • Among epistemically marginal participants, socially embedded participants provide highly valued knowledge contributions.
Setia et al. (2012)	Open source software (Source Forge)	• Open source software product quality and product diffusion • Participation of peripheral developers and open source software product maturity	• Core developers (retain *control* and *authority* over key aspects of development) • Peripheral developers (*volunteer* contributors without hierarchical or contractual controls)	• Based on control and authority over key aspects of development • Dynamic classification	• Peripheral contributors positively contribute to products' quality and diffusion, especially in OSS products that are at the mature stage.
This paper	Open source software (GitHub)	• Quality and popularity of OCC artifact • Number of star contributors • Relative proportion of star contributions • OCC artifact's environmental dynamism	• Star contributors (disproportionate contributions to an OCC artifact)	• Based on disproportionate contribution frequency • Recency of contributions • Dynamic classification	• Inverted U-shaped relationship between the number of star contributors and OCC artifact's quality and popularity • Relative proportion of star contributors' contributions moderate the relationship between the number of star contributors and the artifact's quality and popularity

Note: This table illustrates the key differences of this study in comparison to selected studies from the literature and does not provide an exhaustive list of related work.

2.2 Categories of Contributors

Research on OCCs has identified core and periphery contributors as the broad set of contributors based on access rights (Rullani & Haefliger, 2013). First, core contributors possess the authority to edit, maintain, design, lead, and evaluate others' contributions to the OCC artifact. Examples include project owners in open source projects, Wikipedia page administrators, Listserv owners, and administrators in Usenet. Related conceptualizations of core contributors have considered their position in the OCC network (Daniel et al., 2013; Safadi et al., 2021) and their level of contribution (Daniel et al., 2013; Lin & Wang, 2020; Setia et al., 2012). Second, peripheral contributors make limited contributions, typically localized in scope, size, and quantity. For example, Setia et al. (2012) operationalized peripheral contributors as those contributing "between 0% to 12% percent of the total code contributions" (p.149). Dahlander and O'Mahony (2011) suggested a dynamic transition, where increased contributions can elevate a peripheral contributor to the core, granting them greater influence over the OCC artifact.

In the context of open source software (empirical context for our study), the distinction between core and peripheral contributors is particularly evident in code and communication channels. Core contributors have direct access to modify the project's codebase, while peripheral contributors' code changes require core member approval. However, communication channels, such as comments and issue reporting, are generally more accessible. Therefore, "a joint analysis of [code and communication] channels can thus lead to the identification of a clear core-periphery distinction" (Rullani & Haefliger, 2013, p. 942).

2.3 Conceptualizations of Star Contributors

Star contributors have been conceptualized in traditional organizational settings, such as teams, and platform-based settings, such as contests. In traditional organizational studies, conceptualizations of *stars* have focused on high-performing, visible team members with status and significant social capital (Call et al., 2021), effective boundary spanners who assimilate tacit knowledge (Hess & Rothaermel, 2011), or highly productive and visible individuals (Groysberg et al., 2008, 2011). However, these conceptualizations have limited applicability to OCC context due to their non-collaborative contexts.

In platform-based settings, stars are often identified as top-ranked contestants (Bockstedt et al., 2022; Zhang et al., 2019) or contributors with significantly higher demand than their peers (Foerderer et al., 2023). However, these conceptualizations have limited applicability to OCCs because they primarily (1) focus on non-collaborative contexts (i.e., contributors compete rather than collaborate), and (2) take a platform-wide (i.e., use global ranking) notion of stars.

Studies related to the OCC context have also considered the notion of star contributors. For example, Lin and Wang (2020) conceptualized core members as those who are "frequently involved in the editing of the article" (p. 329) and occasional members as those who "occasionally participate in editing work" (p. 329). However, this frequency-based approach (e.g., classifying contributors accounting for 80% of cumulative contributions as stars) has limitations. Consider three contributors, A, B, and C, with the following contribution patterns over 10 periods: User A contributes regularly (e.g., 20 edits weekly for the first five weeks), totaling 100 contributions; User B contributes intermittently (e.g., 100 contributions in week 1, 150 in week 2, and none thereafter), totaling 250 contributions; and User C contributes consistently (e.g., 8 edits weekly), totaling 80 contributions. The respective contribution shares are 23.2%, 58.1%, and 18.6%. Applying the 80% threshold as used in Lin and Wang (2020), both Users A and B are classified as core contributors. This approach, however, presents two issues: (1) it fails to distinguish between Users A and C, despite their comparable contributions, and (2) it disregards the recency of contributions, overlooking User C's consistent engagement over all periods, unlike User A's limited, early contributions. In dynamic OCCs that evolve over extended periods, a static, threshold-based approach can misidentify star contributors.

Beyond comparability and recency issues, the 80% threshold implies: (1) the presence of core and occasional contributors in every project, as contributions are always ranked, with the top 80% deemed core, and (2) a constant 80% contribution share for core contributors. Our conceptualization departs from these along two dimensions: (1) It accounts for scenarios with no star contributors (i.e., when contributions are comparable), and (2) it recognizes varying star contribution proportions. For example, Contributors A, B, and C with 6, 2, and 2 contributions, respectively, are classified by Lin and Wang (2020) as having two core contributors (A and either B or C) to meet the 80% threshold. Our approach identifies User A as the sole star contributor, accounting for 60% of contributions.

Table 2 summarizes prior conceptualizations of star contributors in the OCC context. Our contribution-based conceptualization aims to address these limitations by (1) moving beyond the rigid core-periphery classification, (2) accounting for the recency of contributions, and (3) accounting for the comparability of contributions.

2.4 Performance Outcomes Associated With Star Performers in Collaborative Work

Research on star performers has yielded mixed results, demonstrating both positive (Grigoriou & Rothaermel, 2014; Rothaermel & Hess, 2007) and negative (Groysberg et al., 2008) impacts. While star performers can enhance innovation output and facilitate knowledge transfer among peers (Burke et al., 2007; Grigoriou & Rothaermel, 2014; Rothaermel & Hess, 2007), they have also been linked to decreased firm value and diminished team effectiveness (Groysberg et al., 2008; Groysberg et al., 2011; Lam et al., 2011). More recent studies have explored nonlinear effects, revealing nuanced impacts on team and peer performance (Call et al., 2021; Taylor & Bendickson, 2021). However, this body of research primarily focuses on traditional organizational settings, which differ significantly from open collaborative communities (OCCs) where formal employment contracts are rare.

Table 2. Conceptualizations of Star Contributors in Online Collaboration Communities

Label	Conceptual definition	OCC context and example	Related papers
Core versus periphery	Core members are contributors who are officially listed as core members of the artifact.	Context: open source software, question and answer Example: Creator of an open source software project	Dahlander & Frederiksen (2012); Setia et al. (2012); Rullani and Haefliger (2013);
Embedded versus peripheral	Using a network of contributors, core embedded members are central nodes.	Context: open source software, online encyclopedia Example: A node with a high centrality score in a network of contributors across OSS projects	Ahuja (2000); Wasko & Faraj (2005); Grewal et al. (2006); Feller et al. (2008); Singh et al. (2011); Peng (2019); Safadi et al. (2021)
Star versus non-star (at the platform level)	Disproportionately large contributions across all contributors.	Context: online encyclopedia Example: Contributors who account for first 80% of the cumulative contributions after sorting contributors in a descending order	Lin & Wang (2020)
Star versus non-star (at the artifact, community, or platform level)	Recency and disproportionality of contributions across the set of contributors in a period.	Context: open source software Example: Contributors who account for a disproportionate (e.g., more than 3 times the average contributor) size of contributions in a period.	This paper

Note: This table classifies prior conceptualizations of *star* contributors in OCC contexts. Also, this table provides a conceptualization of related concepts such as core contributors and embedded contributors that refers to central contributors (e.g., decisions related to project direction) to the focal OCC artifact. Studies in contexts characterized by non-collaborative artifact development, organizational setting, and/or adopting a platform-level conceptualization of stars are not considered due to their misalignment with the OCC context.

In their review of the literature on star performers, Asgari et al. (2021) suggested that many fields have a vested stake in the study of star performers, as they may have certain strategic implications and may play a significant role in value creation under a range of contexts and environments. Within information systems, recent studies have examined star performers on online platforms, primarily in non-collaborative, competitive environments (e.g., Bockstedt et al., 2022; Foerderer et al., 2023; Zhang et al., 2019). These platforms, such as online contests and streaming services, feature star performers competing against other users, unlike OCCs, where *collaboration* is central to artifact creation. Research in these competitive contexts suggests that star performer presence can negatively affect participation (Bockstedt et al., 2022; Zhang et al., 2019) and that their departure can hinder overall production (Foerderer et al., 2023). However, these findings may not translate to collaborative online environments, where star performers contribute alongside others.

Two key points emerge from this review of star performer literature. First, most of the research is rooted in traditional offline organizational settings, underscoring the need to explore diverse contexts such as OCCs. Second, while studies in platform settings exist, they have been confined to non-collaborative settings with platform-wide star definitions and neglect the quality and popularity of collaboratively produced content.

2.5 Research Gap

This research addresses two significant gaps in the existing literature. First, Faraj et al. (2015, p. 395) highlight the discrepancy between formal roles and actual contribution, noting that "even when formal roles do exist in online communities, such as listserv owner and administrator, they are often not the ones who make the most significant contributions (Butler et al. 2008)." This observation underscores the dynamic nature of contributor behavior, which can fluctuate based on artifact specifics, external factors, motivations, and time. Consequently, rigid core-periphery classifications fail to capture the fluid boundaries inherent in OCC boundaries (Faraj & Sproull, 2000). To address this, our research advances a contribution-based conceptualization that identifies contributors providing recent and disproportionately high numbers of contributions. While prior conceptualizations have typically assumed a fixed ratio of contributions (e.g., 80-20 rule) in their core-periphery classifications, our approach assumes and models for variability in the ratio of contributions while also considering the recency of contributions. Moreover, our conceptualization also allowed us to examine how the variability in the proportion of contribution across the core and periphery can affect OCC outcomes, which has not been explored in the literature.

Second, while the impact of contributors on OCC quality is recognized (Setia et al., 2012), the effect of disproportionate contributors (stars) on artifact quality and popularity remains underexplored. This gap necessitates longitudinal data to empirically examine these effects.

This paper further distinguishes itself from prior work in two key aspects. First, studies within the open-source software context often use *stars* to denote the GitHub feature, indicating user interest in a project. For instance, Jarczyk et al. (2018) consider stars to be the number of GitHub platform users that are watching (similar to bookmarking) the focal OSS project, whereas Medappa and Srivastava's (2019) use of stars "indicates approximately the number of people who are interested in and show support for that project" (p. 774). In contrast, our study defines stars as individual contributors who provide a disproportionate share of contributions to a specific OSS project. Second, unlike research on star contributors in traditional settings, this paper investigates their role in a collaborative context, adopts a content-level perspective of stars, and focuses on their impact on both the quality and popularity of collaboratively produced artifacts.

3 A Theoretical Framework of Star Contributors

This section outlines the theoretical framework for understanding star contributors in open collaborative communities (OCCs). In this section, we discuss a theoretical framework for star contributors. In Section 3.1, we conceptualize and discuss star contributors across the artifact, community, and collaboration platform. In Section 3.2, we employ the concept of unequitable contributions and the theory of collective action to explore how star contributors influence other community members. Section 3.3 discusses the impact of environmental dynamism on the influence of star contributors on OCC artifacts. Finally, Section 3.3 provides our study hypotheses, derived from the theoretical framework.

3.1 Star Contributors and Open Collaboration Communities

We conceptualize *star* contributors as individuals providing recent and disproportionate numbers of contributions to a focal OCC artifact. This conceptualization can be extended to the collaboration platform, community, or individual artifact, depending on the OCC's context. At the platform level, star contributors provide a disproportionate number of contributions across the entire platform. For example, a star contributor on Stack Overflow might provide a high number of questions, answers, edits, and votes across diverse topics (Xu et al., 2020). Within a collaboration community, star contributors provide a disproportionate number of contributions to a specific community. For instance, a star contributor on Reddit's personal finance subreddit might contribute significantly more posts, comments, and votes than other members (Burtch et al., 2022). Finally, at the artifact level, a contributor might provide a disproportionate number of edits to a specific Wikipedia article but have minimal contributions to other articles, making them a star contributor for that article but not the platform as a whole (Lin & Wang, 2020).

This multilevel conceptualization of star contributors has two important implications. First, platform-level star contributors primarily concern platform owners, with limited direct impact on individual contributors. For example, while a list of top GitHub contributors might be interesting, it's unlikely to significantly affect contributions to individual projects (Wasko & Faraj, 2005). Similarly, identifying top contributors to the Python programming language community may have limited influence on individual contributions (Wasko et al., 2009). However, at the artifact level, star contributors significantly influence the artifact's outcomes and signal its dynamics to the broader platform community. Second, unlike our contribution-based conceptualization, which applies across artifact, community, and platform levels, the traditional core-periphery model (Setia et al., 2012) is limited to the artifact level. This broader applicability enhances the generalizability of our approach within OCC contexts.

Beyond its multilevel (platform, community, and artifact) applicability, our conceptualization of stars introduces the notion of variability in the level of contributions that make a star because the identification of stars should be dependent on both the OCC artifact and time. The level of contribution it takes a contributor to be identified as a star in one OCC artifact during a particular period may not be the same for another OCC artifact because of the differing nature of the OCC artifacts. The notion of variability in the proportion of the overall OCC contributions by stars further provides insights into a context characterized by contributor and contribution fluidity. Such fluidity may result in periods in the OCC artifact lifecycle that may have no stars because contributions are comparable among contributors.

Star contributors are driven to maintain high performance levels by a combination of extrinsic and intrinsic motivations. Extrinsically, they seek to stand out, gain attention, increase their visibility, and acquire other positive externalities (Huang & Zhang, 2016; Xu et al., 2020). Intrinsically, they derive benefits such as happiness, satisfaction, and a sense of community. In OCC artifact development, star contributors are recognized for their contributions and may gain increased authority, privileges, or even governing positions (Daniel et al., 2013).

3.2 Unequitable Contributions to Open Collaboration Communities

Our conceptualization of star contributors is rooted in the phenomenon of unequitable contributions observed in OCCs, where a small percentage of contributors produce a disproportionately large share of the output (Kuk, 2006; Mindel et al., 2018). Unequitable contributions have both positive and negative implications. Positively, they can lead to better coordination, tighter coupling, and improved skill-task fit, as specific contributors are often better suited to specific contribution needs (Hann et al., 2013). Negatively, they can introduce vulnerability due to the inherent fluidity of OCCs, characterized by unrestricted resource inflow and outflow (Faraj et al., 2011), and facilitate free-riding behavior, where individuals benefit without contributing.

The theory of collective action (Oliver & Marwell, 1988) posits that unequitable contributions by a small, heterogeneous group can generate the critical mass necessary for widespread collective action within OCCs. For instance, a small group's initial efforts can attract broader community participation. However, empirical evidence from OCCs demonstrates a tendency for contributions to concentrate among a subset of members (Kuk, 2006; Von Krogh et al., 2012). The concept of strategic interaction suggests that individuals make strategic decisions about their participation (Oliver & Marwell, 1988). Specifically, individuals are drawn to resourceful, successful, popular communities and individuals that align with their objectives, while avoiding participation when they perceive a risk of failure. Consequently, "strategic interaction has not only resulted in participation inequality but also concentrated OSS participation on the types of epistemic interactions that matter most to OSS development" (Kuk, 2006, p. 1033).

In Section 3.4, we examine unequitable contributions and draw on the theory of collective action to identify underlying theoretical mechanisms that can explain the impact of star contributors on OCC artifact quality and popularity.

3.3 Star Contributors and Environmental Dynamism

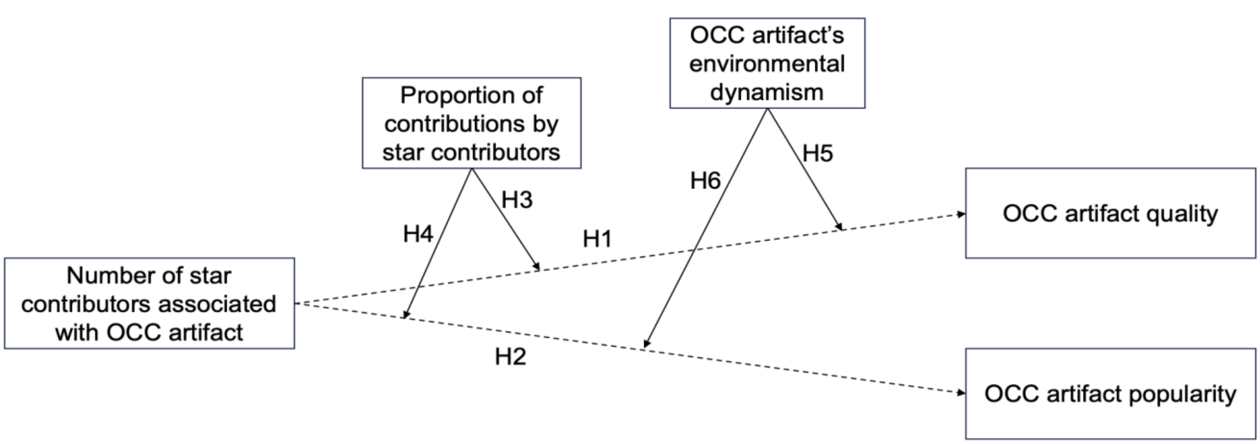
The artifact's environment is a significant contextual factor that can influence the performance of star contributors (Aguinis & O'Boyle, 2014). OCC artifacts typically operate within either relatively static or dynamic environments (Baskerville et al., 2003). Static environments are characterized by predictable resources, tasks, and a plan-driven development approach (Harris et al., 2009). Examples include incremental feature additions to existing artifacts or applications where rapid market entry is not critical. Conversely, dynamic environments are marked by uncertainty regarding resources and tasks, necessitating flexible approaches that adapt to changing conditions (e.g., speed to market, critical updates) and user feedback (Baskerville et al., 2003).

In dynamic environments, adaptive and iterative approaches, such as agile methodologies, are favored for their ability to incorporate user feedback and tame uncertainty (Harris et al., 2009). These approaches emphasize collaboration and require specific resources, such as team members with domain and application expertise. The primary goal is to facilitate timely responses to environmental dynamism (Maruping et al., 2009).

Prior research suggests that star performers are particularly valuable in dynamic environments (Asgari et al., 2021; Campbell, 2014). In peer production models, especially OCC software development, we argue that the disproportionate size and recency of star contributors' contributions are crucial for navigating increasing dynamism. Specifically, a high proportion of recent contributions equips star contributors to identify critical challenges, propose effective solutions, rapidly incorporate user feedback, and communicate effectively with the community (Cram et al., 2016).

3.4 Hypotheses

Figure 1 illustrates our research model.



Note: Dashed lines indicate nonlinear relationships.

Figure 1. Research Model

3.4.1 Effect of Star Contributors on Artifact Quality

We hypothesize that an increase in the number of star contributors increases the quality of focal OCC artifacts up to a certain threshold, beyond which an increase in the number of star contributors decreases the quality of focal OCC artifacts. While contributions from star contributors address quality-related issues (Setia et al., 2012; Von Krogh et al., 2012), a scarcity of such contributors can impede OCC quality. This is due to factors such as concentrated workload leading to cognitive strain, limited resource availability, the potential for select contributors to dominate discussions, and constraints on the exploration of diverse design solutions (Jones et al., 2004; Kuk, 2006). Conversely, an excessive number of star contributors may also negatively affect OCC quality. This can result from heightened coordination costs, diminished group cohesiveness, and increased inefficiencies stemming from overlapping or redundant efforts (Overbeck et al., 2005). Furthermore, as contributions increase, so does the contributor's influence over the OCC artifact (Dahlander & O'Mahony, 2011). Consequently, an overabundance of star contributors can escalate tensions regarding the artifact's design and overall direction (Faraj et al., 2011), fostering dysfunction and stagnation, which ultimately compromises artifact quality. Hence, we hypothesize:

H1: The *number of star contributors* contributing to an online open collaboration community artifact is ***curvilinearly*** related to the artifact's *quality*, such that a moderate number of star contributors is associated with the highest quality (inverted U-shaped relationship).

3.4.2 Effect of Star Contributors on Artifact Popularity

The popularity of an OCC artifact is influenced by community interest, which is driven by motivations such as learning, utilizing the artifact's solutions (e.g., addressing a novel problem), and contributing to its development. While static artifact properties such as topic, programming language, and administrator influence popularity, we hypothesize that the number of star contributors also plays a significant role. Specifically, we propose an inverted U-shaped relationship between the number of star contributors and OCC artifact popularity: Increasing the number of star contributors enhances popularity up to a critical threshold, beyond which further increases lead to a decline.

Initially, an increasing number of star contributors signals the presence of resourceful individuals. Drawing upon the theory of strategic interactions (Oliver & Marwell, 1988), the concentration of resourceful individuals attracts community members seeking connections. Consequently, the artifact's popularity, as measured by user interest, increases. Furthermore, platform mechanisms reinforce this trend. In collaborative settings, platform-level star contributors exert influence and attract attention to OCC artifacts (Blincoe et al., 2016; Lee et al., 2013; Weng & Soh, 2023). When star contributors possess significant followings, their contributions trigger notifications, driving followers to explore the artifact and boosting its popularity (Blincoe et al., 2016; Lee et al., 2013; Weng & Soh, 2023). Even when star contributors lack large followings, their activity signals the artifact's active status to platform users. OCC platforms often highlight recently active or highly contributed artifacts, thereby increasing visibility. Thus, an increase in star contributors leads to increased artifact popularity.

However, based on the theory of collective action (Oliver & Marwell, 1988) and strategic interactions (Kuk, 2006), users strategically select OCC artifacts to connect with resourceful individuals. As the number of star contributors surpasses a critical threshold, users face challenges in identifying contributors aligned with their participation goals. Additionally, reciprocity, a crucial mechanism for epistemic interactions in OCC artifacts (Ye et al., 2018), is affected. While an increasing number of star contributors can facilitate reciprocity by distributing the interaction load, an excessive number diminishes the bandwidth for meaningful reciprocal discussions. Hence, we hypothesize:

H2: The *number of star contributors* contributing to an online open collaboration community artifact is ***curvilinearly*** related to the artifact's *popularity*, such that a moderate number of star contributors is associated with the highest increase in popularity (inverted U-shaped relationship).

3.4.3 Moderating Role of the Proportion of Star Contributors' Contributions on Artifact Quality

We propose that the curvilinear relationship between the number of star contributors and OCC artifact quality is moderated by the relative proportion of star contributors' contributions. Specifically, we identify distinct mechanisms that explain both the increase and decrease in artifact quality associated with varying proportions of star contributor involvement.

We identify four mechanisms that explain the increase in artifact quality. First, OCCs are characterized by flat organizational structures, where coordination is paramount (Faraj et al., 2015). An increased proportion of star contributors' contributions reduces coordination costs (Lerner & Tirole, 2005). These costs, encompassing resource allocation for minimizing redundancy, ensuring comprehensive problem coverage, and aligning disparate contributions, directly impact available resources, thereby positively influencing OCC quality. Second, a disproportionate number of contributions from star contributors reduces the resource burden for community reciprocation and engagement. Star contributors, having internalized OCC norms, require less engagement, freeing resources for artifact improvement. Third, equitability in OCC highlights the importance of aligning contributors' skills to the task at hand (Kuk, 2006; Mindel et al., 2018). Increased star contributor involvement enhances this alignment, leading to improved task execution and artifact quality. Finally, star contributors exert a "peer productivity effect," motivating non-star contributors to increase their productivity (Falk & Ichino, 2006; Ichniowski & Preston, 2014). Mas and Moretti (2009) suggest that the increase in productivity by low-performing workers is driven by the need to minimize productivity differentials, hence leading to an increase in overall team productivity with a positive effect on outcomes. In the OCC context, non-star contributors internalize star contributors' higher proportion of total contributions to improve their own contributions and minimize the productivity differential. The increased contribution will lead to more issues being resolved and defects fixed in the OCC artifact, and by extension, will increase the quality of the OCC artifact.

A concentration of star contributors' contributions can negatively impact OCC artifact quality through four key mechanisms. First, it can increase the artifact's vulnerability to contributor attrition (Mindel et al., 2018). Attrition, in this context, refers to contributors diverting their efforts, driven by personal motivations or external factors, away from the focal artifact to other community projects or entirely outside the community. Consequently, fluctuations in star contributors' contributions can significantly destabilize the artifact. Second, an excessive concentration of contributions can overwhelm contributors and strain available resources, reducing the time allocated for thorough design exploration (Brooks, 1987). This time constraint can lead to an increase in errors associated with proposed solutions. Third, the resulting increase in errors can create a critical dilemma: prioritizing progress by limiting features or addressing existing errors. Both choices negatively affect artifact quality. Finally, a disproportionate reliance on star contributors can generate skill gaps, where the available expertise does not align with the necessary tasks. This misalignment can lead to suboptimal solutions, ultimately diminishing the overall quality of the OCC artifact.

In summary, these arguments suggest that the effect of star contributors on OCC artifact quality will vary with the relative proportion of star contributors' contributions to the artifact. Hence, we hypothesize:

H3: The *relative proportion of the star contributors' contributions* ***moderates*** the relationship between the *number of star contributors* and artifact *quality*, such that an increase in the relative proportion of their contributions ***strengthens*** the effect on artifact quality (i.e., the curve is more pronounced).

3.4.4 Moderating Role of the Proportion of Star Contributors' Contributions on Artifact Popularity

We propose that the curvilinear relationship between the number of star contributors and OCC artifact popularity is moderated by the relative proportion of star contributors' contributions. Drawing upon the theory of collective action (Oliver & Marwell, 1988) and strategic interactions (Kuk, 2006), users strategically associate with resourceful individuals to achieve participation objectives, such as learning artifact norms before contributing, and to engage with successful artifacts (Kuk, 2006; Oliver & Marwell, 1988). As the proportion of star contributors' contributions increases, community members can more readily identify and connect with these resourceful individuals and the associated OCC artifact, due to its perceived likelihood of success. In practice, a disproportionate increase in individual contributions attracts community attention (Yang & Shi, 2011), often operationalized through follower counts (Wu et al., 2009). This heightened visibility fosters a perception of increased artifact success, further drawing community interest. For example, in open source software OSS contexts, star contributors' contributions positively influence their followers' engagement (Lee et al., 2013; Moqri et al., 2018).

However, a disproportionate proportion of contributions attributed to star contributors can also negatively impact OCC artifact popularity. Specifically, it can signal vulnerabilities related to contributor attrition, resource strain, and the homogeneity of contributions. Consequently, even when star contributors initially attract attention, potential contributors may refrain from participation due to an "anticipatory fear of failure in collective action" (Kuk, 2006, p. 1032). In summary, these arguments suggest that the effect of star contributors on OCC artifact popularity is contingent on the relative proportion of their contributions. Hence, we hypothesize:

H4: The *relative proportion of star contributors' contributions* ***moderates*** the relationship between the *number of star contributors* and artifact *popularity*, such that an increase in the relative proportion of their contributions ***strengthens*** the effect on artifact popularity (i.e., the curve is more pronounced).

3.4.5 Moderating Role of OCC Artifact's Environmental Dynamism on Artifact Quality

We propose that the level of environmental dynamism moderates the curvilinear relationship between the number of star contributors and artifact quality. Specifically, we identify distinct mechanisms that explain both the increase and decrease in artifact quality under varying levels of environmental dynamism.

We identify three mechanisms to explain the increase in artifact quality. First, star contributors, embedded in epistemic exchanges, possess a deep understanding of the rules, norms, and social structures of the OCC (Wasko & Faraj, 2005; Wasko et al., 2009). Consequently, an increase in star contributors provides readily deployable resources to address the demands of environmental dynamism and enhance artifact quality. Second, their embeddedness affords star contributors superior insight into OCC norms, problems, design solutions, and problem-solution matching. This expertise minimizes the time required for efficient task execution (Brooks, 1987), leading to positive downstream effects on artifact quality. Finally, given their familiarity with contribution norms, an increase in star contributors offers resources that can be deployed with minimal coordination costs (Faraj & Sproull, 2000), such as integrating contributions, reducing redundancy, and facilitating key decision-making. In environments characterized by high dynamism, these readily available, proven solutions significantly enhance artifact quality.

Conversely, under conditions of high environmental dynamism, an excessive number of star contributors can diminish artifact quality through two primary mechanisms. First, while star contributors internalize OCC rules and norms, exceeding a critical threshold increases coordination costs, yielding diminishing returns in terms of artifact quality (Faraj & Sproull, 2000). Second, high environmental dynamism necessitates rapid decision-making and direction. OCC research indicates that contributors ascend to leadership roles based on their contributions, influencing the design and direction of OCCs (Dahlander & O'Mahony, 2011). However, an overabundance of star contributors can lead to competing directions within a flat organizational structure, hindering swift decision-making and negatively impacting artifact quality. Hence, we hypothesize that:

H5: The level of *OCC artifact environmental dynamism* ***moderates*** the relationship between the *number of star contributors* and artifact *quality*, such that an increase in the OCC artifact environmental dynamism ***strengthens*** the effect on artifact quality (i.e., the curve is more pronounced).

3.4.6 Moderating Role of OCC Artifact Environmental Dynamism on Artifact Popularity

We propose that the level of environmental dynamism moderates the curvilinear relationship between the number of star contributors and artifact popularity. Specifically, we identify distinct mechanisms that explain both the increase and decrease in artifact popularity under varying levels of environmental dynamism.

We identify three mechanisms to explain the increase in artifact quality. First, heightened environmental dynamism often necessitates rapid responses. Consequently, contributions lead to shorter outcome cycles. With an increase in the number of star contributors, community members perceive a greater likelihood of artifact success (Oliver & Marwell, 1988), thereby increasing artifact popularity. Second, in environments characterized by high dynamism, an increased number of star contributors fosters positive community synergy, attracting members for socialization (Malgonde et al., 2023) and subsequently enhancing artifact popularity. Finally, OCC platforms often promote artifacts based on contribution metrics. Frequent actions, such as votes in Stack Overflow discussions or open source software releases, in response to environmental dynamism and an increased number of star contributors, may elevate these metrics, thereby attracting OCC members outside the immediate contributor network.

Conversely, under conditions of high environmental dynamism, an excessive number of star contributors can diminish artifact popularity through two primary mechanisms. First, increased coordination challenges and competing directions can negatively impact perceived artifact success. Consequently, community members are less likely to associate with artifacts deemed likely to fail (Kuk, 2006). Second, high environmental dynamism and an increased number of star contributors can overwhelm community members with cognitive load, such as tracking design changes, issues, and proposed solutions. This perceived volatility and rapid pace may misalign with members' participation objectives, such as learning or contributing, thereby reducing artifact popularity. Hence, we hypothesize:

H6: The level of *OCC artifact environmental dynamism* for an artifact ***moderates*** the relationship between the *number of star contributors* and artifact *popularity*, such that an increase in the OCC artifact environmental dynamism ***strengthens*** the effect on artifact popularity (i.e., the curve is more pronounced).

4 Method

4.1 Data

Our empirical setting for online collaborative communities is open source software (OSS) development, where each OSS project serves as an artifact. We utilized data from GitHub, a prominent OSS platform facilitating contributions from geographically distributed IT professionals. Appendix Figure A1 details our sample selection procedure, which drew from data spanning 2015 to 2019. Initially, we identified over 1.5 million projects featuring releases, defined as packaged, production-ready code versions. For each project, we programmatically extracted profile information, including owner type, project creation timestamp, popularity metrics, and the number of forks (copies) created on the platform.

Projects were excluded from the sample if they: (1) were deleted from GitHub, (2) exhibited inconsistent panel data (i.e., missing data creating temporal gaps), or (3) involved only a single contributor. To ensure sufficient data for empirical analysis and following prior research (Safadi et al., 2021; Zaheer et al., 1999), we aggregated project-level data annually. Our final sample comprised 21,456 OSS projects, with an average of 17.7 unique contributors per project.

4.2 Variables

4.2.1 Dependent Variables

This study had two primary dependent variables: project quality and project popularity. Project quality was operationalized as the number of closed issues. Issues, in this context, represent formal requests submitted by OSS community members, enabling project teams to systematically address and resolve quality-related concerns. Project popularity was measured by the number of bookmarks for the focal project. GitHub's bookmarking feature allows platform users to track projects of interest and receive updates on their development.

4.2.2 Independent Variables

This study employed three key independent variables: the number of star contributors (*NoOfStars*), the proportion of contributions by star contributors (*PropOfStarCont*), and project environmental dynamism (*ProjDyn*).

First, the *number of star contributors (NoOfStars)* within an OSS project during a given year was considered. Extant research has identified star contributors as those whose contributions exceed the mean (Baba et al., 2009) or are 3 standard deviations above the mean (Hess & Rothaermel, 2011; Rothaermel & Hess, 2007). Following Rothaermel and Hess (2007) and Hess and Rothaermel (2011), we identified star contributors as individuals whose contributions are 3 standard deviations[2] above the mean for a specific OSS project in a given year. Consistent with Daniel et al. (2013), we adopted a broad definition of OSS project contributions, encompassing both code and non-code activities (e.g., commits, comments, issue creation/updates, and wiki creation/updates). For each project-year dyad, we calculated the count of star contributors (*NoOfStars*).

Second, the *proportion of contributions by star contributors (PropOfStarCont)* was operationalized as the ratio of (1) the total contributions made by star contributors to a focal project in a given year to (2) the total contributions made to that focal project in that year. For instance, if star contributors contributed 64 out of 100 total contributions to a project in a given year, the *PropOfStarCont* would be 0.64.

[2] Appendix Table A1 presents robustness tests using one standard deviation, demonstrating qualitatively consistent results.

Finally, *project environmental dynamism (ProjDyn)* was operationalized as the average annual software release rate. A higher release rate indicates a project team's adaptive response to a dynamic environment, reflecting rapid project changes and enhancements. We used the average release rate as a reflective measure of project dynamism.

4.2.3 Control Variables

To account for potential confounding factors, we included several control variables. These include: the number of non-star contributors (*NoOfNonStars*), project tenure (*ProjTenure*), owner tenure on the OSS platform (*OwnTenure*), owner type (*OwnType*, indicating individual or organizational ownership), average annual contribution to the project (*AveYrCont*), and total annual contributions to the project (*TotYrCont*). Additionally, we controlled for the number of issues opened in the project during the year (*IssOpen*), as this may have influenced the number of issues that were closed. Table 3 outlines the measurement of these variables, and Table 4 presents descriptive statistics for the key variables in this study.

4.3 Econometric Considerations

We employed hierarchical linear modeling (HLM; Raudenbush & Bryk, 2002) to analyze our data for two primary reasons: first, our data exhibited a panel structure with yearly observations nested within OSS projects; second, this nested structure violates the independence assumption inherent in standard regression methods. HLM effectively addresses the statistical limitations of standard regression when analyzing nested data (Hofmann, 1997). Moreover, given our expectation that period-level effects would vary across OSS projects, HLM allowed us to account for both period-varying and project-varying factors in our hypothesis tests.

Following an incremental modeling approach (Kreft et al., 1998), we proceeded through several stages. Initially, we specified a null model (Model 1 in Tables 4 and 5), devoid of period- or project-level predictors. This model, analogous to a one-way ANOVA with random effects, enabled us to assess significant variance in our dependent variables at each level (period and project), validating the necessity of a multilevel analysis (Kreft et al., 1998). Subsequently, we introduced control variables (Model 2 in Tables 4 and 5), followed by our key predictors (Models 3 and 4 in Tables 4 and 5) to examine the relationship between star contributors and the dependent variables. We then included the period-level moderator (Model 5 in Tables 4 and 5) to test hypotheses regarding the relative proportion of stars' contributions. Finally, we added the project-level moderator (Model 6 in Tables 4 and 5) to assess the moderating effect of environmental dynamism. This incremental approach allowed us to observe the variance changes in outcomes across the models. We utilized random effects modeling to control for unobserved heterogeneity and account for interproject variation.

We performed several supporting tests to ensure the robustness of our findings. First, the distributional assumptions of HLM were met. Second, the Kolmogorov-Smirnov test confirmed the normality of residuals at the 0.1% significance level for all models. We observed low multicollinearity, with variance inflation factor values below 10. Third, the Breusch-Pagan test (Raudenbush & Bryk, 2002) indicated no evidence of heteroskedasticity at the 0.1% significance level. Fourth, we group-mean centered period-level variables and grand-mean centered project-level variables to mitigate non-essential multicollinearity and enhance result robustness. Finally, we estimated our models using full maximum-likelihood estimation (Raudenbush & Bryk, 2002; Setia et al., 2012). The following are equations for the one-way ANOVA model (Model 1) and full model (Model 6). One-way ANOVA with random effects model (Model 1):

$$Perf_{ij} = \beta_{0j} + r,$$

$$\beta_{0j} = \gamma_{00} + u_0$$

Full model with cross-level effects (Model 6):

$$\begin{aligned} Y_{ij} = \beta_{0j} &+ \beta_{1j} * (NoOfStars) + \beta_{2j} * (NoOfStars)^2 + \beta_{3j} \\ &* (NoOfStars) * (PropOfStarCont) \\ &+ \beta_{4j} * (NoOfStars)^2 \\ &* (PropOfStarCont) + \beta_{5j} \\ &* (PropOfStarCont) + \beta_{6j} \\ &* (NoOfStars) * (ProjVel) + \beta_{7j} \\ &* (NoOfStars)^2 * (ProjVel) + \beta_{8j} \\ &* (NoOfNonStars) + \beta_{9j} * (TotYrCont) \\ &+ \beta_{10j} * (AveYrCont) + \beta_{11j} * (IssOpen) \\ &+ r, \end{aligned}$$

$$\begin{aligned} \beta_{0j} = \gamma_{00} &+ \gamma_{01} * (ProjTenure) + \gamma_{02} * (OwnTenure) + \gamma_{03} \\ &* (OwnType) + \gamma_{04} * (ProjVel) + u_0, \end{aligned}$$

$\beta_{1j} = \gamma_{10};\ \beta_{2j} = \gamma_{20};\ \beta_{3j} = \gamma_{30};\ \beta_{4j} = \gamma_{40}; \beta_{5j} = \gamma_{50}; \beta_{6j} = \gamma_{61} * (ProjTenure) + \gamma_{62} * (OwnTenure) + \gamma_{63} * (OwnType) + \gamma_{64} * (ProjVel); \beta_{7j} = \gamma_{71} * (ProjTenure) + \gamma_{72} * (OwnTenure) + \gamma_{73} * (OwnType) + \gamma_{74} * (ProjVel); \beta_{8j} = \gamma_{80}; \beta_{9j} = \gamma_{90}; \beta_{10j} = \gamma_{100}; \beta_{11j} = \gamma_{110}$

The dependent variable, Y_{ij}, represents project quality and project popularity for a focal project in a focal year. The periodic observations are denoted as *i*, with a range from 1 (2015) to 5 (2019), and *j* denotes the OSS project, which ranges from 1 to 21,456. The γ_{ij} represents project level variable *j* on the corresponding β_{ij} that measures the effect of periodic level variable *i* on the performance variables.

Table 3. Variables

	Variable	Description and measurement
Dependent variables	OSS project quality (*issues closed*)	Number of issues closed in the year. Issues are formal requests logged in the system by OSS community and/or project members, allowing the project team to systematically address quality issues in the project.
	OSS project popularity (*watch events*)	Number of bookmarks for the focal project in the year. The OSS platform allows users to bookmark a focal project to receive regular updates related to the focal project.
Independent variables	Number of star contributors (*NoOfStars*)	Count of contributors whose contributions are three standard deviations above the mean contribution to an OSS project in a specific year.
	Proportion of contributions by star contributors (*PropOfStarCont*)	Ratio of (1) the sum of all the contributions to a focal project in a focal year made by star contributors to (2) the sum of contributions made to the focal project in the focal year.
	Project Dynamism (*ProjDyn*)	Average rate of software release per year in the project.
Control variables	Number of non-star contributors (*NoOfNonStars*)	Number of contributors for each year-project dyad with contributions less than or equal to three standard deviations of the mean contributions.
	Project Tenure (*ProjTenure*)	Age (in years) of the focal project at the start of a given year.
	Owner Account Age (*OwnTenure*)	Age (in days) of the focal project's owner at the start of a given year.
	Owner Type (*OwnType*)	Classification of a focal project owner as individual or organization.
	Average contributions in the year (*AveYrCont*)	For a focal project and year, average contributions across all contributors.
	Total contributions in the year (*TotYrCont*)	For a focal project and year, total contributions across all contributors.
	Issues Opened in the year (*IssOpen*)	For a focal project and year, total issues opened.

Note: This table provides a description and measurement for each variable used in our empirical analysis. The context of our analysis is an open source software platform (GitHub). All variables are derived from data provided by GitHub.

Table 4. Descriptive Statistics and Correlations

		Mean	*SD*	Min	Max	1	2	3	4	5	6	7	8	9	10	11
1	*Issues Closed*	17.07	91.31	0	7,412	-										
2	*Watch Events*	79.05	418.37	0	20,416	0.43***	-									
3	*NoOfStars*	0.30	0.63	0	21	0.42***	0.39***	-								
4	*PropOfStarCont*	0.13	0.24	0	0.995	0.22***	0.22***	0.76***	-							
5	*ProjDyn*	3.68	27.56	0	4144.33	0.06***	0.03***	0.05***	0.05***	-						
6	*NoOfNonStars*	18.69	92.42	2	8,138	0.75***	0.57***	0.49***	0.20***	0.04***						
7	*ProjTenure*	1.47	1.05	0.08	3.92	0.00	0.00	0.03***	0.00	0.00	0.00	-				
8	*OwnType*	0.34	0.47	0	1	-0.02***	0.07***	0.03***	0.12***	0.02***	-0.12***	0.02***	-			
9	*OwnTenure*	3.82	2.39	-7.91	10.92	-0.02***	0.02***	0.03***	0.03***	-0.02***	-0.03***	0.48***	0.27***	-		
10	*IssOpen*	20.34	98.18	0	9,107	0.94***	0.46***	0.46***	0.23***	0.06***	-0.23***	-0.01***	-0.02***	-0.03***	-	
11	*AveYrCont*	23.41	527.33	1.06	1,03,824	0.01**	0.00	-0.01*	-0.01*	0.22***	0.01*	0.00	-0.01	-0.01	0.01**	-
12	*TotYrCont*	299.39	3,011.23	3	4,32,971	0.61***	0.27***	0.21***	0.09***	0.11***	-0.09***	0.00	-0.03***	-0.01**	0.58***	0.46***

Note: $N = 21,456$ at the open source software project level. Pairwise correlations and univariate statistics are at the periodic level. The significance of coefficients is evaluated as $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Minimum value for *OwnTenure* is negative.[3] Upon investigation, we observed that certain users in our sample had activity before and after creation of their account. For example, consider User A whose account is created on May 25, 2012. In our data, we might observe that User A has created project *abc* on May 26, 2012, and project *xyz* on April 23, 2012. Consequently, the owner's tenure for project *xyz* would be logged as a negative value for project *xyz*. A possible explanation of this observation is that User A may have deleted and re-created their account. Since *OwnTenure* is a control variable that captures how long User A has been an account holder on the GitHub platform, a negative value for project *xyz* would just show that User A has been on the platform longer than their most recent account.

5 Results

5.1 Main Results

Tables 5 and 6 present the results of our HLM analyses. Table 5 details the findings for project quality, while Table 6 reports the results for project popularity. For each dependent variable, we first examined the variance across levels and then assessed the variance explained by the introduction of independent variables.

The intraclass correlation coefficient (ICC) from the null model (Model 1 in Tables 5 and 6), which includes only the intercept, indicates the relative variance in the dependent variables across periodic and project levels (Raudenbush & Bryk, 2002). The ICC reveals that a substantial portion of the variance resided at the project level (60.92% for project quality and 70.49% for project popularity), with the remaining variance at the periodic level. These ICC values justify our utilization of a multilevel structure and provide a baseline for comparing model fit. For both dependent variables, we observe a progressive reduction in variance relative to the null model as additional independent variables are introduced. The hypothesis tests for the specific effects of our key independent variables are presented in Models 4, 5, and 6 in Tables 5 and 6. Model comparisons were conducted using the deviance statistic, and deviance differences were assessed via a variance-covariance comparison test.

H1 proposed a curvilinear (inverted U-shaped) relationship between the number of star contributors and OCC artifact quality. In alignment with our predictions, the results indicate an inverted U-shaped relationship, with project quality peaking at a moderate number of star contributors. Specifically, Model 4 of Table 5 reveals a negative and statistically significant coefficient for the squared term $NoOfStars^2$ ($\beta = -1.466$, $p < 0.001$), supporting H1. This inverted U-shaped relationship is visually depicted in Panel (a) of Appendix Figure A2.

H2 posited a curvilinear (inverted U-shaped) relationship between the number of star contributors and project popularity. In accordance with our predictions, the results demonstrate an inverted U-shaped relationship, with project popularity peaking at a moderate number of star contributors. Specifically, Model 4 of Table 6 reveals a negative and statistically significant coefficient for the squared term $NoOfStars^2$ ($\beta = -2.983$, $p < 0.001$), supporting H2. This inverted U-shaped relationship is visually depicted in Panel (b) of Appendix Figure A2.

H3 proposed that the proportion of contributions by star contributors moderates the relationship between the number of star contributors and artifact quality, such that an increase in the proportion of star contributions strengthens the inverted U-shaped relationship. Model 5 of Table 5 reveals a statistically significant and negative coefficient for the interaction term $NoOfStars^2 \times PropOfStarCont$ ($\beta = -1.413$, $p < 0.001$), indicating that a higher proportion of star contributions strengthens the curvilinear effect on artifact quality. This strengthening effect is visually depicted in Panel (a) of Appendix Figure A3.

[3] We thank the anonymous reviewer for this discussion.

Table 5. Results of HLM Estimation (OSS Product Quality)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	15.956*** (0.510)	16.532*** (0.625)	15.541*** (0.625)	14.799*** (0.631)	12.459*** (0.636)	12.589*** (0.645)
NoOfNonStars		0.115*** (0.003)	0.109*** (0.003)	0.122*** (0.003)	0.126*** (0.003)	0.152*** (0.003)
ProjTenure		0.401 (0.219)	0.622** (0.219)	0.895*** (0.219)	0.583** (0.218)	0.276 (0.230)
OwnTenure		-0.098 (0.178)	-0.337 (0.178)	-0.600*** (0.179)	-0.24 (0.178)	-0.086 (0.182)
AveYrCont		-0.008*** (0.000)	-0.008*** (0.000)	-0.007*** (0.000)	-0.007*** (0.000)	-0.006*** (0.000)
TotYrCont		0.005*** (0.000)	0.005*** (0.000)	0.004*** (0.000)	0.004*** (0.000)	0.004*** (0.000)
OwnType		-2.276* (1.090)	-2.146* (1.079)	-2.235* (1.088)	-3.744*** (1.078)	-4.040*** (1.113)
ProjDyn		0.133*** (0.016)	0.130*** (0.016)	0.129*** (0.016)	0.124*** (0.016)	0.085*** (0.016)
IssOpen		0.685*** (0.002)	0.682*** (0.002)	0.684*** (0.002)	0.680*** (0.003)	0.692*** (0.003)
NoOfStars			3.110*** (0.278)	7.919*** (0.342)	13.516*** (0.588)	10.136*** (0.615)
***NoOfStars*^{2}**				**-1.466*** (0.059)**	-1.936*** (0.080)	-0.969*** (0.088)
PropOfStarCont					-39.282*** (1.765)	-42.394*** (1.824)
NoOfStars × *PropOfStarCont*					44.657*** (2.360)	61.149*** (2.557)
NoOfStars*^{2} × *PropOfStarCont					**-1.413*** (0.415)**	-7.506*** (0.567)
NoOfStars × *ProjTenure*						0.797** (0.243)
NoOfStars × *OwnTenure*						-0.078 (0.156)
NoOfStars × *OwnType*						1.794* (0.808)
NoOfStars × *ProjDyn*						0.644*** (0.020)
NoOfStars^2 × *ProjTenure*						0.004 (0.031)
NoOfStars^2 × *OwnTenure*						-0.100*** (0.026)
NoOfStars^2 × *OwnType*						-1.490*** (0.206)
NoOfStars*^{2} × *ProjDyn						**-0.187*** (0.005)**
Deviance (-2 log likelihood)	984517.4	898237.0	898118.0	897511.6	896825.0	895168.3
Deviation difference (Δ Dev)		86280.4***	119.0***	606.4***	686.6***	1656.7***

Note: There are 86,728 observations at the periodic level that correspond with 21,456 projects at Level 2. Deviation differences were calculated as the difference between the current model and the previous model, i.e., Δ D2 = D2-D1 and Δ D5 = D5-D4. The significance of difference was tested after accounting for the estimated parameters in the two models. Significance levels: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$; standard errors in parentheses.

Table 6. Results of HLM Estimation (OSS Product Popularity)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	73.867*** (2.455)	52.110*** (3.070)	31.858*** (2.998)	30.542*** (3.020)	22.298*** (3.085)	24.271*** (3.079)
NoOfNonStars		1.699*** (0.018)	1.582*** (0.019)	1.607*** (0.019)	1.598*** (0.019)	1.766*** (0.020)
ProjTenure		-3.944** (1.293)	-1.407 (1.270)	-1.065 (1.273)	-2.411 (1.271)	3.587** (1.358)
OwnTenure		0.095 (1.006)	-3.097** (0.983)	-3.437*** (0.987)	-2.816** (0.983)	-2.876** (1.012)
AveYrCont		-0.007** (0.003)	-0.009** (0.003)	-0.008** (0.003)	-0.008** (0.003)	-0.006* (0.003)
TotYrCont		0.004*** (0.001)	0.005*** (0.001)	0.004*** (0.001)	0.004*** (0.001)	0.003*** (0.001)
OwnType		65.348*** (5.347)	65.700*** (5.132)	65.282*** (5.158)	62.092*** (5.127)	39.584*** (5.294)
ProjDyn		0.326*** (0.080)	0.264*** (0.076)	0.261*** (0.077)	0.237** (0.076)	0.121 (0.077)
IssOpen		0.166*** (0.017)	0.095*** (0.017)	0.099*** (0.017)	0.089*** (0.018)	0.059*** (0.018)
NoOfStars			67.676*** (1.842)	77.233*** (2.293)	111.071*** (3.686)	100.373*** (3.926)
NoOfStars^2				**-2.983*** (0.401)**	-5.152*** (0.522)	-4.759*** (0.590)
PropOfStarCont					-107.483*** (11.417)	-155.986*** (11.801)
NoOfStars × *PropOfStarCont*					15.043 (15.769)	18.112 (17.236)
NoOfStars^2* × *PropOfStarCont					**7.636** (2.802)**	9.904* (3.911)
NoOfStars × *ProjTenure*						-15.349*** (1.686)
NoOfStars × *OwnTenure*						-1.961 (1.061)
NoOfStars × *OwnType*						77.978*** (5.489)
NoOfStars × *ProjDyn*						1.446*** (0.131)
NoOfStars^2 × *ProjTenure*						-1.050*** (0.215)
NoOfStars^2 × *OwnTenure*						-1.235*** (0.175)
NoOfStars^2 × *OwnType*						-3.435* (1.433)
NoOfStars^2* × *ProjDyn						**-0.378*** (0.032)**
Deviance (-2 log likelihood)	1232581	1219069	1217800	1217747	1217523	1216346
Deviance difference (Δ Dev)		13512***	1269***	53.7***	223.3***	1177.6***

Note: There are 86,728 observations at the periodic level that correspond with 21,456 projects at level 2. Deviation differences were calculated as the difference between the current model and the previous model, i.e., Δ D2=D2-D1 and Δ D5=D5-D4. The significance of difference was tested after accounting for the estimated parameters in the two models. Significance levels: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$; standard errors in parentheses.

H4 posited that the proportion of contributions by star contributors moderates the relationship between the number of star contributors and artifact popularity, such that an increase in the proportion of star contributions strengthens the effect on artifact popularity. Contrary to our expectations, Model 5 of Table 6 reveals a statistically significant and positive coefficient for the interaction term $NoOfStars^2 \times PropOfStarCont$ (β = 7.636, $p < 0.01$), indicating that a higher proportion of star contributions weakens rather than strengthens the relationship. Therefore, H4 is not supported. This weakening effect is visually depicted in Panel (b) of Appendix Figure A3. Theoretically, this empirical result suggests that a disproportionate proportion of contributions attributed to star contributors does not necessarily provide a consequential negative signal related to vulnerabilities associated with attrition, contributor stress, resource limitations, and the homogeneity of contributions.

H5 proposed that the level of environmental dynamism moderates the relationship between the number of star contributors and artifact quality, such that increased environmental dynamism strengthens the inverted U-shaped relationship. We tested this hypothesis using a cross-level interaction analysis. The results in Model 6 of Table 5 reveal a statistically significant and negative coefficient for the interaction term $NoOfStars^2 \times ProjDyn$ (β = -0.187, $p < 0.001$), indicating that higher environmental dynamism strengthens the curvilinear effect on artifact quality. Therefore, H5 is supported. This strengthening effect is visually depicted in Panel (a) of Appendix Figure A4.

H6 posited that the level of environmental dynamism moderates the relationship between the number of star contributors and artifact popularity, such that increased environmental dynamism strengthens the inverted U-shaped relationship. Consistent with H5, we tested this hypothesis using a cross-level interaction analysis. The results in Model 6 of Table 6 reveal a statistically significant and negative coefficient for the interaction term $NoOfStars^2 \times ProjDyn$ (β = -0.378, $p < 0.001$), indicating that higher project dynamism strengthens the curvilinear effect on artifact popularity. Therefore, H6 is supported. This strengthening effect is visually depicted in Panel (b) of Appendix Figure A4.

Table 7 provides a concise summary of our main findings, alongside their corresponding theoretical justifications.

5.2 Robustness Analyses

We conducted several robustness checks to ensure the reliability of our findings. Given the panel structure of our data, the potential for omitted variable bias is mitigated (Wooldridge, 2010).

5.2.1 Measurement Errors

Measurement error can arise when the operationalization of variables does not accurately capture their true values. To mitigate this concern, we demonstrate the robustness of our results by employing alternative measures and operationalizations for our key variables. First, while our star contributor identification criteria, based on prior literature (Hess & Rothaermel, 2011; Rothaermel & Hess, 2007), utilized a threshold of 3 standard deviations above the mean contribution, we acknowledge that this may be overly restrictive, potentially excluding high contributors who do not meet this criterion. Therefore, we relaxed the threshold to 1 standard deviation above the mean contribution. The results, presented in Models 1 through 3 (for project quality) and Models 4 through 6 (for project popularity) in Appendix Table A1, remain qualitatively consistent with our main findings. Second, our primary sampling strategy included projects with at least two contributors per year. Recognizing that this threshold might bias the identification of star contributors, we extended the criterion to include only projects with at least five contributors per year, a threshold consistent with prior OSS studies (e.g., Daniel et al., 2013). The results, presented in Models 1 through 3 (project quality) and Models 4 through 6 (project popularity) in Appendix Table A2, are qualitatively consistent with our main findings.

5.2.2 Alternate Measures for OSS Product Quality and Popularity

In our primary analysis, project quality was operationalized using the number of issues closed. For this robustness check, we employed the number of bugs/issues reported in an OSS project as an alternative proxy for project quality (Setia et al., 2012). This approach assumes that a project with zero or a relatively low number of reported issues indicates higher quality than a project with a high number of reported issues. The results, presented in Models 1 through 3 of Appendix Table A3, revealed a U-shaped relationship between the number of star contributors and the number of reported issues. Specifically, the number of reported issues was lowest at a moderate number of star contributors, corroborating our main findings regarding OSS project quality. Similarly, in our primary analysis, project popularity was operationalized using the number of bookmarks received. For this robustness check, we utilized the number of times a project was forked (i.e., making a copy of the project for study, editing, or contribution) as an alternative measure of project popularity. The results, presented in Models 4 through 6 of Appendix Table A3, remain qualitatively consistent with our main findings.

Table 7. Summary of Main Findings and Theoretical Justification

Hypotheses	Theoretical and empirical justification
H1: The number of star contributors contributing to an online open collaboration community artifact is curvilinearly related to the artifact's quality, such that a moderate number of star contributors correlates with the highest quality (inverted U-shaped relationship).	• Optimal levels of star contributors provide a balance between coordination cost, redundancy reduction, and heterogeneity of ideas, and a balance between available resources and work. • Model 4 in Table 5 shows a negative and significant coefficient for the squared term $NoOfStar^2$ (β = -1.466, p < 0.001).
H2: The number of star contributors contributing to an online open collaboration community artifact is curvilinearly related to the artifact's popularity, such that a moderate number of star contributors correlates with the highest increase in popularity (inverted U-shaped relationship).	• Optimal levels of star contributors attract OCC members, allow reciprocity, identify resourceful individuals to associate with, enjoy significant followership, and underscore the activeness of the artifact to attract OCC members. • Model 4 of Table 6 shows negative and significant coefficients for the squared term $NoOfStars^2$ (β = -2.983, p < 0.001).
H3: The relative proportion of the star contributors' contributions moderates the relationship between the number of star contributors and the artifact's quality, such that an increase in the relative proportion of their contributions strengthens the effect on artifact quality (i.e., the curve is more pronounced).	• Proportion of star contributors' contributions at an optimal threshold supports coordination, reciprocity, skill-task match, and influences peers' productivity. • Model 5 of Table 5 shows a significant and negative coefficient for the term $NoOfStars^2 \times PropOfStarCont$ (β = -1.413, p < 0.001), indicating that the proportion of total contribution made by stars strengthens the relationship.
H4: The relative proportion of star contributors' contributions moderates the relationship between the number of star contributors and artifact popularity, such that an increase in the relative proportion of their contributions strengthens the effect on artifact popularity (i.e., the curve is more pronounced).	• Proportion of star contributors' contributions at optimal threshold supports associating with resourceful individuals and draws community attention. • Model 5 of Table 6 shows a significant but positive coefficient for the term $NoOfStars^2 \times PropOfStarCont$ (β = 7.636, p < 0.01), indicating that the proportion of total contribution made by stars weakens the relationship.
H5: The level of OCC artifact environmental dynamism moderates the relationship between the number of star contributors and artifact quality, such that an increase in the OCC artifact environmental dynamism strengthens the effect on artifact quality (i.e., the curve is more pronounced).	• Increase in environmental dynamism is supported by star contributors' knowledge of norms and rules, efficiency, and reduced coordination costs. • Model 6 of Table 5 shows a significant and negative coefficient for the term $NoOfStars^2 \times ProjDyn$ (β = -0.187, p < 0.001), indicating that environmental dynamism strengthens the relationship.
H6: The level of OCC artifact environmental dynamism for an artifact moderates the relationship between the number of star contributors and artifact popularity, such that an increase in the OCC artifact environmental dynamism strengthens the effect on artifact popularity (i.e., the curve is more pronounced).	• Increase in environmental dynamism is supported by star contributors' influence on artifact success, positive synergy, and contribution metrics. • Model 6 of Table 6 shows a negative and significant coefficient for the term $NoOfStars^2 \times ProjDyn$ (β = -0.378, p < 0.001), indicating that project dynamism strengthens the relationship.

5.2.3 Accounting for Endogeneity

To address potential endogeneity concerns, specifically Level 2 (cross-level) endogeneity, where the random intercept may be correlated with a Level 1 independent variable, we utilized the endogeneity-robust Mundlak approach (Mundlak, 1978) by incorporating correction terms. Mundlak's approach involves including the project-level means of time-varying covariates in the HLM. This helps control for unobserved heterogeneity that may correlate with our key independent variables, and it separates within-project variation from between-project variation (Snijders & Berkhof, 2008), thereby mitigating potential endogeneity. The results, presented in Models 1 through 3 (for project quality) and Models 4 through 6 (for project popularity) of Appendix Table A4, remain consistent with our main findings.

5.2.4 Falsification Test

To rule out the possibility of spurious correlations in our HLM results, we conducted a falsification check. This check examined the hypothesized relationships between the number of star contributors and the dependent variables (project quality and popularity) using reshuffled time periods. Specifically, we randomly shuffled the dependent variable entries for each project, disrupting their chronological order and thus misaligning them with their corresponding independent and control variable entries. If significant estimates supporting our hypothesized relationships were observed in this randomized, non-chronological data, it would suggest spurious correlations. However, the results of our falsification tests, presented in Models 1 through 3 (for project quality) and Models 4 through 6 (for project popularity) of Appendix Table A5, do not support our hypotheses and are inconsistent with our main analyses. This indicates that our HLM results are unlikely to have been driven by spurious correlations.

6 Discussion

6.1 Theoretical Contributions

This study makes three theoretical contributions. First, this study contributes to the growing interdisciplinary research on the role and impact of star contributors in collaborative work settings. Existing research has mostly focused on their role and effect in traditional offline organizational work settings (Call et al., 2021; Hess & Rothaermel, 2011; Taylor & Bendickson, 2021), where individuals' compensation and work are managed by employers, and their contributions are governed by organizational rules. Our findings build on and extend the literature on the role of stars by showing their impact in non-traditional online self-organizing work settings, where the boundaries are more fluid, individual contributors are unpaid and work on their own terms, and there are often no organizationally imposed rules. Also, limited research exists on the effect of the relative proportion of stars' contributions while recognizing how the disparity in contributions within a group affects work outcomes (Daniel et al., 2013). This research is one of the first to show that disparity in contributions arising from the relative proportion of contributions made by star contributors in OCC artifact moderates the relationship between star contributors' contributions and artifacts' quality and popularity. Prior studies have maintained a fixed proportion (usually based on the 80-20 rule) between star and non-star contributors (e.g., Lin and Wang, 2020; Setia et al., 2012). Our findings indicate that while the relationship between star contributors' contributions and OCC artifact quality is stronger when stars contribute a higher proportion of the overall efforts in the artifact, the relationship between star contributors' contributions and OCC artifact popularity is weaker when stars contribute a higher proportion.

Second, we contribute to research on OCC, particularly studies investigating how different categories of OCC participants affect key outcomes (Jarczyk et al., 2018; Lin & Wang, 2020; Setia et al., 2012). These studies have predominantly taken the core-periphery view in categorizing participants, where they identify the participant's category by their network position (Dahlander & Frederiksen, 2012; Safadi et al., 2021) or a fixed contribution level (Lin & Wang, 2020; Setia et al., 2012). Although the core-periphery participant structure is important, we extend this literature by introducing the concept of the star contributor, a category of participant that, while not always present, can significantly reshape community dynamics. Star contributors' recent and disproportionate contributions can drive significant improvements in artifact quality and influence its popularity. We show that this category of contributor can affect OCC artifact quality and popularity in a nonlinear manner, highlighting the importance of considering this distinct group in OCC research.

Finally, we extend the literature by theorizing the role of the OCC artifact environment on OCC outcomes. Prior research has shown that the characteristics of OCC environments align with the impact of different categories of contributors. For instance, Lin and Wang (2020) and Setia et al. (2012) showed that peripheral contributors are most impactful on established or matured OCC artifacts. Our research contributes by highlighting that the effect of star contributors is more pronounced in dynamic environments, which are characterized by a high rate of change and uncertainty. In such environments, the demand for contributions is more intense, as the community grapples with new information, challenges, and opportunities. Consequently, the impact of occasional contributions is diminished, while the focused and sustained efforts of star contributors become critical for driving artifact development and success.

6.2 Implications for Online Collaboration Communities

Our findings have three implications for research on online collaboration communities. First, earlier studies on OCCs identify intrinsic (e.g., happiness, sense of community) (Kankanhalli et al., 2005; Wasko & Faraj, 2005) and extrinsic (Lerner & Tirole, 2002; Xu et al., 2020) motivations to contribute. This research complements these streams of research to advance research focusing on OCC members' strategic behavior (e.g., association with resourceful OCC members) to satisfy their participation objectives. Strategic participation highlights the important role of signals emitted, received, and perceived by OCC members and artifacts. Second, a prevalent view in research on OCCs is that contributions are essential for sustaining OCC artifacts (Butler, 2001; Chengalur-Smith et al., 2010; Mindel et al., 2018). Our findings indicate that while star contributors' contributions positively affect an artifact's quality and popularity, this effect is moderated by the relative proportion of star contributors' contributions. These findings also offer opportunities for future research related to the impact of the relative proportion of star contributors' contributions on artifact takeoff (Setia et al., 2020), the impact of external factors (e.g., nudge by OCC network members) (Qian & Jain, 2024), and exogenous shocks (Kummer et al., 2020; Malgonde et al., 2023). Finally, this research extends the core-periphery distinction adopted in prior work using a data-driven approach that accounts for the OCC artifact's fluidity (Faraj et al., 2011). Prior research suggests that peripheral contributors tend to be more impactful in the later stages of the OCC artifact (Setia et al., 2012). Our findings complement this by highlighting the role of environmental dynamism.

This research also extends the theory on collective action (Oliver & Marwell, 1988). Specifically, the theory of collective action suggests that a small group of contributors from a relatively larger group is sufficient to develop the critical mass required to instigate broader contributions. However, our findings suggest that the proportion of contributors by the initial group of contributors may negatively impact artifacts' quality and popularity, with a downstream effect on community participation.

6.3 Managerial Implications

We note two managerial implications of this research. First, our results suggest a positive effect of the proportion of star contributors' contributions on artifact quality but a negative effect on artifact popularity. Consequently, a key implication for OCC artifact managers and platform owners is how to devise policies (e.g., throttle type of contributions), incentive mechanisms (e.g., rewards for critical vulnerabilities), and platform governance mechanisms (e.g., recommender systems) to manage (e.g., identify alternate contributors, recommend alternate artifacts) the proportion of star contributors' contributions. Importantly, devised mechanisms are part of a portfolio of mechanisms that are available to artifact managers.

Second, we discuss the moderating role of the OCC artifact's environmental dynamism. For OCC artifact managers, the use of action levers that alter signals of dynamism is important. For example, OSS projects may alter their schedule of releases to signal a shift in dynamism. Similarly, question-and-answer-based artifacts may alter administrative edits to signal reduced dynamism. By strategically adjusting these signals, OCC artifact managers can influence the level and breadth of participation, ultimately affecting the artifact's quality and popularity.

6.4 Limitations and Future Research Directions

Three limitations of this study offer opportunities for future studies. First, while based on existing literature, defining star contributors solely by contribution volume (three standard deviations above the mean) may be a limitation. For example, Asgari et al. (2021) suggested that star contributors might be identified not only by their performance (contributions) but also by a combination of performance, status, visibility, and social capital. Hence, future studies could consider expanding the operationalization of star contributors. Second, our study sample was drawn exclusively from GitHub, focusing on open source software projects. Because OCCs and participant contribution behaviors can differ significantly across domains and platforms, the generalizability of our findings may be limited. Future studies could extend this inquiry to other domains and platforms. Finally, although our study focuses on stars, future research could explore the role of non-stars in artifacts' quality and popularity using our conceptualization.

In this research, we focus on star contributors and the effect of their contributions on OCC artifacts' quality and popularity. This research complements existing studies on factors contributing to OCC artifacts' success and extends prior work by focusing on the critical yet under-researched role of star contributors. Our findings suggest that star contributors play a significant role in driving the success of OCC artifacts.

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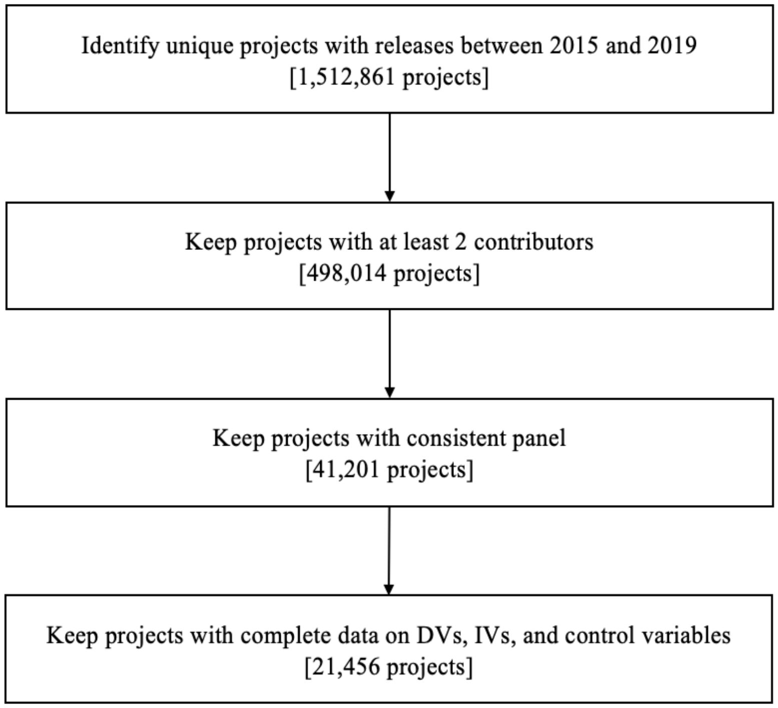
Appendix



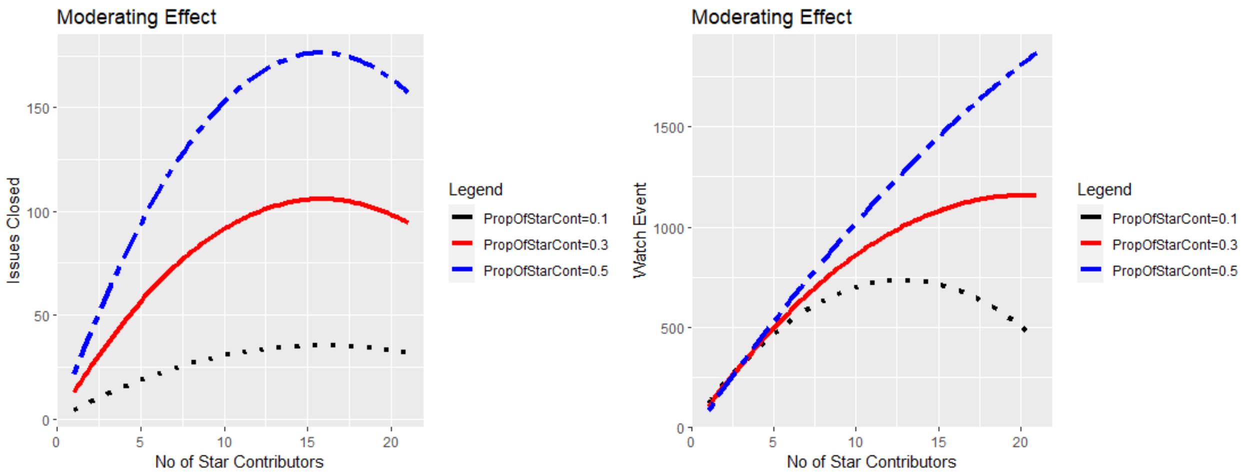
Note: We collected data from GitHub from 2015-2019. First, we identified 1,512,861 unique projects with releases between 2015 and 2019. Second, we retained 498,014 unique projects that received contributions from at least two contributors. Third, we retained 41,201 projects with at least 4 years of consistent panels. In other words, each project had either 4 or 5 years of panel data beginning either in 2015 or 2016. Finally, we retained 21,456 projects with data on dependent, independent, and control variables. For example, we used project owner information such as account age and owner type (individual or organizational). We dropped projects where the owner account was deleted or owner information was incomplete or unavailable.

Figure A1. Random Sample Selection

Note: This figure shows the inverted U-shaped relationship between the number of star contributors and (a) the quality or (b) the popularity of the OSS project. In our context of open source software, quality was measured using issues closed for a focal open source software project (artifact). Similarly, popularity was measured using the number of open source platform users watching the focal project (artifact). From Panel (a), we note that the number of star contributors contributing to an online open collaboration community artifact is curvilinearly related to the artifact's quality, such that a moderate number of star contributors is associated with the highest quality (inverted U-shaped relationship). From Panel (b), we note that the number of star contributors contributing to an online open collaboration community artifact is curvilinearly related to the artifact's popularity, such that a moderate number of star contributors is associated with the highest increase in popularity (inverted U-shaped relationship).

Figure A2. How Does the Number of *Star* Contributors Affect an Open Source Software Project's Quality and Popularity?

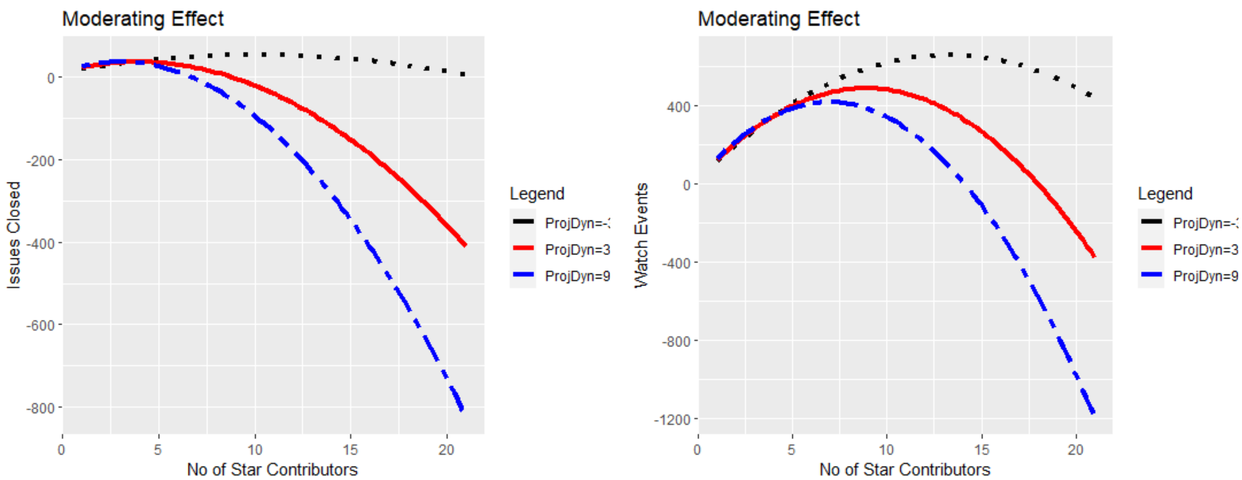
(a) Quality of OSS project **(b) Popularity of OSS project**



Note: This figure illustrates the moderating effect of the proportion of star contributors' contributions on the relationship between the number of star contributors and the (a) quality or (b) popularity of the OSS project. From Panel (a), we note that the relative proportion of star contributors' contributions moderates the relationship between the number of star contributors and the project's quality, such that an increase in the relative proportion of their contributions *strengthens* the effect on project quality (i.e., the curve is more pronounced). From Panel (b), we note that the relative proportion of star contributors' contributions moderates the relationship between the number of star contributors and project popularity, such that an increase in the relative proportion of their contributions *diminishes* the effect on project popularity (i.e., the curve flattens). For each panel, we show three levels (0.1, 0.3, and 0.5) of the proportion of star contributors' contributions. In our OSS context of open source software, quality was measured using issues closed for a focal open source software project (artifact). Similarly, popularity was measured using the number of open source platform users watching the focal project (artifact).

Figure A3. How Does the Relative Proportion of Contributions by Star Contributors Affect the Relationship Between the Number of Star Contributors and the Open Source Software Project's Quality and Popularity?

(a) Quality of OSS project **(b) Popularity of OSS project**



Note: This figure illustrates the moderating effect of the OSS project's environmental dynamism on the relationship between the number of star contributors and the (a) quality or (b) popularity of the OSS project. From Panel (a), we note that the level of OSS project environmental dynamism moderates the relationship between the number of star contributors and project quality, such that an increase in the OSS project environmental dynamism *strengthens* the effect on project quality (i.e., the curve is more pronounced). From Panel (b), we note that the level of OSS project environmental dynamism for a project moderates the relationship between the number of star contributors and project popularity, such that an increase in the OSS project environmental dynamism *strengthens* the effect on project popularity (i.e., the curve is more pronounced). For each panel, we show three levels (-3, 3, and 9) of environmental dynamism. In our OSS context of open source software, quality was measured using issues closed for a focal open source software project (artifact). Similarly, popularity was measured using the number of open source platform users watching the focal project (artifact).

Figure A4. How Does the Open Source Software Project's Environmental Dynamism Affect the Relationship Between the Number of Star Contributors and the Open Source Software Project's Quality and Popularity?

Table A1. Results of HLM Estimation With Star Contributors Operationalized as Contributors Whose Contributions Are 1 Standard Deviation Above the Mean

Variables	OSS project quality			OSS project popularity		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
(Intercept)	14.226*** (0.666)	13.406*** (0.680)	16.068*** (0.705)	25.788*** (3.325)	26.087*** (3.454)	35.766*** (3.449)
NoOfNonStars	0.128*** (0.003)	0.132*** (0.003)	0.115*** (0.003)	1.657*** (0.019)	1.673*** (0.019)	1.691*** (0.0190
ProjTenure	0.672** (0.219)	0.605** (0.219)	-0.589* (0.259)	-2.650* (1.286)	-3.392** (1.287)	6.069*** (1.567)
OwnTenure	-0.367* (0.179)	-0.175 (0.179)	0.651*** (0.192)	-1.903 (1.001)	-1.799 (1.001)	2.515* (1.129)
AveYrCont	-0.007*** (0.000)	-0.007*** (0.000)	-0.004*** (0.000)	-0.007** (0.003)	-0.008** (0.003)	-0.002 (0.003)
TotYrCont	0.004*** (0.000)	0.004*** (0.000)	0.003*** (0.000)	0.004*** (0.001)	0.004*** (0.001)	0.001 (0.001)
OwnType	-1.732 (1.105)	-1.878 (1.105)	-1.896 (1.204)	72.800*** (5.276)	73.152*** (5.262)	38.705*** (5.834)
ProjDyn	0.132*** (0.016)	0.133*** (0.016)	0.077*** (0.017)	0.304*** (0.078)	0.301*** (0.078)	-0.056 (0.077)
IssOpen	0.689*** (0.002)	0.687*** (0.002)	0.741*** (0.002)	0.137*** (0.017)	0.113*** (0.018)	0.196*** (0.018)
NoOfStars	2.413*** (0.164)	2.625*** (0.199)	0.089 (0.218)	20.444*** (1.124)	19.886*** (1.357)	8.246*** (1.545)
NoOfStars^2	-0.274*** (0.008)	-0.282*** (0.010)	-0.01 (0.013)	-0.259*** (0.052)	0.071 (0.072)	1.132*** (0.090)
PropOfStarCont		-7.656*** (0.766)	-4.273*** (0.749)		-11.637* (5.367)	-19.739*** (5.529)
NoOfStars × *PropOfStarCont*		11.786*** (0.868)	11.662*** (0.920)		-15.218* (6.064)	-2.16 (6.607)
NoOfStars^2 × *PropOfStarCont*		-0.251*** (0.056)	-0.371*** (0.092)		3.429*** (0.387)	-0.106 (0.622)
NoOfStars × *ProjTenure*			0.967*** (0.121)			-7.268*** (0.734)
NoOfStars × *OwnTenure*			-0.586*** (0.076)			-4.306*** (0.485)
NoOfStars × *OwnType*			-0.693 (0.393)			33.940*** (2.704)
NoOfStars × *ProjDyn*			0.323*** (0.008)			1.077*** (0.051)
NoOfStars^2 × *ProjTenure*			-0.043*** (0.005)			0.250*** (0.026)
NoOfStars^2 × *OwnTenure*			0.063*** (0.004)			0.224*** (0.029)
NoOfStars^2 × *OwnType*			-0.118*** (0.023)			-1.775*** (0.156)
NoOfStars^2 × *ProjDyn*			-0.043*** (0.001)			-0.118*** (0.004)
Deviance (-2 log likelihood)	896784.0	896586.1	889883.3	1218647.3	1218520.0	1216856.6
Deviance difference (Δ Dev)		197.9***	6702.8***		127.3***	1663.4***

Note: There are 86,728 observations at the periodic level that correspond with 21,456 projects at Level 2. Deviation differences were calculated as the difference between the current model and the previous model, i.e., Δ D2 = D2-D1 and Δ D5 = D5-D4. The significance of difference was tested after accounting for the estimated parameters in the two models. Significance levels: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$; standard errors in parentheses.

Table A2. Results of HLM Estimation Using Projects with a Minimum of Five Contributors Per Year

Variables	OSS project quality			OSS project popularity		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
(Intercept)	32.984*** (1.694)	30.104*** (1.756)	30.131*** (1.788)	79.598*** (8.268)	70.578*** (8.771)	70.212*** (8.821)
NoOfNonStars	0.150*** (0.004)	0.157*** (0.004)	0.185*** (0.005)	1.629*** (0.029)	1.629*** (0.029)	1.823*** (0.031)
ProjTenure	2.124*** (0.558)	1.703** (0.559)	1.520* (0.633)	-3.678 (3.190)	-5.368 (3.196)	8.748* (3.729)
OwnTenure	-1.136* (0.464)	-0.456 (0.466)	-0.309 (0.490)	-5.960* (2.559)	-5.268* (2.562)	-6.597* (2.758)
AveYrCont	0.271*** (0.012)	0.272*** (0.012)	0.275*** (0.012)	-0.358*** (0.084)	-0.340*** (0.084)	-0.223** (0.083)
TotYrCont	0.006*** (0.000)	0.005*** (0.000)	0.004*** (0.000)	0.004*** (0.001)	0.005*** (0.001)	0.002 (0.001)
OwnType	-9.077** (2.860)	-10.373*** (2.859)	-11.173*** (3.033)	123.371*** (13.686)	121.859*** (13.650)	89.071*** (14.796)
ProjDyn	0.953*** (0.079)	0.953*** (0.079)	0.643*** (0.084)	2.049*** (0.377)	1.990*** (0.375)	1.163** (0.413)
IssOpen	0.623*** (0.004)	0.618*** (0.004)	0.633*** (0.004)	0.179*** (0.029)	0.159*** (0.029)	0.135*** (0.030)
NoOfStars	9.076*** (0.628)	10.612*** (1.026)	8.441*** (1.068)	66.889*** (4.101)	83.376*** (6.540)	81.255*** (6.873)
NoOfStars^2	-1.602*** (0.094)	-1.655*** (0.131)	-1.013*** (0.142)	-3.656*** (0.621)	-3.980*** (0.848)	-5.334*** (0.933)
PropOfStarCont		-29.430*** (3.172)	-33.865*** (3.302)		-54.975** (20.698)	-100.444*** (21.719)
NoOfStars × *PropOfStarCont*		42.225*** (4.159)	59.107*** (4.535)		-23.652 (27.451)	-6.12 (30.206)
NoOfStars^2 × *PropOfStarCont*		-0.075 (0.678)	-6.090*** (0.928)		14.938*** (4.484)	16.248** (6.233)
NoOfStars × *ProjTenure*			0.312 (0.464)			-15.431*** (3.116)
NoOfStars × *OwnTenure*			0.059 (0.284)			-1.967 (1.892)
NoOfStars × *OwnType*			3.152* (1.524)			47.664*** (10.191)
NoOfStars × *ProjDyn*			0.649*** (0.035)			1.594*** (0.233)
NoOfStars^2 × *ProjTenure*			-0.003 (0.051)			-1.289*** (0.342)
NoOfStars^2 × *OwnTenure*			-0.133** (0.041)			-1.073*** (0.274)
NoOfStars^2 × *OwnType*			-1.842*** (0.337)			3.917 (2.266)
NoOfStars^2 × *ProjDyn*			-0.185*** (0.008)			-0.454*** (0.051)
Deviance (-2 log likelihood)	378861.2	378639.0	378008.8	502809.0	502761.3	502309.5
Deviance difference (Δ Dev)		222.2***	630.2***		47.7***	451.8***

Note: There are 33,924 observations at the periodic level that correspond with 7,706 projects at Level 2. Deviation differences were calculated as the difference between the current model and the previous model, i.e., Δ D2 = D2-D1 and Δ D5 = D5-D4. The significance of difference was tested after accounting for the estimated parameters in the two models. Significance levels: *p < 0.05, **p < 0.01, ***p < 0.001; standard errors in parentheses.

Table A3. Results of HLM Estimation Using the Number of Issues Open and Fork Events as Alternative Measures for OSS Product Quality and Popularity, Respectively

	Project quality measure as issues open			Project popularity as fork event		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
(Intercept)	12.598 *** (0.637)	10.318 *** (0.641)	9.595 *** (0.615)	12.917*** (0.933)	10.498*** (0.944)	11.758*** (0.964)
NoOfNonStars	0.381 *** (0.004)	0.378 *** (0.004)	0.346 *** (0.004)	0.601*** (0.005)	0.604*** (0.005)	0.589*** (0.005)
ProjTenure	-1.454 *** (0.277)	-2.014 *** (0.273)	0.226 (0.286)	-0.284 (0.356)	-0.804* (0.355)	-0.603 (0.377)
OwnTenure	-1.094 *** (0.212)	-0.833 *** (0.208)	-0.892 *** (0.208)	-0.206 (0.285)	0.092 (0.284)	0.849** (0.292)
AveYrCont	-0.031 *** (0.001)	-0.030 *** (0.001)	-0.032 *** (0.001)	-0.009*** (0.001)	-0.009*** (0.001)	-0.008*** (0.001)
TotYrCont	0.019 *** (0.000)	0.018 *** (0.000)	0.019 *** (0.000)	0.005*** (0.000)	0.005*** (0.000)	0.004*** (0.000)
OwnType	-2.342 * (1.085)	-2.910 ** (1.060)	-1.876 (1.057)	5.197** (1.603)	4.273** (1.586)	2.452 (1.661)
ProjDyn	0.127 *** (0.016)	0.119 *** (0.016)	0.105 *** (0.015)	0.064** (0.024)	0.057* (0.024)	0.041 (0.024)
IssOpen				-0.024*** (0.004)	-0.037*** (0.004)	-0.020*** (0.004)
NoOfStars	21.064 *** (0.513)	29.338 *** (0.802)	38.105 *** (0.841)	17.957*** (0.593)	25.986*** (0.991)	19.393*** (1.043)
NoOfStars^2	1.703 *** (0.090)	2.093 *** (0.115)	0.079 (0.128)	-1.702*** (0.103)	-1.637*** (0.137)	-0.185 (0.152)
PropOfStarCont		-34.302 *** (2.508)	-27.667 *** (2.542)		-35.498*** (3.012)	-33.754*** (3.109)
NoOfStars × *PropOfStarCont*		-20.922 *** (3.493)	-68.830 *** (3.762)		1.137 (4.082)	0.281 (4.422)
NoOfStars^2 *xPropOfStarCont*		18.439 *** (0.619)	32.513 *** (0.854)		10.994*** (0.720)	11.197*** (0.989)
NoOfStars × *ProjTenure*			-5.891 *** (0.373)			-1.071* (0.425)
NoOfStars × *OwnTenure*			-1.103 *** (0.233)			-5.114*** (0.270)
NoOfStars × *OwnType*			1.499 (1.203)			4.022** (1.402)
NoOfStars × *ProjDyn*			-0.470 *** (0.028)			0.388*** (0.034)
NoOfStars^2 × *ProjTenure*			-0.283 *** (0.048)			0.402*** (0.054)
NoOfStars^2 × *OwnTenure*			-0.066 (0.039)			1.464*** (0.044)
NoOfStars^2 × *OwnType*			-2.135 *** (0.317)			2.193*** (0.361)
NoOfStars^2 × *ProjDyn*			0.290 *** (0.007)			-0.144*** (0.008)
Deviance (-2 log likelihood)	957056.1	954948.6	951035.4	988004.8	987176.0	985566.6
Deviance difference (Δ Dev)		2107.5***	3913.2***		828.8***	1609.4***

Note: There are 86,728 observations at the periodic level that correspond with 21,456 projects at Level 2. Deviation differences were calculated as the difference between the current model and the previous model, i.e., Δ D2 = D2-D1 and Δ D5 = D5-D4. The significance of difference was tested after accounting for the estimated parameters in the two models. Significance levels: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$; standard errors in parentheses.

Table A4. Results for Estimation of Random Effects with Endogeneity Correction

	OSS Project quality			OSS project popularity		
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
(Intercept)	-0.753 *** (0.149)	-1.017 *** (0.152)	-1.313 *** (0.156)	-13.569 *** (2.617)	-13.537 *** (2.628)	-8.434 ** (2.612)
AveNoOfNonStars	0.138 *** (0.004)	0.142 *** (0.004)	0.129 *** (0.004)	-0.465 *** (0.053)	-0.452 *** (0.053)	-0.371 *** (0.053)
ProjTenure	0.285 ** (0.103)	0.404 *** (0.104)	0.304 ** (0.116)	-2.859 * (1.128)	-2.507 * (1.131)	-0.050 (1.217)
OwnTenure	-0.007 (0.052)	0.019 (0.052)	0.007 (0.059)	-1.246 (0.837)	-1.193 (0.838)	-0.255 (0.865)
AveYrCont	0.002 *** (0.000)	0.002 *** (0.000)	0.003 *** (0.000)	-0.028 *** (0.007)	-0.028 *** (0.007)	-0.028 *** (0.006)
AveTotYrCont	0.001 *** (0.000)	0.001 *** (0.000)	0.000 *** (0.000)	0.011 *** (0.001)	0.011 *** (0.001)	0.010 *** (0.001)
OwnType	0.376 (0.233)	0.207 (0.234)	0.384 (0.269)	66.937 *** (4.152)	66.547 *** (4.162)	42.548 *** (4.311)
ProjDyn	0.012 ** (0.004)	0.012 ** (0.004)	-0.001 (0.004)	-0.027 (0.065)	-0.027 (0.065)	-0.099 (0.066)
AveIssOpen	-0.183 *** (0.004)	-0.186 *** (0.004)	-0.173 *** (0.004)	0.086 (0.052)	0.085 (0.052)	0.024 (0.052)
NoOfNonStars	-0.002 (0.003)	0.001 (0.003)	0.036 *** (0.003)	2.213 *** (0.050)	2.214 *** (0.050)	2.345 *** (0.050)
YrCont	-0.009 *** (0.000)	-0.008 *** (0.000)	-0.008 *** (0.000)	0.023 *** (0.006)	0.023 *** (0.006)	0.027 *** (0.006)
TotYrCont	0.003 *** (0.000)	0.003 *** (0.000)	0.003 *** (0.000)	-0.008 *** (0.001)	-0.008 *** (0.001)	-0.009 *** (0.001)
IssOpen	0.873 *** (0.003)	0.873 *** (0.003)	0.872 *** (0.003)	0.073 (0.049)	0.071 (0.049)	0.120 * (0.049)
AveNoOfStars	-3.956 *** (0.456)	0.014 (0.701)	-0.892 (0.703)	2.287 (6.009)	22.039 ** (7.294)	-1.004 (7.304)
AveNoOfStars^2	0.864 *** (0.084)	0.503 *** (0.095)	0.019 (0.096)	34.669 *** (1.166)	33.028 *** (1.223)	33.706 *** (1.222)
AvePropOfStarCont		-25.331 (20.895)	-23.595 (20.712)		-685.602 * (321.073)	-566.305 (316.380)
NoOfStars	3.384 *** (0.342)	-2.176 *** (0.619)	-3.211 *** (0.626)	49.749 *** (2.438)	29.355 *** (4.555)	19.873 *** (4.695)
NoOfStars^2	-1.940 *** (0.059)	-1.368 *** (0.078)	-0.750 *** (0.083)	-9.595 *** (0.419)	-7.780 *** (0.584)	-8.834 *** (0.640)
PropOfStarCont		1.016 (1.492)	-1.959 (1.508)		37.003 ** (12.655)	-23.013 (13.092)
NoOfStars × *PropOfStarCont*		15.042 *** (1.623)	25.501 *** (1.754)		7.917 (15.800)	25.750 (17.083)
NoOfStars^2 *xPropOfStarCont*		-1.869 *** (0.317)	-1.601 *** (0.456)		3.256 (2.825)	8.700 * (3.864)
NoOfStars × *ProjTenure*			0.568 ** (0.198)			-3.266 * (1.649)
NoOfStars × *OwnTenure*			-0.003 (0.104)			-3.148 ** (1.020)
NoOfStars × *OwnType*			-1.265 * (0.540)			70.444 *** (5.312)
NoOfStars × *ProjDyn*			0.369 *** (0.011)			1.307 *** (0.124)
NoOfStars^2 × *ProjTenure*			-0.161 *** (0.027)			-2.626 *** (0.212)
NoOfStars^2 × *OwnTenure*			0.082 *** (0.018)			-1.400 *** (0.170)
NoOfStars^2 × *OwnType*			0.042 (0.169)			6.905 *** (1.415)
NoOfStars^2 × *ProjDyn*			-0.162 *** (0.004)			-0.522 *** (0.032)
Deviance (-2 log likelihood)	827751.1	827344.9	825088.3	1207061.5	1207023.4	1205346.8
Deviance difference (Δ Dev)		406.2***	2256.6***		38.1***	1676.6***

Note: There are 86,728 observations at the periodic level that correspond with 21,456 projects at Level 2. Deviation differences were calculated as the difference between the current model and the previous model, i.e., Δ D2 = D2-D1 and Δ D5 = D5-D4. The significance of difference was tested after accounting for the estimated parameters in the two models. Significance levels: **p* < 0.05, ***p* < 0.01, ****p* < 0.001; standard errors in parentheses.

Table A5. Results of Falsification Test

	Project quality			Project popularity		
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
(Intercept)	12.057 *** (0.631)	8.006 *** (0.640)	7.674 *** (0.644)	39.153 *** (2.968)	26.706 *** (3.028)	26.102 *** (3.011)
NoOfNonStars	0.196 *** (0.005)	0.191 *** (0.005)	0.215 *** (0.005)	0.069 *** (0.021)	0.041 (0.021)	0.097 *** (0.022)
ProjTenure	0.156 (0.301)	-0.427 (0.298)	1.391 *** (0.324)	1.234 (1.320)	-0.431 (1.315)	-0.141 (1.417)
OwnTenure	-1.169 *** (0.219)	-0.919 *** (0.215)	-0.972 *** (0.226)	-2.163 * (0.999)	-1.502 (0.991)	-1.305 (1.025)
AveYrCont	0.001 (0.001)	0.001 (0.001)	0.002 ** (0.001)	0.016 *** (0.003)	0.015 *** (0.003)	0.015 *** (0.003)
TotYrCont	-0.001 ** (0.000)	-0.000 * (0.000)	-0.001 *** (0.000)	-0.008 *** (0.001)	-0.008 *** (0.001)	-0.008 *** (0.001)
OwnType	-1.785 (1.067)	-3.356 ** (1.044)	-1.932 (1.108)	68.678 *** (5.050)	63.716 *** (4.993)	50.966 *** (5.176)
ProjDyn	0.124 *** (0.016)	0.112 *** (0.016)	0.045 ** (0.016)	0.280 *** (0.075)	0.244 ** (0.074)	0.195 ** (0.075)
IssOpen	-0.170 *** (0.005)	-0.170 *** (0.005)	-0.171 *** (0.005)	-0.214 *** (0.019)	-0.202 *** (0.019)	-0.234 *** (0.020)
NoOfStars	14.320 *** (0.599)	31.144 *** (0.890)	31.943 *** (0.968)	16.756 *** (2.488)	71.618 *** (3.879)	71.792 *** (4.173)
NoOfStars^2	0.145 (0.106)	-1.163 *** (0.132)	-0.316 * (0.152)	14.641 *** (0.437)	9.622 *** (0.560)	9.794 *** (0.639)
PropOfStarCont		-55.112 *** (2.872)	-49.381 *** (2.955)		-155.155 *** (12.201)	-192.529 *** (12.628)
NoOfStars × *PropOfStarCont*		12.359 ** (4.093)	-9.859 * (4.478)		42.128 * (17.076)	52.775 ** (18.767)
NoOfStars^2 *xPropOfStarCont*		-0.138 (0.739)	5.509 *** (1.042)		-12.850 *** (3.052)	-16.145 *** (4.306)
NoOfStars × *ProjTenure*			-5.308 *** (0.451)			-0.630 (1.859)
NoOfStars × *OwnTenure*			-1.584 *** (0.277)			1.948 (1.159)
NoOfStars × *OwnType*			0.288 (1.432)			68.722 *** (5.990)
NoOfStars × *ProjDyn*			0.815 *** (0.033)			0.177 (0.142)
NoOfStars^2 × *ProjTenure*			-0.216 *** (0.058)			-0.445 (0.239)
NoOfStars^2 × *OwnTenure*			0.680 *** (0.046)			-2.003 *** (0.192)
NoOfStars^2 × *OwnType*			-3.135 *** (0.384)			-24.275 *** (1.582)
NoOfStars^2 × *ProjDyn*			-0.183 *** (0.009)			0.048 (0.035)
Deviance (-2 log likelihood)	981330.9	980602.2	979380.1	1229920.0	1229592.6	1229128.2
Deviance difference (Δ Dev)		728.7***	1222.1***		327.4***	464.4***

Note: There are 86,728 observations at the periodic level that correspond with 21,456 projects at Level 2. Deviation differences were calculated as the difference between the current model and the previous model, i.e., Δ D2 = D2-D1 and Δ D5 = D5-D4. The significance of difference was tested after accounting for the estimated parameters in the two models. Significance levels: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$; standard errors in parentheses.

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