# Platform competition and strategic trade-offs for complementors: Heterogeneous reactions to the entry of a new platform*

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**Abstract**

We study how the entry of a rival platform affects the strategies of complementors of the incumbent. They face a trade-off: on the one hand, it threatens their network benefits. On the other, it lets them escape the intense within-ecosystem competition on the incumbent. We show that this trade-off does not resolve uniformly across complementors, driving heterogeneity in strategic reactions. After "Epic Games" entered the PC video game market (previously dominated by the incumbent "Steam"), two types of complementors were more likely to multihome, but became less responsive to the incumbent's orchestration attempts. This was the case for those with a weak competitive ability and those that use the entrant's upstream technology. In contrast, these reactions are reversed for those that heavily rely on network effects.

## 1 Introduction

Competition between multi-sided platforms has raised the interest of scholars and policymakers over the past decades (Rietveld & Schilling, 2020; Thatchenkery & Katila, 2022). These systems consist of a central firm – the platform owner – that connects complementor firms to end consumers via an

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indirect network (Kretschmer et al., 2022; McIntyre & Srinivasan, 2017). For example, mobile app stores – such as Google Play – connect smartphone users to app developers, enabling transactions between them. They are subject to strong economies of scale: If more developers are present in the store, consumers benefit from indirect network effects as they get to choose from a larger variety of apps (Rochet & Tirole, 2003, 2006). Platforms are therefore heavily reliant on complementors for value creation (Agarwal et al., 2023; Loh & Kretschmer, 2023) and their ability to successfully compete in the market (e.g. Cennamo & Santalo, 2013; Shankar & Bayus, 2003). Consequently, scholars have studied owners' strategies to attract platform participants, such as pricing (e.g. Cabral et al., 1999; Liu, 2010; Rochet & Tirole, 2003), exclusivity agreements (Cennamo & Santalo, 2013; Corts & Lederman, 2009), or compatibility choices (Kretschmer & Claussen, 2016; Schilling, 2003). Another stream highlights the role of platform orchestration (or governance) as a determinant of market success, studying the rules and design features owners use to regulate and coordinate complementors' value creation within their ecosystems (e.g. Claussen et al., 2013; Tiwana et al., 2010; Wareham et al., 2014).

These studies provide rich insights into *owner*'s strategies to grow and manage their ecosystems. In contrast, we know surprisingly little about the strategic choices made by *complementors*, despite their importance for platform-level outcomes. On the one hand, the fate of owners and complementors are interdependent – the one relies on the other for value creation (Jacobides et al., 2018). On the other hand, a defining feature of platforms is the legal independence of its participants (Kretschmer et al., 2022). That is, complementors are autonomous organizations that pursue their own goals, and their strategies may therefore not always be aligned with the goals of the platform owner. While orchestration attempts aim to remedy such misalignment (Tiwana et al., 2010), complementors' agency still presents a managerial challenge for platform owners. Put simply, they will only support a platform – either by joining or complying with its orchestration strategies – if it serves the pursuit of their own goals. In addition, complementors are not homogeneous in their characteristics (Agarwal et al., 2023; Boudreau & Hagiu, 2009), which makes the occurrence of misaligned goals and incentives likely. However, our understanding of how complementor agency and heterogeneity shape their strategic choices in relation to platform owners is limited.

In this paper, we investigate how (some of) complementors' strategic choices are shaped by the level of competition in the platform market. Complementors do not only affect platform-level outcomes, but they are also affected by them in ambiguous ways (Panico & Cennamo, 2022; Rietveld et al., 2020). As a platform grows, they benefit from increased indirect network effects arising from a growing consumer base. At the same time, they are confronted with increased within-ecosystem competition as more complementors also join the platform (Boudreau & Jeppesen, 2015). In addition, many platform markets are dominated by a single player (Biglaiser & Crémer, 2020; Shapiro & Varian, 1998) that is able to extract a large fraction of the co-created ecosystem value (Rietveld et al., 2020). Hence, platform growth presents a double-edged sword for complementors, and this tension is exacerbated in the case of platform dominance. Yet, how competition in the platform market affects complementors' behavior is hitherto an open question, and we aim to address it here.

In particular, we study how complementors react when a new platform enters a market that has previously been dominated by a powerful incumbent. We argue that a challenge to the incumbent's dominance – similar to dominance itself – has ambiguous implications for complementor behavior: One the one hand, the entrant threatens the network benefits they can attain by luring away consumers. On the other, it offers an alternative with less intensive within-ecosystem competition. Their reaction to the entry will then depend on which of the two dominates. However, because complementors are heterogeneous, the resolution of this tension is likely not uniform. That is, some will primarily be hurt by the entry (decreased network benefits), and some will primarily benefit (less competitive outside option). To study the ambiguous implications for complementors' choices, we ask the following research questions: *how does the entry of a rival platform affect (some of) the strategic choices complementors make? And how does this reaction differ across heterogeneous complementors?*

We focus on two strategic choices: First, we investigate their decision to multihome by joining the new rival. Before the entry, complementors had little choice but to only affiliate with the dominant incumbent. As multihoming is not costless (Cennamo et al., 2018), different complementor types will vary in their motivation to do so. Second, we study how the entry impacted complementors' responsiveness to the incumbent's orchestration attempts. With the entrant as an alternative for value creation, some complementor types will have less motivation to align their goals and activities with the incumbent owner, which will drive difference in their readiness to comply with these attempts. Further, we explore three dimensions of complementor heterogeneity, namely (i) their ability to compete in the complement market, (ii) their reliance on network effects, and (iii) whether or not they are subject to specific adoption incentives that arise from them using upstream technology provided by the entrant.

The PC video game distribution market presents the empirical setting of our study. In December

2018, the dominant incumbent platform *Steam* was faced with the entry of a powerful rival, the *Epic Games Store* (EGS). First, to study *multihoming*, we analyze which types of developers subsequently made their games, that have previously been available on Steam, available on EGS. Second, Steam's most salient ecosystem *orchestration attempts* come in the form of semi-regular platform-wide sales promotions. We study how game developers' tendency to participate in these sales changed after the entry.

We find broad support for our theoretical predictions: Complementors who derived a net-benefit from the entry of the rival platform were more likely to multihome, and decreased their responsiveness to the incumbent's orchestration attempts. This is the case for those with a weak competitive ability – they had been unable to thrive in the highly competitive incumbent ecosystem, which makes the entrant an attractive outside option. In addition, we find that complementors using the entrant's upstream technology are subject to dedicated adoption incentives, which is why they multihome at higher rates. In contrast, complementors who are primarily hurt by the entrant were less likely to multihome, but became more responsive to the incumbent's orchestration attempts. This has been the case for those that are heavily reliant on network effects: Because the entrant threatens the size of the incumbent ecosystem, they pursue strategies to protect its competitive standing, and with it their own profitability.

These findings make four contributions to the literature on platform competition: First, we show that platform-level competition affects the strategic choices made by complementors in ambiguous ways. While the bulk of existing studies focused on owners' competitive strategies (e.g. Cennamo & Santalo, 2013; Corts & Lederman, 2009; Kretschmer & Claussen, 2016; Seamans & Zhu, 2014), we put complementors' agency at the forefront. Second, we demonstrate how different dimensions of complementor heterogeneity drive multihoming choices; prior literature (Cennamo et al., 2018; Hagiu & Lee, 2011) has focused on platform characteristics. Third, we provide novel insights on the conditions of successful market entry (Sheremata, 2004; Zhu & Iansiti, 2012) by laying out how complementors differ in their willingness to support a new platform. Finally, we demonstrate how platform-level competition constitutes an important determinant of the effectiveness of platform orchestration (Claussen et al., 2013; Ghazawneh & Henfridsson, 2013; Hukal et al., 2020) by showing how it can impact the willingness of complementors to align their activities with the goals of owners.

## 2 Related literature

Our study connects to prior work on platform competition. First, much of this stream explores the implications of network effects (Eisenmann et al., 2006; Katz & Shapiro, 1985) for platform adoption and market outcomes (e.g. Clements & Ohashi, 2005; Shankar & Bayus, 2003). Often, one platform manages to tip the market and attain a dominant position (Biglaiser & Crémer, 2020; Katz & Shapiro, 1994; Shapiro & Varian, 1998). In addition, the competitive strategies of platform owners have been studied, such as pricing (e.g. Armstrong, 2006; Cabral et al., 1999; Liu, 2010; McIntyre & Srinivasan, 2017; Rochet & Tirole, 2003, 2006), exclusivity agreements with complementors (Cennamo & Santalo, 2013; Corts & Lederman, 2009), backward compatibility (Kretschmer & Claussen, 2016), and versioning (Csorba & Hahn, 2006; Parker & van Alstyne, 2005). We know less about how platform-level competition affects complementors. Loh & Kretschmer (2023) and Nagaraj & Piezunka (2024) demonstrate multi-faceted ways in which competition at the platform-level relates to the productivity of complementors in the context of crowdsourcing. Rietveld et al. (2020) show that stronger market positions enable platform owners to extract more value from their complementors' activities. Similarly, Thatchenkery & Katila (2022) demonstrate how antitrust interventions against dominant platforms can "free" complementors from such practices, which manifests in greater innovation, but not necessarily performance. These studies show that complementors are clearly affected by the competitive standing of the platforms that host them. Still, it remains a largely open question how this relates to strategic choices they make, in particular when it comes to their support of different platforms in the form of homing choices and their responsiveness to orchestration attempts. We therefore add to this discussion by studying how variation in platform-level competition impacts the support incentives of heterogeneous complementors.

Second, our study connects to the discussion around the determinants of successful platform market entry. Because of network effects, incumbents enjoy particularly strong advantages that can prevent potential rivals from entering (Biglaiser & Crémer, 2016, 2020; Farrell & Klemperer, 2007). Existing studies show that this is still possible if entrants exhibit higher quality (Zhu & Iansiti, 2012), technologically "leapfrog" the incumbent (Sheremata, 2004), or leverage an existing user base for "envelopment attacks" (Eisenmann et al., 2011). In addition, scholars have investigated incumbent platform owners' reactions to market entry (Casadesus-Masanell & Zhu, 2010; Economides & Katsamakas, 2006; George & Waldfogel, 2006; Jin & Rysman, 2015; Park et al., 2021; Seamans & Zhu, 2014). However, little is known about complementors' reactions, even though their support of a new platform (or lack thereof) is a crucial determinant of its success. We add to this discussion by studying how heterogeneity in complementor characteristics creates heterogeneity in their incentives to do so. In particular, our study therefore connects to the idea of "divide-and-conquer" entry strategies (Jullien, 2011) that target specific segments to get an initial foothold in the market.

Third, platform competition is also shaped by multihoming, that is, users or complementors joining multiple platforms (Belleflamme & Peitz, 2019). In particular, multihoming increases the competitive pressure for platforms, leading to lower profits (Landsman & Stremersch, 2011). However, our understanding of complementors' motivation to do so is limited. While prior studies have analyzed the role of platforms' technological complexity (Cennamo et al., 2018) or the allocation of control rights (Hagiu & Lee, 2011), we study how differences in complementor characteristics shape their incentives to join multiple platforms.

Finally, our paper relates to the literature on platform orchestration (or governance). This stream studies the set of rules and design features that regulate and coordinate complementors' behavior (Claussen et al., 2013; Tiwana et al., 2010; Wareham et al., 2014). Platform owners attempt to align goals with their complementors, either by regulating access and activities (e.g. Abou-El Komboz et al., 2023; Boudreau, 2010, 2012) or by deploying incentives for productive value creation (e.g. Ghazawneh & Henfridsson, 2013; Hukal et al., 2020; Rietveld et al., 2021). Further, these rules codify the distribution of value between the owner and complementors (e.g., via revenue-sharing agreements) (Sun & Zhu, 2013; Uzunca et al., 2022). Rietveld et al. (2020) discuss how dominance enables owners to apply more exploitative orchestration practices; still, complementors retain agency over their compliance with the platform's orchestration attempts.[1] Yet, little is known about the factors that shape their motivation to do so. We add to this discussion by demonstrating how the level of platform competition affects complementors' motivations to align their activities and goals with platform owners, which drives their responsiveness to orchestration attempts. In so doing, we therefore demonstrate how between-platform competition shapes the effectiveness of within-ecosystem orchestration strategies.

[1] For instance, YouTube faced criticism due to malicious content on its platform, despite rules and guidelines being in place to prevent this (Abou-El Komboz et al., 2023).

# 3 Theoretical framework and hypotheses

## 3.1 Platform dominance and complementor heterogeneity

We study a situation in which a new platform enters the market. This challenges the dominance of the previous incumbent. To analyze how this increase in platform market competition affects the optimal strategic choices of complementors, we first discuss how they are impacted by a lack of competition, that is, platform dominance.

Platform dominance presents a double-edged sword for complementors (Panico & Cennamo, 2022). On the one hand, consumer-side platform growth enhances indirect network effects (Cennamo & Santalo, 2013). If demand is concentrated in a single platform, complementors benefit from being able to transact with the entire market. In contrast, if consumer and complementor networks are splintered across multiple platforms, the overall value of the offerings is diminished (Kretschmer, 2008; Simcoe & Watson, 2019).[2] On the other hand, supply-side platform growth increases the level of within-platform competition each complementor faces (Boudreau & Jeppesen, 2015). As a dominant platform hosts the entirety of the supply side of the complement market, this means that complementors encounter the toughest competitive landscape here. Moreover, this enables a dominant platform owner to use governance mechanisms that extract a large share of the value that complementors help create (Rietveld et al., 2020). Therefore, while platform dominance comes with the greatest potential for indirect network effects, the intense competitive pressure encountered by complementors creates significant hurdles to actually reap the benefits.

The resolution of this trade-off is unlikely to be uniform. Complementors are heterogeneous in their needs and characteristics (Boudreau & Hagiu, 2009). This means that, for some, the network benefits from the demand side outweigh the competitive pressure on the supply side, creating a net benefit. For others the opposite holds true and they are primarily hurt by platform dominance. This is determined by two sources of complementor heterogeneity: First, they vary in their ability to compete in the complement market. That is, some possess a competitive advantage (Barney, 1991) which can stem from professional marketing and legal departments, vast financial resources, or a strong reputation for high-quality products. They are therefore able to prevail in the hyper-competitive supply side of a dominant platform. In contrast, complementors lacking such resources are commonly only able to compete within narrow market niches. While this limits the number of direct competitors, it also vastly reduces the number of consumers they can attract. Therefore, they

[2] Note that splintering can be an efficient outcome under some conditions, such as a high degree of consumer heterogeneity (Afuah, 2013; Suarez, 2005).

are unable to reap the full benefits of a dominant platform's large consumer base. Together, this means that the trade-off between demand-side benefits and supply-side competition is more likely to resolve in a beneficial way for complementors with an advantage in the complement market, than for those that lack it.

Second, complementors' reliance on network effects is another determinant. The returns to a larger consumer base may vary, for example, when complement-level direct network effects play a role (Agarwal et al., 2023; Rietveld & Ploog, 2022). In this case, a larger demand side not only determines the potential market size, but it directly affects the value of the complement to consumers. For example, Microsoft's Office Suite offers more utility to consumers if more are using it. It creates direct networks through the use of compatible file formats (e.g., DOC or XLS) which eases sharing of and co-working on files. Before the software package became available on competing PCs (e.g., the Mac), it was necessary to run it on a Windows machine. Hence, users of Office (a complement) benefited from Microsoft's strong competitive standing in the market for operating systems (the platform). More Windows users meant that there were also more Office users, which made the complement more valuable. Therefore, this complementor type experiences greater marginal returns to demand-side platform growth than other types. Hence, a larger consumer base benefits them more. In the context of a dominant platform, they are therefore more likely to experience a net benefit in the trade-off between network effects and competitive pressure.

### 3.2 Platform competition and strategic complementor choices

Until now, we discussed how the dominance of an incumbent platform affects complementors in ambiguous ways. How, then, do they react when a new platform enters the market? As dominance itself presents a double-edged sword to complementors, so too does a challenge to the incumbent's dominance. On the one hand, the installed base of consumers becomes splintered if a number of them decides to move from the incumbent to the entrant. Network effects arise from *increasing* returns to scale (Katz & Shapiro, 1994), that is, they are subject to *superadditivity* of installed bases. In other words, the sum of two splintered consumer bases does not bring the same network benefits as a unified one of the same size. For complementors, this means that a challenge to the incumbent's dominance can be detrimental, as it threatens the potential network benefits they can attain, even when joining multiple platforms – in addition to the multihoming costs they would have to bear. On the other, the entrant constitutes an alternative for complementors to join. Especially in the earlier stages of its diffusion, they would face less within-platform competition on the entrant platform (Boudreau & Jeppesen, 2015; Panico & Cennamo, 2022). Hence, it provides a way to escape the tough competitive landscape on the incumbent. Together, the trade-off of increased platform level competition that complementors face is therefore similar to the one connected to platform dominance itself, but in reverse: The entrant threatens potential network benefits, but offers a less competitive ecosystem to participate in. In addition, this trade-off too is unlikely to resolve uniformly across heterogeneous complementors, but will be determined by the factors discussed above.

Consequently, the situation of complementors is intertwined with the structure of the platform market (Loh & Kretschmer, 2023; Nagaraj & Piezunka, 2024), and changes to its competitive landscape likely impact the strategic choices they make in the maximization profits. While complementors make decisions over a wider range of strategic variables[3], we focus on two in our paper: Multihoming by joining the entrant, and their responsiveness to orchestration attempts by the incumbent.

First, the entry of a potentially powerful rival platform introduces the possibility to *multihome* in the first place. Doing so brings two potential benefits for complementors. They gain access to consumers that are not affiliated with the incumbent (Belleflamme & Peitz, 2019), and it enables them to partly escape the intense competitive pressure in the incumbent ecosystem. In contrast, multihoming is not costless, but may require investments into technological compatibility (Cennamo et al., 2018), paying a fee to join (Armstrong, 2006), or significantly increased effort in managing multiple customer bases and accounts. Hence, complementors have to trade off these potential benefits and costs when considering to join the entrant. Given the heterogeneity in the extent to which they are affected by the double-edged sword of platform competition, we also expect heterogeneity in the multihoming choice: Those who are – on balance – detrimentally affected by the entry have less of an incentive to multihome, either because they rely on an unsplintered consumer base on the incumbent, or because they are able to thrive in its competitive ecosystem. For others, the entrant is more likely to present a welcome outside option that enables them to escape the intensive competitive pressure.

Second, the *responsiveness to the incumbent's orchestration attempts* is likely to be affected by the shift in platform market competition. These attempts aim to align the activities of complementors towards common objectives, such as growing the platform ecosystem or enhancing its

[3]Such as pricing (Wen & Zhu, 2019), technology (Cennamo et al., 2018), horizontal positioning (Cennamo & Santalo, 2013), or innovation (Thatchenkery & Katila, 2022; Wen & Zhu, 2019)

reputation (Tiwana, 2013; Wareham et al., 2014). However, platform owners' control over complementor activities remains limited (Loh & Kretschmer, 2023; Rietveld et al., 2021) and they rely on their buy-in for orchestration attempts to be effective (Abou-El Komboz et al., 2023; Altman et al., 2019; Nickerson et al., 2017). The entry of the rival platform can impact complementors' incentives to align with the incumbent platform's goals for two reasons. For one, dominant platforms are able to use practices that extract much of the value created by complementors (Rietveld et al., 2020). A challenge to its dominance can then foster resistance, because governance in the form of "take-it-or-leave-it" propositions (Uzunca et al., 2022) becomes untenable. In addition, growing the incumbent ecosystem and its reputation may not be in some complementors' best interest anymore if they would benefit from the presence of a strong alternative in the platform market. Hence, the incentives to respond to the incumbent's orchestration attempt are linked to the competitive landscape in the platform market: If the entrant brings a net benefit for complementors, they should become less responsive. The reason is that they have less of an incentive to contribute to the incumbent's growth and reputation as it would hurt the rival's competitive standing. Instead, they should show less alignment with the incumbents goals, in an effort to increase their benefits from the heightened level of platform competition. In contrast, if they are primarily hurt by the entry, they should increase their responsiveness in an effort to protect the incumbent's dominance.

### 3.3 Heterogeneous complementor reactions to the entry of a new platform

Based on the arguments above, we develop hypotheses about how the reaction to the entry of the rival platform varies between different complementor types in terms of the two choices under study. The initial two sets of hypotheses directly connect to the trade-off between diminished network effects and softened within-ecosystem competition and explain choice variety along complementors' *competitive ability* (Hypothesis 1) and their *reliance on network effects* (Hypothesis 2). Then, we discuss the role adoption incentives put into place by the entrant – an important "pull factor" that can explain complementor behavior. In particular, we explore variation in incentives connected to complementors' *use of the entrant's upstream technology* (Hypothesis 3). Figure 1 illustrates the hypothesized relationships.

=== Figure 1 here ===

### 3.3.1 The role of complementors' competitive ability

How the entry of the rival platform affects complementors' subsequent choices is in part determined by their ability to compete within the incumbent's ecosystem. In the field of strategic management, it is a long-standing view that this ability stems from the presence of strategic resources that are valuable, rare, inimitable, and non-substitutable (Barney, 1991), such as a strong reputation or brand, unique technological or managerial capabilities, or highly capable human resources (Helfat et al., 2023). Hence, differences in competitive ability are driven by differences in resource endowment. This has implications for complementor choices: As pointed out above, complementors with a strong competitive ability tend to benefit from platform dominance. Because they are able to thrive in the incumbent's hyper-competitive ecosystem, the prospect of a less competitive landscape on the entrant is relatively less attractive to them. In contrast, complementors lacking strong strategic resources are unable to prevail in the incumbent ecosystem. Because their products are of inferior technical quality and lower innovativeness, an opportunity to escape to the less competitive entrant's ecosystem is relatively more attractive. Therefore, the trade-off between diminished network effects and softened within-ecosystem competition connected to the entry is more likely to resolve in a beneficial way for complementors with lower competitive ability.

As a result, we expect them to be more likely to multihome by joining the entrant than those with a strong competitive ability. In addition, their responsiveness to the incumbent's orchestration attempts should decrease after the entry. Their relative preference for a heightened platform-level competition means that their goals become misaligned with the incumbent. Hence, the motivation to contribute to the growth of its ecosystem and reputation should be diminished after the entry. Together, we therefore hypothesize:

**Hypothesis 1a** ***(Multihoming)*** *Complementors with a <u>low</u> competitive ability are <u>more</u> likely to join the entrant than those with a high competitive ability.*

**Hypothesis 1b** ***(Orchestration responsiveness)*** *Complementors with a <u>low</u> competitive ability are <u>less</u> responsive to orchestration attempts by the incumbent platform owner after the entry of the rival than those with a high competitive ability.*

### 3.3.2 The role of complementors' reliance on network effects

Some complementors derive greater marginal returns to platform size than others (Rietveld & Ploog, 2022). Especially in the case of complement-level network effects, a greater consumer side does not only provide indirect network benefits via its enhanced demand potential, but it directly determines a significant part of its value to consumers (Agarwal et al., 2023). Such a high reliance on network effects adds an additional dimension to the incumbency advantage in platform markets. This advantage arises from the incumbent's larger consumer base compared to the entrant (Biglaiser et al., 2019) and constitutes a significant barrier to entry. Because of this, it is challenging for the entrant to attract complementors (Zhu & Iansiti, 2012). This is particularly true for complementors that are highly reliant on network effects. Not only is the entrant unattractive due to its smaller consumer base, but it also threatens to splinter the network across multiple platforms. This would directly challenge complement-level network effects, their value to consumers, and, therefore, their overall profitability. As a result, the trade-off between diminished network effects and soften within-ecosystem competition connected to the entry is more likely to resolve in a detrimental way for complementors that are highly reliant on network effect.

This means that this complementor type has less of an incentive to join the entrant, that is, multihome. In addition, it means that their goals are highly aligned with the incumbent platform: To prevent a splintered consumer network, growing its ecosystem (or at least protecting its current size) are very much in its interest. Hence, they should exhibit an increased responsiveness to the incumbent's orchestration attempts, essentially dedicating parts of its value creating activities to benefit the entire ecosystem. We therefore hypothesize:

**Hypothesis 2a** ***(Multihoming)*** *Complementors that are highly reliant on network effects are less likely to join the entrant than those that are less reliant on network effects.*

**Hypothesis 2b** ***(Orchestration responsiveness)*** *Complementors that are highly reliant on network effects are more responsive to orchestration attempts by the incumbent platform owner after the entry of the rival than those that are less reliant on network effects.*

#### 3.3.3 The role of complementors' use of the entrant's upstream technology

So far, our discussion has focused on how within-ecosystem competition and network effects shape complementors' choices. A further determinant comes in the form of the entrant creating additional platform adoption incentives. For instance, it may target specific complementor types for initial adoption to help jumpstart network effects. In addition, entrants in platform markets may already be established in other markets. For example, Sony had already been a very successful consumer electronics firm before entering the video game console market with its PlayStation in 1994. Similarly, Google had already occupied a near-monopolistic position in online search before entering the market for mobile operating systems with Android, or the market for internet browsers with Chrome. Prior success offers a range of advantages when trying to enter a platform market. For one, it provides the often-times necessary financial "deep pockets" for such an endeavor. In addition, it can be particularly advantageous if the entrant owns and develops upstream technology that is relevant to the platform market it targets. In this case, it can leverage an existing base of technology users to enter, because it already has a potential set of customers that it can attract by creating incentives that tie upstream technology use to platform adoption. Eisenmann et al. (2011) refer to such an entry strategy as "platform envelopment". For example, Sony leveraged the (prospective) users of its PlayStation 3 to push its BluRay disc technology. The fact that all PlayStation users constituted an installed base for this disc created an incentive for other electronics manufacturers to also adopt this technology. The same is possible on the complementor side, when they use the entrant's technology in the development of its product.

If sufficiently attractive, these incentives make joining the rival more likely among those complementors that do use its upstream technology. In addition, it should negatively impact their responsiveness to the incumbent's orchestration attempts. If these incentives are setup in a way that increases the marginal returns to each transaction on the entrant relative to the incumbent platform, the complementor has a strong motivation to encourage consumption on the entrant. For example, platform owners commonly regulate these returns via revenue-sharing agreements, and the entrant can provide incentives in the form of deals that are more favorable for complementors. In this case, they have a diminished motivation to align their activities with the goals of the incumbent owner – they benefit relatively more from enhanced (demand-side) growth and reputation of the entrant. Therefore we would expect them to become less responsive to the incumbent's orchestration attempts. Together, we therefore hypothesize:

**Hypothesis 3a** ***(Multihoming)*** *Complementors that use the entrant's upstream technology are <u>more</u> likely to join the entrant than those that use another upstream technology.*

**Hypothesis 3b** ***(Orchestration responsiveness)*** *Complementors that use the entrant's upstream technology are <u>less</u> responsive to orchestration attempts by the incumbent platform owner after the entry of the rival than those that use another upstream technology.*

# 4 Setting and data

## 4.1 Institutional background

We empirically study the predictions from our theoretical framework in the context of the PC video game distribution market. Here, the dominant incumbent platform Steam faced a powerful entrant, the Epic Games Store. Video games are typically developed for one or several technology platforms such as the PC (22% of global market value in 2022[4]), smartphones and tablets (49%), or game consoles (29%).[5] In this paper, we focus on PC games. Originally sold in a physical format, they are now mostly downloaded from an online store or played online. In the PC game market, digital revenue represents 98% of total revenue. The value chain involves several players: game developers, publishers, hardware manufacturers, engine developers, and retailers. Game developers are of heterogeneous size, from large studios producing "Triple-A" games to independent ones, often referred to as "Indie". While large developers were predominant in the early stage of the industry, digitization enabled the entry of a large number of smaller players, resulting in an increased quantity and variety of products (Waldfogel, 2019).

Digital games are offered on platforms, sometimes owned by the publisher itself (e.g. Ubisoft or EA games stores) or marketplaces that, in addition to hosting first-party games, also offer third-party ones, such as Steam or EGS. Since 2003, Steam (owned by the American firm "Valve") has remained the leader in the distribution of digital games, with about 130 million monthly active users in 2023, as shown in Figure 2.[6] It offers a large variety of games from all genres, both single- and multiplayer, from independent to large publishers such as Activision Blizzard or Microsoft. While a few games are first-party games[7], most of the games offered on Steam are from third-party developers. They are free to set their own price for their product and the platform charges a fee for each transaction. Beyond being a marketplace where consumers can buy games, Steam developed

[4]Newzoo, December 2023.

[5]`https://newzoo.com/resources/blog/video-games-in-2023-the-year-in-numbers`

[6]Figure 2 also shows an overall increase in the number of users, regardless of platforms, which may speak to a general process of market expansion. In addition, we may be concerned that the launch of EGS caused a market expansion effect. It attracted a completely new set of consumers to the video game industry. However, we are not concerned for two reasons: first, there is no reason to believe that the set of games available on EGS, or the platform's functionality, are sufficiently distinct from Steam to attract a whole new customer segment (like, for example, Nintendo did with its Wii console, which offered a completely distinct set of games, as well as ways in which they are played, compared to the other consoles at the time). Second, we see very similar growth patterns between the two platforms after EGS's launch. Would the two platforms host completely distinct sets of users, we would also expect some asymmetry here. Therefore, we are not concerned that a potential market expansion caused by EGS's launch threatens our analysis. Also, Figures C4 and C5, presented in Appendix C, highlight that the number of active players did not decline after EGS's entry.

[7]That is, games developed or published by the platform owner, such as Half life or Counter Strike

a large number of features that foster the discovery of new products through a recommendation system, engagement of consumers through a review system, network effects through elements such as Steam Workshop, Steam Trading Cards, and various social features, which are designed to enhance the gaming experience on the platform. Steam also organizes semi-regular platform-wide sales during which game developers offer their games at a discounted price for a short period of time. These sales last around two weeks and attract significant attention and stimulate demand for games and the platform as a whole, in particular during the winter and summer sales.[8] Developers are encouraged, but not forced, to participate in these sales promotions. In addition, they can also offer their games at a discount outside these periods. Hence, Steam sales constitute an important attempt at orchestrating its ecosystem towards stimulating a period of high demand.

Even though other digital stores were launched after Steam (Microsoft Store in 2005, Ubisoft's Uplay in 2012, and EA Origin in 2013), these were operated by a large game publisher distributing its own products. For other third-party developers, access to these stores was virtually impossible and alternatives for the distribution of their products were scarce, providing Steam with a dominant market position. By 2018, the its market share was estimated between 50 and 70% of the PC games distribution market (Wu & Zhang, 2019), making it the largest platform. With about 26,000 games at that time, the number of games offered in the store kept on increasing steadily over time, reaching over 71,000 games at the end of 2023,[9] with more than 8,000 new games released every year since 2018.[10]

=== Figure 2 here ===

In December 2018, Epic Games launched the Epic Games Store (EGS). The digital marketplace offers services similar to Steam's, and also sells a few first-party games (e.g., the successful game "Fortnite"). While starting from a much more modest installed base of consumers, Epic's revenue sharing agreement, in which only 12% go to the platform, quickly attracted some game developers. To further grow its installed base, Epic developed two main strategies that turned out to be successful. First, it obtained several exclusivity agreements with developers that agreed not to sell their

[8] In Steam's 2022 *Year in Review*, we can read: "Steam's seasonal sale events have been a big part of the PC gaming landscape for a long time, and 2022 was no exception. These sales are eagerly anticipated by existing players, but they're also a great driver of new customers for your game. For instance, during the 2022 Autumn Sale, 1.4 million accounts made their first-ever purchase on Steam. That's about 134 new customers every single minute, for seven days straight."

[9] https://gamalytic.com/blog/steam-revenue-infographic

[10] https://steamdb.info/stats/releases/

games on Steam (e.g. Tom Clancy's The Division 2 in 2019).[11] Second, Epic also fostered affiliations of consumers by allowing them to download a game for free each week. Further, Epic owns the Unreal Engine, which is a 3D computer graphics tool that is widely used by third-party developers. In addition to offering a more generous revenue-sharing scheme to third-party publishers, Epic waived the engine royalty fee for all games sold through EGS (Wu & Zhang, 2019). Perhaps as a reaction, right before the entry of Epic, in November 2018, Steam announced that the revenue share on their store would be changed to a tiered system that benefits games generating very high revenue on the platform, indicating its attempt to retain high-demand games. By the end of 2023, the average number of monthly users was over 75 million, as shown in Figure 2, and the number of games was approaching 3,000. While Steam remains the largest player, EGS constitutes an alternative that keeps on growing, both in terms of the number of consumers and complementors.[12]

### 4.2 Data collection

We collected data on game characteristics and prices from various sources using web scraping techniques. We then combined our different datasets either using a unique ID each game is assigned on Steam, or fuzzy matching techniques based on their title. The total sample consists of 11,439 games, among which 9,335 are only observed on Steam, 1458 only on EGS, and 645 on both platforms in June 2022.

**Steam** First, we collected a list of games and characteristics for games available on Steam (12,460 games) using its API. We obtained a wide range of game characteristics, namely their genre (e.g. "Action", "Strategy", "Adventure"), steam store categories (e.g. "Multi-Player", "Steam Cloud"), as well as names of the developer and publisher.[13] We also obtained information on the technical characteristics of the game, as well as its date of release on the platform. In addition, we obtained consumer reviews of these games, including information about the reviewing consumer, the time when it was written, and whether it is positive or negative. Lacking information about game sales and revenues, the number of reviews serves as a proxy for their performance on Steam. Finally, we collected daily prices of these games from Steamdb.info, information that is available for the period

[11] Some games stay available on the direct channel of the publisher (Ubisoft's Connect) or other platforms (Playstation, Xbox).

[12] See Figures C4 and C5 for more details on the evolution of the numbers of users on Steam.

[13] In the video game industry, the development studios create the game itself (game design, art, direction), and the publisher typically takes care of marketing, distribution, and financing. When a game is released, this is the result of studios and publishers working together in a vertical relationship. The distinction between the two does not relate to our distinction between complementors of high and low competitive ability.

between January 2015 and June 2022. Steamdb.info continuously scrapes the Steam API, providing the full pricing history for the games in our sample. We were able to obtain this information for 10,746 games. We collected these prices and discounts in US Dollars.[14] In addition, and crucial for parts of our empirical analysis, this data source also contains information about game discounts that are offered as part of Steam-wide sales promotions. Hence, it enables us to track games' participation in these sales. To complement this, we also collected information on concurrent active players on Steam from Steamcharts.com. The site performs daily scrapes of the Steam API and retrieves current active player numbers for the most 13,350 popular games at each point in time. Depending on the game and the site's frequency of API calls,[15] this provides us with time-varying and historical player numbers. As our own scrape of the site concluded in January 2022, our sample reflects the most popular Steam games at that time.

**Epic Games Store** Second, we collected a list of all 1,706 games and their characteristics from EGS directly. We obtained the day of release on the store, as well as some characteristics that are broadly similar to what we were able to observe on Steam.

**Additional sources** We collected information from MobyGames, which is an extensive crowd-sourced database containing extensive information on all video games released for PC, home and portable consoles, and mobile (about 73,840 games). From this source, we retrieved information on the genre, date of release, names of the platforms for which the game was developed (e.g., PC, Playstation, iOS), number of staff who worked on the game, and whether the game was developed with Epic's Unreal Engine. We also complement this with information from the Wikipedia category "Unreal engine games".[16] Finally, we also obtained information on critic scores from Metacritic.

# 5 Empirical framework

In Section 3, we discussed how the entry of a rival platform affects heterogeneous complementors' choices. Some types are more likely to multihome than others, and some are more likely to increase their responsiveness to orchestration attempts by the incumbent than others. In this section, we lay

[14]We also have prices in Euro, British Pound, and Japanese Yen. In an earlier version of the manuscript, prices in Euro were used in some of our regressions, with a very minor impact on the results.

[15]Before 2020, only monthly data is available. For later API calls, data for the most popular games is available at the daily level.

[16]See `https://en.wikipedia.org/wiki/Category:Unreal_Engine_games`.

out how we operationalize the key constructs underlying our hypotheses, as well as our empirical strategy to test them.

## 5.1 Variables

### 5.1.1 Outcomes of interest

We analyze two strategic choices complementors make. First, we study the determinants of multi-homing, that is, their decision to join the entrant's platform in addition to the incumbent's. Hence, we use a dummy indicating games that become available on EGS after its launch as the dependent variable to test this set of hypotheses.

Second, we test how complementors' responsiveness to the incumbent's orchestration attempts changes after EGS's launch by studying their participation in Steam's sales promotions (*Steam sales*). These are promotional periods that semi-regularly take place on the platform. Steam invites, but does not force, game developers to participate in these sales by discounting their games during a certain duration. These promotions generate high attention and increased demand at the platform level, and their effectiveness depends on the participation of developers. We study how the likelihood of participating in these sales changed after the launch of EGS. We consider this an indication of their responsiveness to orchestration attempts, because it shows their willingness to align their goals with the platform owner. Sales participation means that developers time their discounts to coincide with these promotional periods. Of course, discounting games in itself may simply serve to create attention for the product itself. However, during these promotional periods, each participating complementor practically chooses to discount their game at the same time as a high number of other complementors. As a result, they forgo the benefit of creating attention at the product level – they choose not to use it as a competitive action in the complement market. Instead they respond to the incumbent's effort to coordinate discounts across all games to create attention at the platform level. Hence, it constitutes a contribution to the "public good" of platform growth and reputation (Cennamo & Santaló, 2019).[17]

[17]In section 6.2.3, we perform a mechanisms test of how complementors' tendency to discount their games *outside* promotional sales periods changes after the entry and find no significant effects. This supports the idea of orchestration responsiveness.

### 5.1.2 Heterogeneous complementor types

In our hypotheses, we formulate expectations about how different complementor types will react to the entry of a rival platform. In particular, we highlight the role of their competitive ability, their reliance on network effects, and their use of the entrant's technology. Empirically, we identify different types of game developers to reflect these distinctions.

**Low vs. high competitive ability (Hypothesis 1)** Similar to the movie and music industry, video game producers can be roughly divided into major (or "Triple-A") and Indie (independent). The most salient differentiating factor between the two is their endowment with resources, financial and others. Triple-A games have significantly greater development budgets, which are expected to surpass 1bn US Dollars in the near future (Zollner, 2023). These financial resources enable them to form large development teams[18], invest in the latest technology to build games of the highest fidelity, and have in-house marketing capabilities for highly effective promotion. In contrast, indie games – while not a clearly defined term – tend to be connected to "simple gameplay, simple graphics, small teams" (Dutton, 2012). In addition, major developers have large legal departments at their disposal, which enables them to engage in direct negotiations with platform owners like Steam, that is, they wield considerable "persuasive resources" (Ryall, 2013) as well. Together, these differences in resource endowments drive differences in competitive ability in the video game industry. Hence, we capture a low competitive ability via a dummy variable indicating games developed by Indie developers.

**High vs. low reliance on network effects (Hypothesis 2)** Some games offer functionalities that enable consumers to play together online. Such *multiplayer* games are subject to product-level direct network effects (Rietveld & Ploog, 2022), which makes them more reliant on a large, unsplintered consumer base.[19] Without it, they are unable to realize their full value potential. This

[18] In our own data, the average number of development staff is 117 for major, and only 16 for indie games.

[19] Our arguments rely on network effects to be platform-specific. That is, consumers can only play games together using the same platform. For example, Steam users can only play with other Steam users, or – in the home console space – PlayStation owners with other PlayStation owners. This form of incompatibility has been common practice in the video game industry. However, more recently, the industry saw developments towards "cross-platform play", which lets consumers play a game together regardless of the platform they own. This makes the network effects game- rather than platform-specific. For our analysis, this would mean that multiplayer games that allow cross-platform play do not rely on Steam's installed base advantage. To check how prevalent this is in our setting, we collected information about this type of game. It turns out that this is not yet common practice and that only eleven games in our sample allow for this. On the one hand, this alleviates concerns that this would bias our estimates. On the other hand, there are not enough observations to conduct a proper econometric analysis. We collected this information from Wikipedia (`https://en.wikipedia.org/wiki/List_of_video_games_that_support_cross-platform_play`).

is in contrast to singleplayer games, which consumers play by themselves, making them less reliant on a large consumer base. Hence, we capture a greater reliance on network effects via a dummy variable indicating multiplayer games.

**Use of the entrant's upstream technology (Hypothesis 3)** "Game engines" are software tools used in the development of video games. As such, they constitute an important upstream technology. Epic Games is the owner and developer of the "Unreal engine", one of the most popular tools. The company licenses out the technology to other developers for a royalty fee of 5%.[20] In addition, Epic Games leverages the engine to promote the adoption of its platform by waving the royalty fee on revenues achieved through sales on EGS.[21] That is, while game developers have to pay the fee on sales through Steam, they do not have to on sales through EGS. Therefore, this constitutes an additional adoption incentive for game developers that use the engine. In combination with Epic's more favorable revenue-sharing scheme, this means that such developers can retain as much as 23 percentage points more in revenue on sales through EGS than through Steam (Orland, 2018). Hence, we test Hypothesis 3 using a dummy variable indicating games that rely upon the Unreal engine.

## 5.2 Empirical approach: Multihoming analysis

In this part of our analysis, the dependent variable is an indicator variable for multihoming which captures the affiliation with the entrant's platform at the end of our sample, approximately three years after the entry took place. We expect the probability of multihoming to be higher for Indie than non-Indie games (H1a), lower for multiplayer than singleplayer games (H2a), and also higher for games that were developed using Epic's Unreal engine compared to those that were not (H3a).

### 5.2.1 Sample

Because we are interested in how the incumbent's complementors react to the entry of a rival, we focus our analysis on games that are available either only on Steam or on both platforms, but not those that are only available on EGS. We also removed games developed by "Valve", the firm that owns and operates Steam. Then, we model developers' multihoming decision by evaluating which of the games in our sample became available on EGS from December 2018 to June 2022, which is when

[20] The fee needs to be paid above a revenue threshold. In May 2020, Epic increased this threshold from 50.000 USD to 1.000.000 USD (Machkovech, 2020).

[21] See `https://store.epicgames.com/en-US/publish`.

we collected information from the stores. Our final sample, for which all variables are available, consists of a cross-section of 8,101 games, out of which 7.06% are multihoming.[22]

### 5.2.2 Regression model and identification

We use a logit specification where the dependent variable takes a value of one if the game $i$ has also joined EGS by June 2022, and zero otherwise. A zero value can be interpreted as the decision for a game to stay exclusive with Steam even though EGS had been available for over three years. Note that joining EGS is a one-off decision for developers. This means that there is no within-unit variation over time, and we have to resort to a cross-sectional analysis. This bears the challenge that games are not randomly assigned the types we are interested in (Indie, multiplayer, Unreal), but are likely to structurally vary along additional dimensions. The issue is that these dimensions are also likely to partly determine the multihoming decision. That is, endogeneity from omitted variables would bias our estimates if not addressed. Below, we discuss how we address this concern with a combination of control variables, fixed effects, and matching. We model the decision to multihome as follows:

$$Multihoming_i = \alpha + \beta_1 \times Indie + \beta_2 \times Multiplayer + \beta_3 \times Unreal + \beta_4 X_i + \gamma_g + \gamma_r + \epsilon_i$$

$Multihoming_i$ is a dummy variable coded one if the game is available on both platforms and zero otherwise. The terms $Indie$, $Multiplayer$, and $Unreal$ are dummies indicating the types of games we hypothesize about. That is, the main coefficients of interest are $\beta_1$ (H1a), $\beta_2$ (H2a), and $\beta_3$ (H3a).

We also include two sets of fixed effects and a range of controls to address the aforementioned endogeneity concerns. First, we include genre fixed effects, $\gamma_g$. This controls for level of competition a game faces, which is partly determined by its positioning in certain market segments. Hence, its genre may be an alternative explanation for their decision to multihome if not controlled for. Second, we also include release year fixed effects, $\gamma_r$, because the multihoming decision likely differs along a game's life cycle. For example, games typically achieve the majority of their sales within the first twelve months after release (Claussen et al., 2012), which is why older games may expect to gain less from joining EGS.

[22] In addition to our main analysis at the game-level, we also investigate the multihoming choice at the firm-level in Appendix A.6. There, we aggregate the multihoming choice by calculating its prevalence across publishers' game portfolios. The idea is that the multihoming decision may be correlated within each firm. Results (reported in Table A6) are partly robust.

Third, the vector $X_i$ contains a range of control variables: we control for several factors that can carry lock-in effects developers experience on Steam. Here, we add the number of games that both the developer and the publisher have released on Steam as proxies for their experience on the platform. In addition, Steam offers a range of standardized features that developers can include in their games to nourish community engagement, direct network effects, or enable cloud-based services. For each feature, we include a dummy indicating that it is incorporated into a game. In contrast, games' availability on home consoles may indicate the absence of lock-in effects, and we include a dummy to indicate this.

Finally, we include a range of variables to proxy for a game's quality or popularity. Here, we control for its price (a higher price may indicate higher quality and possibly higher demand), the average number of active players (a higher number indicates greater popularity)[23], and the size of the development team (as a proxy for its production costs). In addition, we include a dummy that indicates a game that includes in-app purchases; that is, it relies on recurring revenue streams, which may be a deterrent from "splintering" the player base across multiple platforms. Finally, for the subset of games that had been released before the launch of EGS, we can control for the number of user reviews it had accumulated on Steam up until this point in time, as well as the share of positive ones. These serve as further controls for a game's popularity and quality.[24]

### 5.3 Empirical approach: Sales participation analysis

In Hypotheses H1b, H2b, and H3b we make predictions about how the launch of EGS affects complementors' responsiveness to orchestration attempts. Empirically, we test this by analyzing the probability of their participation in Steam sales. We expect this probability to decrease for Indie games (low competitive ability, H1b), increase for multiplayer games (high reliance on network effects, H2b), and also decrease for games that were developed using Epic's Unreal engine (the entrant's upstream technology, H3b). We test our hypotheses within a difference-in-difference (DiD) framework. Throughout, the dependent variable is a dummy indicating that game $i$ participated in a Steam sale $s$. We, therefore, estimate how the probability of sale participation differs between the periods before and after the launch of the Epic Games Store, and how this change depends on these different game types.

[23]This is an imperfect measure because the average is calculated over a games' entire lifetime until the time of our data collection. That is, in some cases, it includes player numbers from after the time a game had joined EGS.

[24]Our main results are robust to matching on these variables instead of adding them as controls. We describe and discuss this alternative matching strategy in Appendix A.5.

### 5.3.1 Sample

In our main specification, we consider a sample period of one year before and after the launch of EGS, which allows us to account for seasonal effects. Within this two-year period, Steam organized a total of 27 sales. Some of these sales are highly specialized and relevant only for certain types of games[25], while others are of a more general nature. Hence, the overall number of participating games can vary widely between them. We account for this in the following way: We calculated the share of games in our data that participate in each sale. Values range between 0.13 % and 75.17 %, illustrating these vast differences in popularity. To remedy this, we only include sales that have at least one percent of games participating in our main specification.[26] This leaves us with a total of 18 Steam sales, out of which seven took place in the year before EGS's launch and eleven afterwards. Further, as we are interested in how incentives to cooperate with the incumbent changed for complementors, we only include those 4,191 games that have been available on Steam at the beginning of our sample period. Then, the unit of observation in our regressions is a game sale; that is, we observe each game during the period of each sale in our sample, and we evaluate whether or not it participated in that sale. Our final regression sample consists of 75,179 game–sale observations.

### 5.3.2 Regression model and identification

We face several empirical challenges. First, to test our hypotheses, we use three different "treatment" indicators in our DiD framework: Indie, multiplayer, and Unreal engine games. Therefore, we face empirical challenges arising from the fact that we estimate differences between types of games that may not be comparable with regard to their inherent tendency to participate in Steam sales. For example, multiplayer games may rely relatively more on "in-game" monetization (via in-app purchases) compared to singleplayer games, which may drive their inherent tendency to participate in sales. In addition, such differences may also affect their ability to optimally react to EGS's launch. We control for such differences in two ways: (i) we include game fixed effects throughout to account for unobserved and time-invariant differences in their participation tendencies, (ii) we run our regressions using matched samples to further control for observed performance and quality differences.

[25]Table B1 in the Appendix contains a list of all 27 sales. For instance, there are some sales that are specific to relatively small countries (at least in terms of the size of their video game industry). Examples include a "100 Years of Polish Independence Sale" or a "Games from Norway Sale".

[26]Our results are robust to including all sales and only those with a least five percent of games participating.

Second, a challenge arises from heterogeneity across different Steam sales. As pointed out before, some of them target broader sets of games than others. In addition, the platform decides when and what type of sales to organize. This may be subject to changing rationales. Most importantly, the launch of EGS may have sparked the organization of additional sales to keep consumers on the incumbent. We account for these potential confounding factors by including sale fixed effects (e.g. "Winter Sale 2018") throughout our analysis. That is, our estimates can be understood as the probability of a game participating *conditional* on the nature of the sale, which is unobserved by us. This also accounts for games' average tendency to participate in a sale, which is likely a function of how many sales take place within a certain time period. In our case, Steam organized more sales after EGS's launch, which then may make game developers more selective about which ones to participate in. Together, we estimate econometric models of the following form:

$$Y_{is} = \alpha + \beta_i(\text{After}_s \times T_i) + \beta_X X_{is} + \gamma_i + \gamma_s + \epsilon_{is}.$$

Here, $Y_{is}$ is our dependent variable, which is a dummy indicating that game $i$ participated in sale $s$. Further, $\text{After}_s$ indicates sales that occur after the launch of EGS, and $T_i$ is our "treatment" indicator of a certain type of game (i.e. Indie, Multiplayer, or Unreal engine game). In addition to fixed effects, we also include a vector of four time-varying game-level control variables, $X_{is}$: (i) we include the total times a game has been reviewed on Steam at the time of a sale. As we do not have data on game sales, this serves as a proxy for its prior performance (ii) on Steam, players can indicate whether they liked a game or not via a "thumbs up" or "thumbs down", and we control for its share of positive reviews to further account for quality differences in terms of audience reception (iii) we control for a game's age (in days) to capture unobserved differences in their tendency to participate in sales, which may vary over their life cycle. And (iv), we control for the number of games in the same genre that are available on Steam. The positioning in market segments partly determines the level of within-ecosystem competition a game faces. Hence, we control for this potential alternative explanation. For games that position themselves in multiple genres, we add up all other games in them, but then divide this number by the focal game's genre count. Next, $\gamma_i$ and $\gamma_s$ are game- and sale- fixed effects. Note that the latter also controls for unobserved time trends.[27]

[27] We conduct a two-part analysis of potentially non-parallel pre-trends in Appendix B.2. First, we offer a visual inspection in Figure B3. Despite the substantial variation in participation rates between different sales, this does not raise concerns about problematic pre-trends. Still, we also test for pre-entry variation in the tendency to participate in Steam sales between our different game types. The concern is that differences may have existed beforehand. However,

Lastly, we run part of our analysis on matched samples. This serves as a more conservative alternative to our time-varying controls in $X_{is}$. It also controls for observed factors that may otherwise confound our results but ensures that our coefficients only reflect differences between games that are otherwise comparable in their relevant observed characteristics. Specifically, we use coarsened exact matching (CEM) based on the control variables in $X_{is}$, but measured at the time of EGS's launch. The only difference is that we match on games' release year instead of their age in days. Therefore, we only compare (i) Indie to non-Indie, (ii) multiplayer to singleplayer, and (iii) Unreal engine to other engine games that exhibit similar performance, audience reception, age, and intra-platform competition.[28]

# 6 Results

## 6.1 Multihoming analysis

### 6.1.1 Descriptive statistics

Table 1 presents summary statistics for the variables used in our multihoming analysis. The sample contains a total of 8,101 games that are available on Steam, 7% of which multihome by being available on both platforms as of June 2022.[29] In addition, the slight majority of them are Indie games (61%), 30% offer multiplayer functionality, and 4% have been developed with the use of Epic's Unreal engine. While the latter may seem low at first glance, it has to be noted that many alternative engines exist[30], some of which can be licensed for free. In addition, it is not uncommon for game developers to build and use proprietary engines.

as shown in Figure B2, this is not the case. Together, we are therefore confident that our results are not driven by potential differences in game developers' pre-entry choices.

[28]We evaluate the effectiveness of our matching strategy by testing for differences in means in our matching variables between the different complementor types, and if they decrease after matching. Table B2 in the appendix shows the test results for Indie vs. non-Indie, multi- vs. singleplayer, and Unreal vs. non-Unreal games. Before matching (CEM), we find clear and statistically significant differences in means in all matching variables, and for each comparison. After matching, these differences largely disappear. The exception is differences in the pre-EGS review count, which remains statistically significant for each comparison even after matching. However, they become considerably smaller, suggesting that the comparability of our complementor types improves. Moreover, our results are robust to including our linear controls in addition to matching on their pre-EGS values.

[29]Appendix A.1 contains additional descriptive statistics about the timing and sequence of multihoming. For the multihoming games (504 observations in the sample for which we can observe precise release dates), 63% were available on Steam first and then joined EGS, 27% were released simultaneously, and about 9.5% were released on EGS before Steam. To the extent of our knowledge, only three games fully migrated from Steam to EGS. In addition, we provide in Appendix C.1 several descriptive statistics that provide insights about some differentiation between the two platforms in terms of prices, genres, and socio-demographics of their audiences.

[30]For reference, the Wikipedia article "List of game engines" currently lists 182 different engines. See `https://en.wikipedia.org/wiki/List_of_game_engines`.

Turning to our variables capturing potential factors that determine lock-in effects on Steam, we observe that, on average, a developer has around three games on the platform, and a publisher has around ten. For both, this number follows a power law distribution, with few developers and publishers having released a high number of games, and many having released only a few. Further, the share of games that include a certain Steam feature varies between 8% ("Workshop", which enables user-generated game modifications) and 64% ("Achievements", which lets users display their accomplishments in a game in their profile), likely reflecting the specificity of their use and the ease of incorporating them. In addition, around one third of games are also available for at least one home console (e.g. Sony Playstation or Nintendo Switch). While these platforms are usually considered a separate market from PC gaming (e.g. Clements & Ohashi, 2005), this still indicates that most developers are not subject to strong lock-in effects on Steam.

Next, we discuss results obtained for the variables that control for game quality or popularity. The average game on Steam is priced at 14.92 USD[31], with some being offered for free (so-called "free-to-play" games), and others priced as high as 129.99 USD. Further, on average, games have 813.48 concurrent active players, which however also follows a power law distribution, with some exhibiting no active players at all, and others exhibiting an average of almost one million. In addition, the average game has been created by a team of 59.62 developers (also subject to a power law distribution). Moreover, regarding monetization, 2% of games use in-app purchases, which enable consumers to acquire assets while playing. Finally, for the subset of games that had been released before EGS's launch, we observe that they had been reviewed an average of 3,240 times on Steam, with an average share of 78% positive reviews.

=== Table 1 here ===

#### 6.1.2 Main results

Table 2 presents the results from our main analysis of complementors' multihoming decision. Throughout, we report average marginal effects, that is, coefficients represent percentage changes in the probability that a game multihomes. Models 1 to 5 show estimates obtained from regressions in which we add our control variables, with varying combinations of fixed effects. We discuss the results obtained for Model 5, which includes the full set of controls and fixed effects. First, we find

[31] Here, we use information from the Steam storefront as displayed in the US. We also have information about the UK, EU, and Japanese prices and sales promotions, which do not exhibit meaningful differences in terms of our analyses.

strong support for H1a: Indie games are 2.98 percentage points ($p < 0.001$) more likely to multihome than non-Indie games. This is consistent with the notion that they welcome the opportunity to shift their value creation to the (at least initially) less competitive entrant's ecosystem. In addition, considering the sample mean of 7.06% of multihoming games, this is also an economically sizeable effect.

Second, we also find support for H2a, but not as consistently. The coefficient indicating multi-player games is negative and statistically significant in most, but not all, models. In particular, the estimated coefficient becomes smaller (and insignificant) in Model 5, in which release year dummies are added. This may indicate that some dynamic effects are at play, and we conduct am additional analysis of the timing of multihoming to shed light on those dynamics (see Section 6.1.3).

Third, we also find strong support for H3a: games developed with the Unreal engine are 2.9 percentage points ($p < 0.01$) more likely to multihome than games using another engine. Again, this speaks to the notion that EGS constitutes an attractive alternative for this complementor type, likely because Epic is waving the royalty fee for using the technology on sales achieved. This illustrates the effectiveness of the entrant's strategy attract this set of complementors by creating adoption incentives related to the use of its upstream technology – perhaps indicating an "envelopment attack" (Eisenmann et al., 2011). In addition, the effect size is sizeable and similar to our estimate for Indie games. Together, our main analysis provides broad support for the predictions from our theoretical framework and hypotheses. In particular, they highlight how the entrant constitutes an attractive outside option for some (but not all) complementor types.

=== Table 2 here ===

#### 6.1.3 Additional analyses

We run additional regressions to test the robustness of our main results and to shed light on the mechanisms that underlie complementors' multihoming decisions. Here, we briefly describe these tests and the main insights they provide. A more extensive discussion is provided in Appendix A.

**Timing of multihoming** In our main specifications, we run cross-sectional analyses, implicitly treating multihoming as a static choice. However, this approach may hide heterogeneity in timing across game types, which itself might be informative. Therefore, we run additional analyses in Appendix A.2, in which we use information about differences in dates at which games were released on Steam and EGS. Specifically, we analyze a series of hazard rate models, estimating the time between releases on the two platforms, and how this differs between the different complementor types we hypothesize about. The results are consistent with our main results in that they suggest Indie games' "time to multihome" is significantly lower than non-Indie games'. For multiplayer games, the situation is reversed, that is, the time to multihome is greater for them compared to singleplayer games. However, this effect is estimated at lower precision. Finally, the time to multihome is again significantly lower for Unreal games compared to those that use another engine. In all, we therefore consider our main results robust to allowing for a dynamic way of modeling the multihoming decision.

**Games released before and after the EGS launch** We split the sample into games that were released before and after the entry to explore some of the mechanisms that underlie our findings. The main idea is that those games released before the entry already had the opportunity to accumulate sales on the incumbent, therefore potentially incurring switching costs (e.g. related to building their reputation on the platform via reviews and ratings). In contrast, games released after the entry can make the multihoming choice immediately. We present the results from additional regressions in Table A3 in Appendix A.3. We find that Indie games are always more likely to multihome, regardless of their release date. For multiplayer games, the sample split provides no significant results. For Unreal engine games, we find that only those released *after* the EGS launch are more likely to join the entrant. The findings add nuance to the overall picture: While developers of Indie games seem to always find it worthwhile to join EGS, the same is not true for Unreal engine games. This suggests that developers consider the lifetime value of this choice in different ways. That is, Unreal engine game developers do not consider the necessary effort and cost of multihoming worthwhile when they already accumulated the majority of their sales on the incumbent. In addition, for games released before entry, we can additionally control for the number and quality of their reviews on Steam. This does not qualitatively change the estimated coefficients, which we take as evidence that their omission in the full sample does not bias our results.

**The role of game popularity and quality** In Appendix A.4, using a sub-sample of games released before the EGS launch, we investigate if more popular or higher quality games are more likely to multihome, and if this varies by complementor type. We find that games of higher quality are (almost) always more likely to multihome, regardless of type. In contrast, greater popularity is related to increased multihoming for Indie and Unreal engine games. This is consistent with our theoretical framework: The types of complementors that have the most to gain from joining the entrant do so with their most popular products, which promises the highest returns at the margin.

## 6.2 Sales participation analysis

In the following, we lay out the results of our analysis of how EGS's launch affected games' participation in Steam sales. Consistent with H1b, H2b, and H3b, we expect this reaction to differ between Indie and non-Indie games, multiplayer and singleplayer games, as well as games that are developed using Epic's Unreal engine and those that are not.

### 6.2.1 Descriptive statistics

Table 3 contains descriptive statistics for our main sample. On average, 38% of games participate in sales. [32] In addition, more sales fall within the period after than before EGS's launch. In fact, as illustrated in Figure 3, Steam increased the number of sales per year between 2017 and 2020. This may be a reaction to the launch of EGS, and we address this issue by including sale-fixed effects throughout.

=== Table 3 and Figure 3 here ===

Next, 49% of our games are developed by Indie developers, hence in the case of this "treatment" we have an even split. In contrast, 36% offer multiplayer functionality, and only 3% are developed using the Unreal engine. In terms of time-varying control variables, games have an average of 4,130 reviews at the time of a sale, and 77% are positive. Moreover, the average game is 1,518 days old. This relatively high number is driven by a handful of very old, but still popular games. Further, the average game faces competition from 1,639 others in the same genre within Steam.[33]

### 6.2.2 Main results

The main results of our sale participation analysis are presented in Table 4. Throughout, we report linear probability models, as they allow for two-way fixed effects and let us include and interpret interaction terms in a straightforward manner. Standard errors are clustered at the game level. In H1b, we hypothesized that complementors with a low competitive ability are less likely to participate after EGS's launch than those with higher competitive ability. We test this hypothesis in Models 1,

[32] However, as shown in Table B1, this varies considerably across sales.

[33] We also use coarsened exact matching (CEM) in parts of our analysis. There, we match on our control variables, but measured at the time of EGS's launch. At that time, the average game had 3,968.24 reviews, out of which 77% were positive, had been released in 2014, and faced intra-platform competition from 1,567.17 other games.

4, and 5, and we find broad support: in Model 1, we use the full sample without matching and only include the DiD term with our Indie game indicator variable. We find that the probability of sale participation is 1.4 percentage points ($p < 0.01$) lower after EGS's launch for Indie games than for non-Indie games. In Model 4, we run a full model, including the DiD terms involving multiplayer and Unreal engine game indicators. We still find support for H1b, albeit with a slightly smaller coefficient ($\beta = -0.0117$) that is estimated with less precision ($p < 0.05$). Finally, in Model 5, instead of using time-varying controls, we estimate our model using a matched sample.[34] That is, each Indie game is only compared to non-Indie games of similar performance, audience reception, age, and facing similar intra-competition. Such a match is only found for 3,021 games, leading to a reduced sample size. Still, H1b is again supported with an even larger estimated effect size: Indie games are 2.04 percentage points less likely to participate in Steam sales after EGS's launch compared to non-Indie games ($p < 0.01$).

=== Table 4 here ===

Next, in H2b we hypothesized that complementors that are highly reliant on network effects are more likely to participate in sales after EGS's launch. We test this in Model 2, using the full sample and only including the DiD term with the multiplayer game indicator. We find support for the hypotheses: Multiplayer games participate in sales with 2.58 percentage points higher probability ($p < 0.001$) after EGS's launch than singleplayer games. We estimate effects of similar size and with similar precision when using the full model (Model 4, $\beta = 0.0246$, $p < 0.001$), and a matched sample (Model 6, $\beta = 0.0254$, $p < 0.001$).

Finally, in H3b we hypothesized that complementors that use the entrant's upstream technology are less likely to participate in sales after EGS's launch. We test this prediction in Models 3, 4, and 7. However, regardless of the sample considered or the econometric model, we do not find any support. The estimated coefficient is statistically insignificant in all models.

Together, we find support for H1b and H2b, but not H3b. While the effects we estimate are statistically significant, they are rather small in size. On average, games in our sample participate in 38% of sales. Based on our most conservative estimates from matched samples, the probability of participation is 2.04 percentage points lower for Indie than non-Indie games, and 2.54 percentage points higher for multi– than singleplayer games. Hence, our results imply that complementors' reaction in terms of their responsiveness to orchestration attempts is relatively mild.

[34] Note that it is impossible to estimate effects on a matched sample with all three relevant DiD terms. The reason is that the CEM weights have to be obtained for each treatment group indicator separately.

### 6.2.3 Additional analyses

We again run a series of additional analyses to shed additional light on the underlying mechanisms. We again provide a brief description of these tests and their main insights here, and offer a more detailed discussion in Appendix B.

**Interdependence between decisions** First, it may be the case that the decisions to multihome and to continue participating in Steam sales are interdependent. To test this conjecture, we run an additional set of regressions in which we allow the sales participation to vary between games that multihome and those that do not (see Appendix B.4). In addition, we analyze if this relationship varies between our different complementor types. However, we do not find any evidence that the two strategic choices are interrelated.

**Minor vs. major sales** Second, we dig deeper into the role of heterogeneity across different types of Steam sales (see Appendix B.5). In particular, we are interested whether our results are driven by highly popular or more targeted niche sales. To that end, we split the main sample into "major" and "minor" sales, based on the share of participating games. We find that the results are entirely driven by minor sales. This suggests that complementors are not willing to forego the high-demand periods generated by major sales but instead react to the entry by reducing their participation in more targeted governance attempts. This also puts into perspective our previous assessment of the economic significance: For minor sales, the estimated effect sizes are quite substantial, speaking to a strong reaction from complementors.

**Discounts outside sales** Third, we analyze how EGS's launch affected complementors' tendency to offer their product at a discount *outside* Steam's sale promotions (see Appendix B.6). The idea is to test whether our findings reflect a change in their responsiveness to orchestration attempts, or simply a reduced incentive to discount games generally. We do not find any evidence that the EGS launch had an effect on game developers discounting of games outside Steam's sales promotions. Hence, we are confident in interpreting our main results as a reaction in terms of complementors' responsiveness to orchestration attempts.[35]

[35] We conducted additional analyses to assess the impact of the entry on prices across different complementors types in Appendix C.2. Here, we do not find any impact of games' *current* prices (i.e., discounted or undiscounted). However, we do find a significant change in *list* prices (i.e. undiscounted). Indie and Unreal engine games tended to increase their prices after the entry (in particular those that multihome), while multiplayer games tended to decrease them. This may indicate that developers use these prices to steer demand across platforms in ways that are consistent with our theoretical arguments.

**Interaction between games characteristics** Different complementor types are not mutually exclusive. That is, Indie games can include multiplayer functionality. Therefore, as an additional analysis, we are interested in how these two dimensions interact, and which of the two opposing effects dominates (see Appendix B.7). In all, the results obtained from this conjecture are in line with our theoretical predictions, and we do not find any evidence that one complementor type dominates the other.

# 7 Discussion and conclusion

We study how the level of between-platform competition relates to the strategic choices of complementors. In particular, we investigate how the entry of a powerful rival platform challenged the dominance of the incumbent, and how this affected complementors' (i) decision to multihome by joining the rival and (ii) their responsiveness to the incumbent's orchestration attempts. We argue that their motivations behind these choices are affected by the entry in ambiguous ways. On the one hand, it threatens the network benefits complementors enjoyed on the incumbent, therefore threatening their overall profitability. On the other hand, the entrant constitutes an opportunity to escape the intensive within-ecosystem competition on the incumbent platform. How this tension resolves will then determine choices about multihoming and their continued responsiveness to orchestration attempts. Further, this tension is unlikely to resolve uniformly across heterogeneous complementors that differ in their needs and characteristics. Hence, some are primarily hurt by the entry (diminished network benefits), and some will primarily gain an attractive alternative for value creation (less intensive within-ecosystem competition). We therefore develop and test hypotheses about how different complementor types will react to the entry, and discuss three sources of heterogeneity in particular: their competitive ability, their reliance on network effects, and their use of the entrant's upstream technology.

Empirically, we study our research questions in the context of the PC video game distribution market. In December 2018, the dominant incumbent "Steam" faced the entry of a powerful competitor, the "Epic Games Store" (EGS). We find broad support for our hypotheses: Complementors who primarily benefited from an attractive alternative option for value creation were more likely to multihomes and became less responsive to the incumbent's orchestration attempts. This was the case for those with a low competitive ability (Indie game developers), which made it particularly challenging to prevail in the incumbent ecosystem. In addition, complementors that use the entrant's upstream technology (the Unreal engine) – who were subject to dedicated adoption incentives – were more likely to multihome than those that use a different technology, but we do not find a change in their responsiveness to orchestration attempts. In addition, those that were primarily affected by a decrease in network benefits were less likely to multihome, but became more responsive to the incumbent's orchestration attempts. This has been the case for complementors that are highly reliant on network effects (multiplayer game developers) and therefore prefer an unsplintered network of consumers on the incumbent platform.

**Implications** Our findings have several implications for platform owners and complementors. First, the level of platform competition is an important determinant of complementors' strategic choices. This is because their fates are intertwined in complex and ambiguous ways. Platform owners rely on the support of complementors to be successful. However, it is not as clear that complementors benefit from platform success in the same way. The reason is that tensions between network effects and within-ecosystem competition do not resolve uniformly across heterogeneous complementors, which in turn creates heterogeneity in their profit-maximizing strategic choices, such as which platforms to join and what orchestration attempts to respond to. For platform owners, this means that growing in size likely comes with increased challenges in managing and orchestrating an increasingly heterogeneous ecosystem.

Second, our findings carry implications for firms that seek to enter a platform market. This is challenging because of the so-called "chicken-and-egg problem" (Caillaud & Jullien, 2003) – initially, network benefits are very limited compared to the incumbent, which hinders adoption by complementors and consumers. However, our findings suggest that entrants can apply a "divide-and-conquer" strategy by identifying and targeting certain complementor types at the initial stage. In particular, complementors with a low competitive ability are more susceptible to joining the entrant, which can provide an important initial foothold in the market. In addition, if the entrant already owns and sells relevant upstream technology, they can apply an "envelopment attack" (Eisenmann et al., 2011) by offering complementors unique incentives to join their platform. At the same time, both strategies imply that they will likely attract an initial set of rather peculiar complementors, that may be of relatively lower value individually, and may contribute to a rather "niche" character of the platform's offerings as a whole. Further, this implies certain challenges for incumbents. While network effects generally raise significant barriers to entry, their dominance may still be vulnerable, because intensifying within-ecosystem competition on a growing platform makes some complementors particularly susceptible to potential entrants. This puts into perspective the value of "incumbency advantage" in platform markets (Biglaiser & Crémer, 2016).

Finally, our findings also contribute to policy discussions related to the market power of platforms. The heterogeneous reactions to the entry show that complementors' welfare is tied to the platform-level market structure in ambiguous ways. This means that potential antitrust remedies that would aim at "breaking up" large, dominant platforms are unlikely to create wholesale benefits for complementors. In particular, those that rely on large, unsplintered consumer bases would likely be hurt by such measures.

**Contributions** We make several contributions to the literature on platforms. First, our findings contain novel insights into the competitive dynamics in platform markets. Prior studies have focused on strategic choices made by platform owners (e.g. Cennamo & Santalo, 2013; Jin & Rysman, 2015; Seamans & Zhu, 2014, 2017), but only little attention has been paid to the choices made by complementors – a crucial determinant of platforms' competitive performance. Our contribution lies in analyzing how platform-level market entry affects complementors' strategic choices, which progresses our understanding of their relevance for platform competition.

Second, we demonstrate how complementor-level factors can determine successful entry into platform markets. Prior studies have focused on platforms' characteristics (Sheremata, 2004; Zhu & Iansiti, 2012) and choices (e.g. Casadesus-Masanell & Zhu, 2010; Seamans & Zhu, 2014). In particular, we show how different complementor characteristics (competitive ability, reliance on network effects, upstream technology use) shape their incentives to support an entering platform. This also provides an empirical test for the effectiveness of "envelopment attacks" (Eisenmann et al., 2011) to enter a market.

Third, we contribute to the discussion around multihoming by showing that heterogeneity in complementor characteristics creates heterogeneity in their likelihood to join multiple platforms. Prior literature has generally been limited in the exploration of antecedents to multihoming, with a few studies analyzing platform-level factors (Cennamo et al., 2018; Hagiu & Lee, 2011). Our findings also have implications for the interplay of multihoming and platform competition (e.g. Armstrong, 2006; Landsman & Stremersch, 2011): differences in complementors' incentive to multihome will determine its prevalence, which in turn determines the competition intensity in platform markets.

Finally, our study adds to the discussion around platform orchestration (or governance). In particular, this stream has largely overlooked that complementors have agency about their responsiveness to or compliance with such owners governance attempts (Abou-El Komboz et al., 2023). Hence, we contribute by highlighting that successful governance is not only determined by the actions of platform owners, but also by the potentially heterogeneous incentives and motivations that drive different complementor types' choices to comply. In addition, we demonstrate that their compliance is partly driven by the level of competition at the platform markets. Prior research has shown how dominance shapes governance practices by owners (Rietveld et al., 2020). We contribute that platform-level competition also shapes complementors willingness to comply with these practices, which also means that it constitutes an important determinant of their effectiveness.

**Limitations and future research** Our study also contains several limitations. First, we only consider the reaction of complementors on the incumbent platform, Steam, and how they react to the entry of Epic. However, the PC video game distribution market also contains additional players, such as GOG ("Good old games") with its focus on offering games free of digital rights management (that otherwise protects against piracy) or larger publishers' own distribution platforms. The main reasons are the availability of detailed data on Steam games (but not other platforms), and that the entry of Epic constitutes a compelling shift in the competitive landscape. Still, future research should offer a more holistic analysis of how competitive dynamics at the platform level impact complementor strategy. Second, we analyze two particular strategic choices, namely multihoming and responsiveness to orchestration attempts. However, complementors also make other strategic choices such as those related to their market positioning or pricing across different platforms and over time. Hence, there are plenty of opportunities for future studies to explore how such choices are affected by platform competition. Finally, our empirical setting exhibits some peculiarities that may limit the generalizability of our results. For instance, the development of video games follows similar processes as in the movie industry, which is distinct from other types of software development. In addition, consumers can be prone to "fandom", which implies a degree of bounded rationality in their choices. Hence, future research should conduct similar studies in a more diverse set of empirical contexts.

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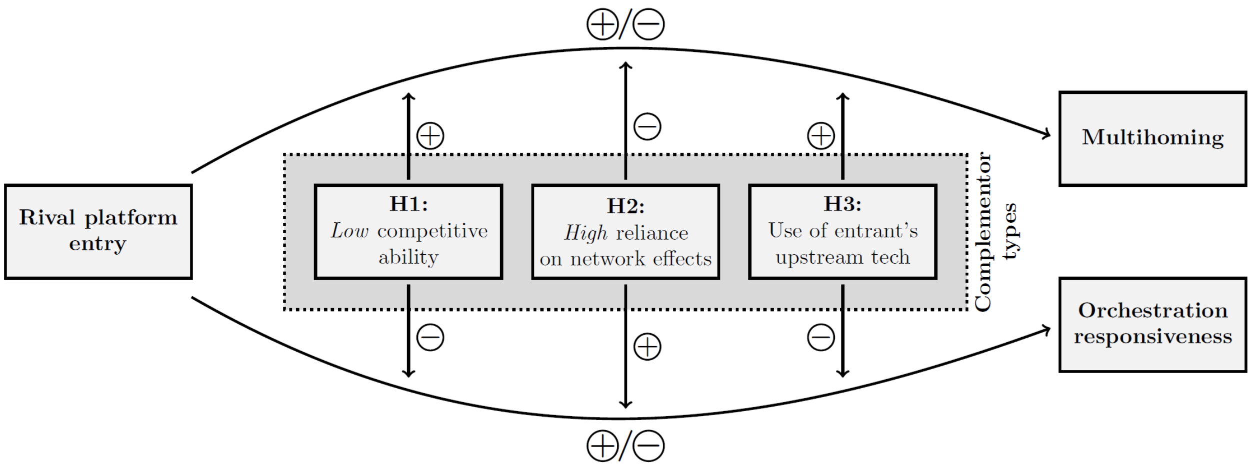
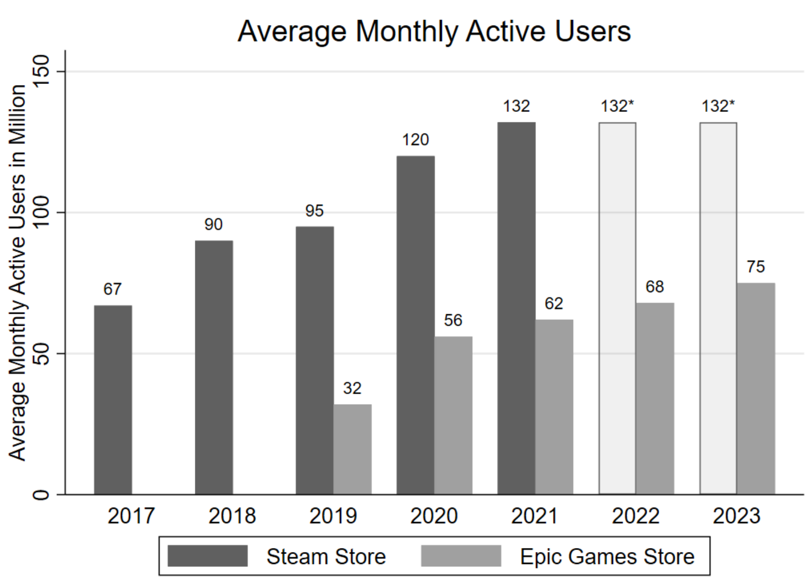
# Figures

Figure 1: Conceptual model



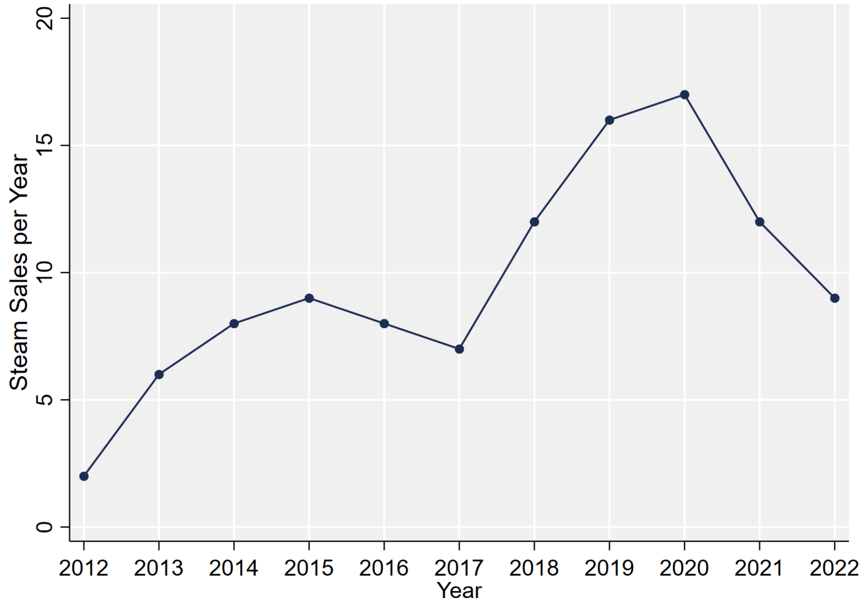

Note: The entry of the rival platform affects complementors' multihoming and responsiveness to orchestration attempts ambiguously. Complementor heterogeneity then determines whether we observe a positive or negative effect.

Figure 2: Number of active users on each platform




Source: Steam and EGS annual reports. Note: Steam's average number of users in 2022 and 2023 are estimations based on 2021's numbers, as the firm did not publish this information in recent years.

Figure 3: Number of Steam sales per year



# Tables

Table 1: Multihoming analysis: Summary statistics

| Variable | Mean | Std. Dev. | Min. | Max. | N |
|---|---|---|---|---|---|
| Multihoming | 0.07 | 0.26 | 0 | 1 | 8,101 |
| Indie game | 0.61 | 0.49 | 0 | 1 | 8,101 |
| Multiplayer game | 0.3 | 0.46 | 0 | 1 | 8,101 |
| Unreal game | 0.04 | 0.19 | 0 | 1 | 8,101 |
| Number of games by the same developer on Steam | 3.1 | 6.16 | 1 | 72 | 8,101 |
| Number of games by the same publisher on Steam | 10.22 | 17.17 | 1 | 93 | 8,101 |
| Game has Steam Workshop | 0.08 | 0.27 | 0 | 1 | 8,101 |
| Game has Steam Achievements | 0.64 | 0.48 | 0 | 1 | 8,101 |
| Game has Steam Cloud | 0.46 | 0.5 | 0 | 1 | 8,101 |
| Game has Steam Leaderboard | 0.12 | 0.33 | 0 | 1 | 8,101 |
| Game has Steam Trading Cards | 0.4 | 0.49 | 0 | 1 | 8,101 |
| Available for home consoles | 0.32 | 0.47 | 0 | 1 | 8,101 |
| Average price on Steam in US Dollars | 14.92 | 12.26 | 0 | 129.99 | 8,101 |
| Average number of players on Steam | 813.48 | 14153.18 | 0 | 950999.19 | 8,101 |
| Team size | 59.62 | 225.89 | 0 | 4413 | 8,101 |
| In-app purchases | 0.02 | 0.15 | 0 | 1 | 8,101 |
| Pre-entry review count (in 1000s) | 3.24 | 24.86 | 0 | 1384.08 | 4,456 |
| Pre-entry share of positive reviews | 0.78 | 0.17 | 0 | 1 | 4,426 |

Table 2: Multihoming analysis: Main results

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| **H1a:** Indie game | -0.0051 | 0.0346*** | 0.0320*** | 0.0313*** | 0.0298*** |
| | (0.0058) | (0.0072) | (0.0072) | (0.0072) | (0.0072) |
| **H2a:** Multiplayer game | -0.0019 | -0.0196** | -0.0159* | -0.0156* | -0.0112 |
| | (0.0061) | (0.0065) | (0.0063) | (0.0073) | (0.0072) |
| **H3a:** Unreal engine game | 0.1050*** | 0.0386*** | 0.0290** | 0.0388*** | 0.0290** |
| | (0.0095) | (0.0103) | (0.0101) | (0.0103) | (0.0101) |
| Genre dummies | | | | Y | Y |
| Release year dummies | | | Y | | Y |
| Controls | | Y | Y | Y | Y |
| Observations | 8,101 | 8,101 | 8,101 | 8,101 | 8,101 |
| Mean DV | 0.0706 | 0.0706 | 0.0706 | 0.0706 | 0.0706 |
| Pseudo-R2 | 0.0265 | 0.196 | 0.229 | 0.205 | 0.238 |

*** p<0.001, ** p<0.01, * p<0.5, + p<0.1. Robust standard errors in parentheses. The unit of observation is a game. The dependent variable is a dummy indicating if the game multihomes at the end of our observation period. All estimations use logit models, and average marginal effects are reported. All models use the full sample of games.

Table 3: Sales participation analysis: Summary statistics

| | Obs. | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|---|
| **Regression analysis** | | | | | |
| Participation to sales | 75,179 | 0.38 | 0.49 | 0 | 1 |
| After | 75,179 | 0.61 | 0.49 | 0 | 1 |
| Indie game | 75,179 | 0.49 | 0.50 | 0 | 1 |
| Multiplayer (MP) game | 75,179 | 0.36 | 0.48 | 0 | 1 |
| Unreal game | 75,179 | 0.03 | 0.18 | 0 | 1 |
| Review count (1000s) | 75,179 | 4.13 | 28.85 | 0 | 1,702.09 |
| Positive review share | 75,179 | 0.77 | 0.17 | 0 | 1 |
| Game age (days) | 75,179 | 1,518.48 | 1,063.70 | 23 | 8,196 |
| Intra-competition measure | 75,179 | 1,639.24 | 585.18 | 16 | 2,758 |
| **Matching** | | | | | |
| Review count at entry | 4,191 | 3,968.24 | 27,189.76 | 0 | 1,384,079 |
| Positive review share at entry | 4,176 | 0.77 | 0.17 | 0 | 1 |
| Intra-competition measure at entry | 4,191 | 1,567.17 | 510.09 | 21 | 2,270 |
| Game release year | 4,191 | 2,014.42 | 2.86 | 1,997 | 2,017 |

Table 4: Sales participation analysis: Main results

| | Full Sample | | | | CEM | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| **H1b:** After × Indie game | -0.0140** | | | -0.0117* | -0.0204** | | |
| | (0.0048) | | | (0.0048) | (0.0067) | | |
| **H2b:** After × MP game | | 0.0258*** | | 0.0246*** | | 0.0254*** | |
| | | (0.0049) | | (0.0050) | | (0.0068) | |
| **H3b:** After × Unreal | | | 0.0052 | -0.0009 | | | 0.0020 |
| | | | (0.0116) | (0.0116) | | | (0.0146) |
| Game FE | Y | Y | Y | Y | Y | Y | Y |
| Steam sale FE | Y | Y | Y | Y | Y | Y | Y |
| Controls | Y | Y | Y | Y | | | |
| Observations | 75,179 | 75,179 | 75,179 | 75,179 | 54,378 | 55,314 | 14,868 |
| Games | 4191 | 4191 | 4191 | 4191 | 3021 | 3073 | 826 |
| Mean DV | 0.384 | 0.384 | 0.384 | 0.384 | 0.398 | 0.394 | 0.409 |
| Adjusted R-squared | 0.5768 | 0.5769 | 0.5767 | 0.5769 | 0.5787 | 0.5716 | 0.5928 |
| Within-R2 | 0.000574 | 0.000831 | 0.000456 | 0.000913 | 0.000254 | 0.000374 | 1.30e-06 |

*** p<0.001, ** p<0.01, * p<0.5, + p<0.1. Robust standard errors in parentheses are clustered at the game level. The unit of observation is a game-sale. The dependent variable is a dummy indicating that the game participated in a sale. All estimations use linear probability models and include game and sale fixed effects. Models 1–4 use the full sample of games. Models 5–7 use a sample of matched games (CEM). A constant is included but not reported.

# Appendices

## Appendix A: Additional analyses on Multihoming Decision

This appendix presents additional descriptive statistics and estimation results from regressions, highlighting our main results' robustness and uncovering more about the mechanisms underlying complementors' multihoming decisions.

### A.1 Additional descriptive statistics: Timing of multihoming

Our multihoming analyses rely on a cross-section of games for which we code an indicator taking the value of 1 if the game was observed in both catalogs (Steam and Epic) at the end of our observation period, and 0 otherwise. For a subsample of games, we can observe the exact date of the release on Steam (for singlehoming games) and on both platforms (for multihoming games). For this sample, we can compute the number of weeks between the two release dates - if multihoming occurs. Using this duration as a new dependent variable allows to estimate the impact of our key characteristics on the timing of multihoming (including both games that multihomes and those that never multihome).

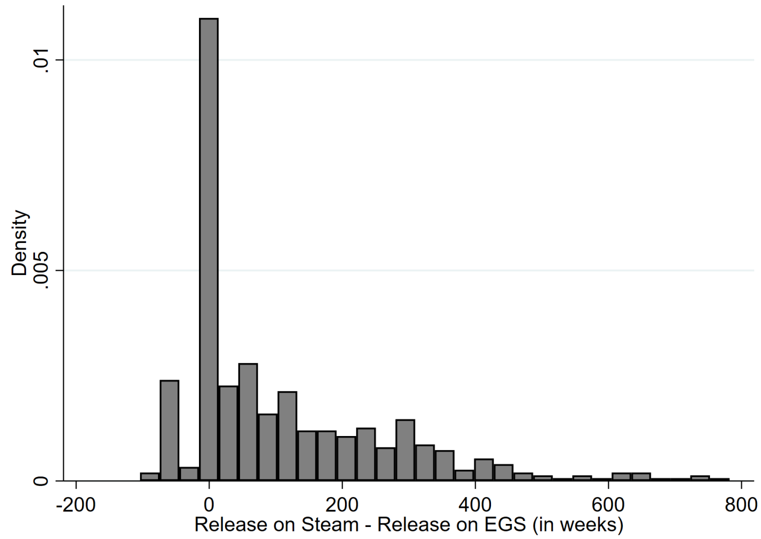
Table A1: Timing of multihoming

| | Freq. | Percent | Cum. |
|---|---|---|---|
| Only Steam (no multihoming) | 7,522 | 93.72 | 93.72 |
| Steam and then EGS | 319 | 3.97 | 97.69 |
| Simultaneous release | 137 | 1.71 | 99.40 |
| EGS and then Steam | 48 | 0.60 | 100 |
| Total | 8,026 | 100.00 | 100 |

Full sample: 8,101 games. The sample presented here consists of 8,026 games. Some games are dropped because we do not have the exact date of release (at the week level). 504 games are multihoming games.

Figure A1 is a histogram of this duration before multihoming. A negative value indicates that

Figure A1: Histogram of the time before multihoming (only multihoming games)



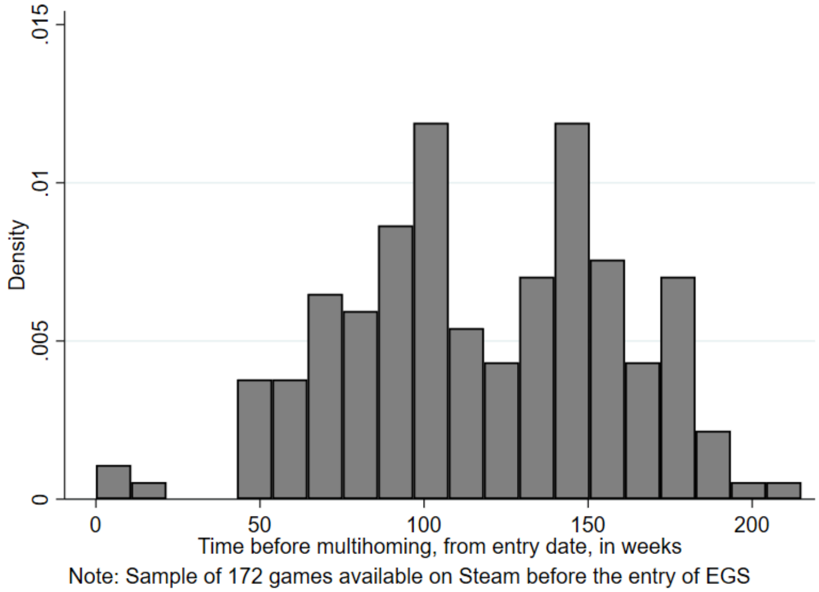

N=504 multihoming games

the game was first released on EGS and then on Steam. Table A1 presents more general statistics and also includes games that never multihomed. If we aim to assess the impact of the entry on the decision to multihome, we study the duration by restricting the sample to the games that were available on Steam before the shock occurred and compute the number of weeks these games were available before effective multihoming. Despite the small sample (172 games), we can get an idea of how long it took for these games to join the rival platform. Figure A2 is a histogram of this duration.

## A.2 Additional analysis: Timing of multihoming

As mentioned in Section A.1, for most of the games in our main sample, we can compute the number of weeks before multihoming occurs, if it occurs. This censored duration (presented in Figure A1) can be used as a dependent variable to conduct further analyses. Here, the goal is to estimate the impact of our key characteristics (i.e., indie, multiplayer, and use of unreal engine) on the likelihood of multihoming (including both games that multihome and those that never multihome) in a setting

Figure A2: Histogram of duration post entry - time from event




N=172 multihoming games released after the entry of EGS

that accommodates some forms of dynamics.

More precisely, we estimate a series of duration models using semi-parametric and fully parametric specifications, using the same covariates as in our main models. The dependent variable is a continuous variable that counts the number of weeks before multihoming, if multihoming occurs. This variable can be obtained for 8,026 games, as presented in Table A1. We keep in our estimation sample games that never multihomed (93.7%), games that were released on Steam and then on Epic (3.97%), and games that were released simultaneously (1.71%). We keep aside the 48 games released on EGS and then Steam. We have to exclude 84 games for which (time-varying) control variables are missing, which leaves us with a cross-section of 7,846 games. From this sample, we created a panel dataset, starting from the entry of EGS, in December 2018. Observations (games) are then repeated (with time-varying and invariant controls) and exit the panel if multihoming occurs. This panel consists of 1,123,805 observations (weekly observations starting from the entry). 429 failures are observed - i.e. games multihoming. We estimate several proportional hazard (PH) and accelerated failure-time (AFT) models. Results from this model enable us to derive insights into the impact of our three variables of interest on the survival of games in the sample, i.e., the absence of multihoming.

We present our estimation results in Table A2. For Proportional Hazard models, a coefficient above 1 indicates that an increase in the regressor is associated with an increase in the hazard rate and, hence, in the likelihood of failure (in our case, multihoming). In AFT models, the interpretation of coefficients is reversed: a coefficient above 1 indicates that an increase in the regressor is associated with an increase in the likelihood to survive, in our case, in the likelihood not to multihome. The results we obtain are fairly consistent across specifications, with differences in signs and significance in some cases. We, therefore, need to identify the best-suited model. First, the result from a formal statistical test (Schoenfeld residuals) indicates that the PH assumption is violated. Therefore, results from AFT models should be preferred. Among AFT models, the specification with the Log Normal hazard function (Column 6) appears to have the best fit if we consider the AIC criterion. Focusing on the results presented in that column, we observe that the indicator for Indie has an exponentiated coefficient of 0.994, with a p-value below 0.001. This means that Indie games are more likely to multihome (as they are less likely to "survive"), and they multihome faster. This suggests further support for our hypothesis H1a. We obtain an exponentiated coefficient of 1.003 for our Multiplayer indicator, significant at the 10% level. This suggests that multiplayer games are less likely multihome, and if they do, their time to multihome is longer. This supports our hypothesis H2a. Finally, the coefficient on the indicator for Unreal Engine is below 1 and significant at the 1% level, which indicates that these games are more likely to multihome, and multihome faster, also in line with our theoretical predictions and our main results. Overall, results from our survival analyses provide broad support for our three hypotheses, H1a, H2a and H3a.

Table A2: Estimation results for our survival analyses

| | Proportional Hazard | | | | Accelerated Failure Time | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) Cox | (2) Exp | (3) Weibull | (4) Gompertz | (5) LogLogistic | (6) LogNorm | (7) Exp | (8) Weibull |
| Indie game | 1.647*** | 1.846*** | 1.642*** | 1.642*** | 0.994*** | 0.994*** | 0.542*** | 0.994*** |
| | (0.229) | (0.264) | (0.232) | (0.232) | (0.002) | (0.002) | (0.077) | (0.002) |
| Multiplayer game | 0.810 | 1.014 | 0.806 | 0.806 | 1.003+ | 1.003+ | 0.986 | 1.003 |
| | (0.114) | (0.141) | (0.114) | (0.114) | (0.002) | (0.002) | (0.137) | (0.002) |
| Unreal engine (0/1) | 1.545* | 1.204 | 1.577* | 1.577* | 0.994* | 0.992** | 0.831 | 0.994* |
| | (0.287) | (0.234) | (0.299) | (0.299) | (0.003) | (0.003) | (0.161) | (0.002) |
| Time since release | 0.997*** | 1.004*** | 0.997*** | 0.997*** | 1.000*** | 1.000*** | 0.996*** | 1.000*** |
| | (0.001) | (0.000) | (0.001) | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,123,805 | 1,123,805 | 1,123,805 | 1,123,805 | 1,123,805 | 1,123,805 | 1,123,805 | 1,123,805 |
| | Subjects = 7,846 | | | | | | | |
| | Failure = 429 | | | | | | | |
| Log Likelihood | -3491.927 | -929.270 | -21.994 | -24.464 | -6.990 | 10.785 | -929.270 | -21.994 |
| AIC | 7041.855 | 1918.540 | 105.987 | 110.927 | 75.980 | 40.429 | 1918.540 | 105.987 |
| BIC | 7387.889 | 2276.507 | 475.886 | 480.826 | 445.879 | 410.328 | 2276.507 | 475.886 |

Exponentiated coefficients; Standard errors in parentheses

$^{+}$ $p < 0.1$ $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

## A.3 Additional analysis: Games released before and after the EGS launch

Second, again using our main specification, we explore some of the underlying mechanisms. In particular, we split the sample between games that have been released before and after the EGS launch. This is a potentially meaningful distinction, because those released before already had the opportunity to generate sales on Steam, thereby potentially experiencing lock-in effects there. They then have to make the decision to split their existing player base by also joining the EGS, thereby incurring switching costs. In contrast, those released after can immediately decide whether to join only one or both platforms, without having been subject to lock-in effects on Steam. The results are presented in Table A3. We split the sample into games released after (Model 1) and before (Model 2) and find that Indie games are more likely to multihome, regardless of their release date. For multihoming games, we do not observe any statistically significant effects when splitting the sample, that is, the analysis is inconclusive for this game type. For Unreal engine games, we find that only those released after the EGS launch are more likely to multihome. Here, in particular, the difference in the reaction between Indie games and Unreal engine games speaks to potential differences in the underlying motivations to multihome. For Unreal engine games, the main draw to the EGS comes from Epic waving the engine royalty fee. However, this may be particularly valuable for new games, that are yet to achieve the majority of their sales. In contrast, this does not seem attractive enough for developers to also port over older titles. For Indie games, however, the difference in revenue sharing agreements between Steam and the EGS appears to be sufficiently attractive to also make older titles available on the EGS. It is also indicative of misaligned value capture expectations: even though older games might be less able to generate meaningful sales on the EGS, Indie developers still make them available there as a manifestation of their discontentment. Finally, for the sub-sample of games released after the EGS launch, we can additionally control for their quality and popularity via their pre-launch Steam review count and the share of positive ones. We enter both in Model 3 of Table A3 and find that this does not lead to a meaningful change in the size or precision of the estimated effects. While we can only perform this analysis for this particular sub-sample, we still take this as evidence that omitting these quality and popularity dimensions is unlikely to be a source of bias in our analysis as a whole.

Table A3: Multihoming analysis: Before and after EGS's launch

| | After | Before | |
|---|---|---|---|
| | (1) | (2) | (3) |
| **H1a:** Indie game | 0.0360** | 0.0297*** | 0.0281** |
| | (0.0122) | (0.0089) | (0.0089) |
| **H2a:** Multiplayer game | -0.0036 | -0.0141 | -0.0141 |
| | (0.0116) | (0.0088) | (0.0089) |
| **H3a:** Unreal engine game | 0.0527** | 0.0102 | 0.0118 |
| | (0.0162) | (0.0133) | (0.0131) |
| Pre-EGS review count (1000s) | | | 0.0004* |
| | | | (0.0002) |
| Pre-EGS positive review share | | | 0.1089*** |
| | | | (0.0290) |
| Genre dummies | Y | Y | Y |
| Release year dummies | Y | Y | Y |
| Controls | Y | Y | Y |
| Observations | 3612 | 4275 | 4236 |
| Mean DV | 0.0927 | 0.0550 | 0.0552 |
| Pseudo-R2 | 0.271 | 0.211 | 0.221 |

*** p<0.001, ** p<0.01, * p<0.5, + p<0.1. Robust standard errors in parentheses. The unit of observation is a game. The dependent variable is a dummy indicating if the game multihomes at the end of our observation period. All estimations use logit models, and average marginal effects are reported. Model 1 uses a sample of games released after EGS's launch. Models 2 and 3 use a sample games released before.

## A.4 Additional analysis: Pre-EGS Quality and popularity of games

Finally, we dig deeper into the role of game popularity and quality in determining the multihoming decision. Again, using a sample of games released before the EGS launch, we are particularly interested in how their Steam review count and positive review share determine multihoming and how this varies across different types of games. To that end, in Table A4, we perform a series of sample splits, namely between Indie and non-Indie (Models 1 and 2), multiplayer and singleplayer (Models 3 and 4), and Unreal engine and others (Models 5 and 6). We find that in almost all models, a higher positive review share is associated with a higher likelihood of multihoming (the only exception being Unreal engine games). Evidently, developers make higher-quality games available on the EGS with the expectation of generating additional sales there. In contrast, we find a more nuanced picture of the role of the review count, which can be perceived as a proxy of prior game sales. We only find a positive association between Indie and Unreal engine games, both of which should consider EGS an attractive outside option. This speaks to the notion that this type of game multihomes if it is a high-demand product. This, however, is not the case for multiplayer games. This is consistent with our theoretical framework: Those complementors that have the most to gain from doing so move value creation to the rival with their high-demand products that promise the highest returns at the margin.

Table A4: Multihoming analysis: Pre-EGS quality and performance of games

| | Indie game | | Multiplayer | | Unreal engine | |
|---|---|---|---|---|---|---|
| | Yes | No | Yes | No | Yes | No |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Pre-EGS review count (1000s) | 0.0011** | 0.0004 | 0.0004 | 0.0010 | 0.0104** | 0.0002 |
| | (0.0004) | (0.0002) | (0.0003) | (0.0007) | (0.0033) | (0.0002) |
| Pre-EGS positive review share | 0.1295** | 0.0818* | 0.0867+ | 0.1218** | -0.2143 | 0.1107*** |
| | (0.0489) | (0.0398) | (0.0512) | (0.0373) | (0.3499) | (0.0290) |
| Genre dummies | Y | Y | Y | Y | Y | Y |
| Release year dummies | Y | Y | Y | Y | Y | Y |
| Controls | Y | Y | Y | Y | Y | Y |
| Observations | 2321 | 1887 | 1264 | 2847 | 92 | 4092 |
| Mean DV | 0.0517 | 0.0604 | 0.0649 | 0.0534 | 0.261 | 0.0513 |
| Pseudo-R2 | 0.289 | 0.235 | 0.218 | 0.274 | 0.364 | 0.226 |

*** p<0.001, ** p<0.01, * p<0.5, + p<0.1. Robust standard errors in parentheses. The unit of observation is a game. The dependent variable is a dummy indicating if the game multihomes at the end of our observation period. All estimations use logit models, and average marginal effects are reported. All models use a sample games released before EGS's launch.

## A.5 Robustness check: Coarsened Exact Matching

We re-run our analysis using matched samples. Instead of adding linear control variables, we use them to match our "treatment" indicators. That is, we match Indie to similar non-Indie games, multiplayer to similar singleplayer games, and Unreal engine to similar other games. Results are presented in Models 1 to 3 of Table A5. Note that it is impossible to match on multiple indicators in the same regression, which is why we let each type enter these models separately. Model 1 shows the robustness of our results for H1a: The difference between Indie and non-Indie games is statistically significant and of similar scope as in our main analysis. Next, Model 2 shows that this is not the case for our results about H2a: Here, we do not find a significant difference between multiplayer and singleplayer games. There are two potential reasons for this: For one, it may indeed be the case that adding control variables linearly does not adequately correct for potential confounders. In addition, the size of our matched sample is only half of the full sample, which may reduce statistical power. In this case, we observe that the estimated marginal effect here (Model 2, ME= $-0.0159$) is of similar size as in our main analysis (Table 2, Model 5, ME=$-0.0122$), but standard errors increased almost two-fold. Hence, while we do contend that this result is not robust to using a matched sample, we tend to attribute this to the reduction in statistical power. And finally, we also observe that our results on H3a (Model 3, ME=$-0.1213$) are robust to using a matched sample.

Table A5: Multihoming analysis: Coarsened Exact Matching

| | CEM | | |
|---|---|---|---|
| | (1) | (2) | (3 |
| **H1a:** Indie game | 0.0294** | | |
| | (0.0092) | | |
| **H2a:** Multiplayer game | | -0.0159 | |
| | | (0.0126) | |
| **H3a:** Unreal engine game | | | 0.1213** |
| | | | (0.0444) |
| Genre dummies | Y | Y | Y |
| Release year dummies | Y | Y | Y |
| Observations | 4019 | 4182 | 686 |
| Mean DV | 0.0488 | 0.0493 | 0.136 |
| Pseudo-R2 | 0.079 | 0.060 | 0.119 |

*** p<0.001, ** p<0.01, * p<0.5, + p<0.1. Robust standard errors in parentheses. The unit of observation is a game. The dependent variable is a dummy indicating if the game multihomes at the end of our observation period. All estimations use logit models, and average marginal effects are reported. All models use the matched samples of games (CEM).

### A.6 Robustness check: Intensity of multihoming at the publisher level

The main analyses of multihoming presented in the paper are at the game level. Given that some publishers handle several games, we can compute the intensity of multihoming at the publisher level and use it as an alternative dependent variable. We first have to create a new sample of games for which the name of the publisher is indicated. Among our 8,101 games, we have this information for only 4,821 observations for 2,400 unique publishers. We observe a highly skewed distribution of the number of games per publisher as 72.6% of them have only one game, 13.33% two games, and 4.75% have three games. The remaining 7.08% have between 4 and 56 games. We then compute an intensity measure which takes the form of a ratio of multihoming games over the total number of games owned by each publisher. This measure takes a value between 0 (no games in the portfolio of the publisher are available on both platforms as of June 2022) and 1 (all games are available on both platforms at the end of the period). We use this intensity measure as a dependent variable and look at how characteristics of games (computed as averages per publisher, ranging from 0 to 1) within their portfolio impact the intensity of multihoming. We control for the total number of games in publishers' portfolios and for various elements already introduced in our main model. Missing values for some of these controls (in particular number of developers) reduce our sample to 1,568 publishers. The average share of indie games in the publishers' portfolio is 0.69, the share of multiplayer games is 0.35, and the share of games relying on the Unreal engine is 0.038. Results from simple OLS regressions are presented in Table A6. Column 1 presents the results obtained with the largest sample possible, and the next columns present results obtained with smaller samples of publishers who own more than one game (Column 2) or more than five games (Column 3). While some of the results confirm what we observe at the game-level, we obtain no significance on other coefficients of interest. For example, we obtain evidence of a positive impact of the share of indie games on the intensity of multihoming, but no significant impact of the share of games relying on Unreal Engine on the intensity of multihoming. Samples being reduced and information aggregated, we would consider these results with particular caution.

Table A6: Estimation results for the intensity of multihoming

| | Intensity of Multihoming | | | | | |
|---|---|---|---|---|---|---|
| | DV = Share of games on both platforms | | | | | |
| | (1) | | (2) | | (3) | |
| | All publishers | | Publishers with > 1 game | | Publishers with > 5 games | |
| Share of indie games | 0.031** | (0.011) | 0.066* | (0.027) | 0.025 | (0.050) |
| Share of multiplayer games | -0.003 | (0.013) | -0.031 | (0.035) | 0.121 | (0.082) |
| Share of unreal engine games | 0.057 | (0.041) | 0.086 | (0.072) | 0.080 | (0.124) |
| Total number of games in publisher's portfolio | 0.002* | (0.001) | 0.000 | (0.001) | 0.001 | (0.002) |
| Average release year | 0.006*** | (0.002) | 0.004 | (0.005) | 0.019* | (0.007) |
| Average number of reviews | 0.000** | (0.000) | 0.000* | (0.000) | 0.000 | (0.000) |
| Average of share of positive reviews | 0.026 | (0.024) | 0.002 | (0.050) | 0.203 | (0.128) |
| Average number of developers | 0.000 | (0.000) | 0.000 | (0.000) | 0.000 | (0.000) |
| Average price | 0.002*** | (0.001) | 0.002* | (0.001) | -0.002 | (0.002) |
| Average number of players | -0.000 | (0.000) | -0.000+ | (0.000) | -0.000 | (0.000) |
| Other controls | Yes | | Yes | | Yes | |
| Observations (publishers) | 1,568 | | 560 | | 132 | |
| R2 | 0.117 | | 0.157 | | 0.465 | |

Robust standard errors in parentheses

$^{+}$ $p < 0.1$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

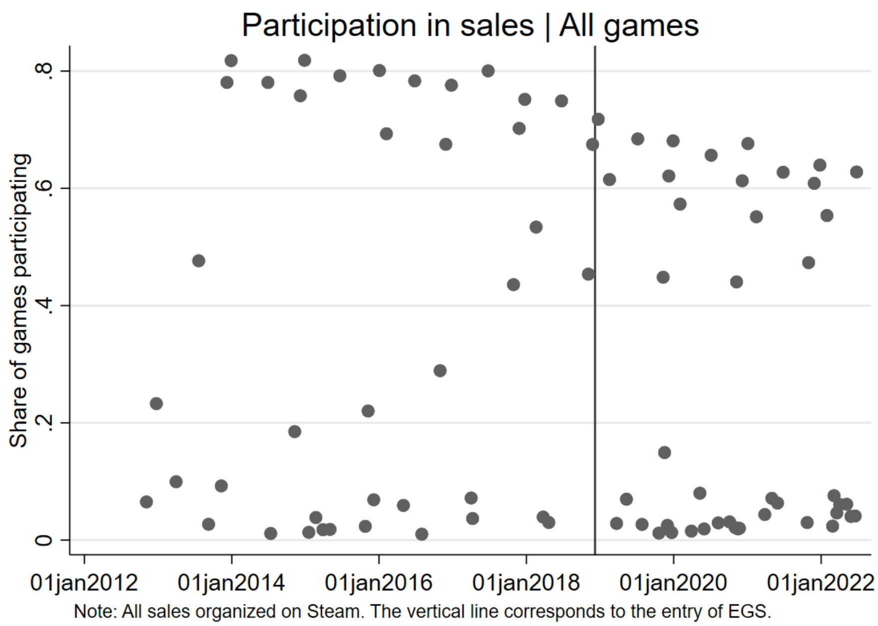
Note: The dependent variable is a continuous measure of the intensity of multihoming (total number of multihoming games/total number of games) at the publisher level, as of June 2022. The intensity measure ranges between 0 and 1. Regressors are averages computed for games in each publisher's portfolio of games.

# Appendix B: Additional analyses on Sales Participations

This appendix presents various descriptive statistics and estimation results which shed additional light on the robustness of our main results and their underlying mechanisms.

## B.1 Additional descriptive statistics: Sales

Figure B1: Participation in sales, over time




Note: The vertical line represents the entry of EGS. Each bullet represents a sale taking place on Steam, at a given time. Some sales are particularly popular, with about 80% of games from our sample participating. Other are smaller sales. The main results presented in the paper are obtained with a sample of these sales, i.e. on the sales taking place 12 months before and 12 months after the entry.

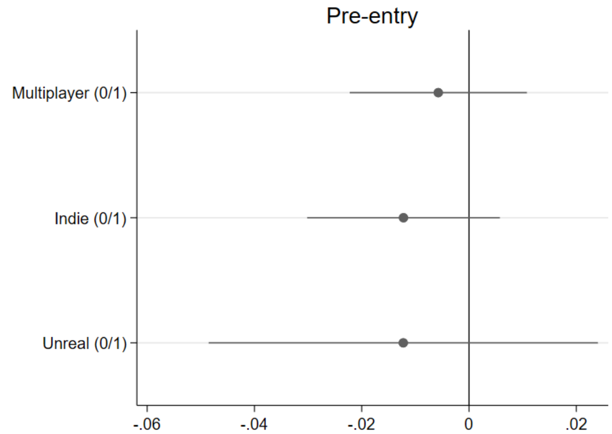
Table B1: Descriptive statistics on Steam sales included in our analyses period

| **Sale** | **Starting calendar week** | **Participation share** | **Main sample** |
|---|---|---|---|
| Finland Anniversary Sale 2017 | 2017-49 | 0.98 % | |
| Winter Sale 2017 | 2017-51 | 75.17 % | YES |
| Lunar New Year Sale 2018 | 2018-07 | 53.39 % | YES |
| GDC Film Festival Sale 2018 | 2018-12 | 3.93 % | YES |
| VR Spring Sale 2018 | 2018-16 | 3.00 % | YES |
| Games from Denmark Sale 2018 | 2018-17 | 0.57 % | |
| Spring Cleaning Event 2018 | 2018-21 | 0.58 % | |
| Summer Sale 2018 | 2018-25 | 74.91 % | YES |
| Day of the Girl Sale 2018 | 2018-41 | 0.74 % | |
| Halloween Sale 2018 | 2018-44 | 45.36 % | YES |
| 100 Years of Polish Independence Sale 2018 | 2018-45 | 0.13 % | |
| Games from Norway Sale 2018 | 2018-46 | 0.42 % | |
| Autumn Sale 2018 | 2018-47 | 67.48 % | YES |
| Winter Sale 2018 | 2018-51 | 71.78 % | YES |
| Lunar New Year Sale 2019 | 2019-06 | 61.50 % | YES |
| SXSW Texas Sale 2019 | 2019-11 | 2.85 % | YES |
| BAFTA Sale 2019 | 2019-14 | 0.94 % | |
| Golden Week Sale 2019 | 2019-18 | 6.98 % | YES |
| Spring Cleaning Event 2019 | 2019-21 | 0.58 % | |
| World Environment Day Sale 2019 | 2019-23 | 0.67 % | |
| Summer Sale 2019 | 2019-26 | 68.43 % | YES |
| Space Exploration Sale 2019 | 2019-29 | 2.68 % | YES |
| LGBTQ+ Games Sale | 2019-41 | 1.20 % | YES |
| Halloween Sale 2019 | 2019-44 | 44.83 % | YES |
| Singles' Day Sale | 2019-45 | 14.76 % | YES |
| Remote Play Together 2019 | 2019-47 | 2.52 % | YES |
| Autumn Sale 2019 | 2019-48 | 62.11 % | YES |

## B.2 Pre-trends in sales participation

Our sales analyses are event studies where we exploit differences before and after a shock. Our outcome of interest (participation in sales by complementors) exhibits a particularly erratic evolution across time periods (with sales being very popular and others much more confidential), as shown in B1, which does not allow for a nice, "visual" approach. However, in this section, we aim to provide evidence that our groups of interest did not differ significantly before the shock. To do so, we will proceed in two steps. First, we compute average participation, at the sale-level, for each group of complementors and present these results in Figure B3. To ease readability, we present, within this figure, a sub-figure for each group of interest. We observe that the groups have similar participation levels before the entry. However, these (unconditional) averages might not be perfectly informative. Therefore, as a second step, we run a regression that is structurally the same as our

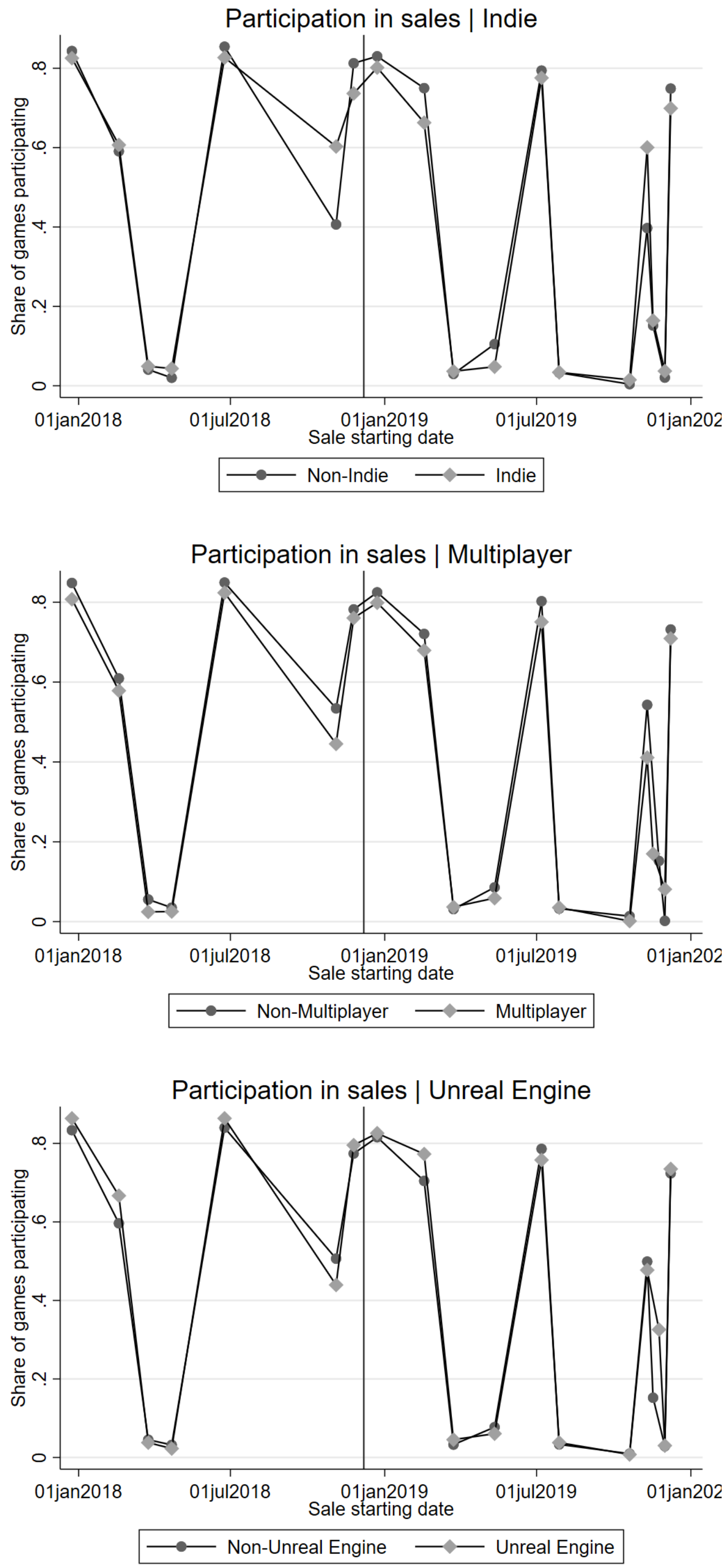
Figure B2: Estimation results for our sales analysis (only pre-period)




Note: Coefficients obtained with a regression that includes sale fixed effects and all game-level controls. 95% confidence intervals are presented. Number of games: 3,680. Number of observations included in the estimation: 25,701 (only pre-shock observations).

main sales regression, with only pre-shock periods. Therefore, we let the indicators for the different complementor types enter the regression without their interaction with a post-period indicator. Given that we cannot use game fixed effects anymore (because of their collinearity with the time-invariant dummy variables for indie, multiplayer, and unreal engine), we include all the controls used in our multihoming regression (these are at the game level, and are both time-variant and invariant). In addition to these controls, we use sale fixed effects that act as time fixed effects. The coefficients we obtain for our variables of interest are presented in Figure B2. We interpret the insignificance of these coefficients as a reliable indication that no significant differences existed before the entry, for our groups of complementors.

Figure B3: Average sales participation, by groups of interest



## B.3 Matching procedure: Differences in means

Table B2: Sales participation analysis: Difference in means before and after matching

| | Before CEM | | | | After CEM | | | |
|---|---|---|---|---|---|---|---|---|
| | Indie | non-Indie | | | Indie | non-Indie | | |
| | Mean | Mean | Diff. | p-value | Mean | Mean | Diff. | p-value |
| Review count at entry | 2825.395 | 5105.045 | 2279.650 | 0.000 | 2293.752 | 2832.085 | 538.333 | 0.000 |
| Positive review share at entry | 0.777 | 0.767 | -0.010 | 0.000 | 0.806 | 0.806 | 0.000 | 0.921 |
| Intra-competition at entry | 1634.031 | 1500.817 | -133.213 | 0.000 | 1665.500 | 1670.785 | 5.285 | 0.093 |
| Game release year | 2015.294 | 2013.592 | -1.702 | 0.000 | 2015.435 | 2015.434 | -0.002 | 0.892 |
| | Multiplayer | Singleplayer | | | Multiplayer | Singleplayer | | |
| | Mean | Mean | Diff. | p-value | Mean | Mean | Diff. | p-value |
| Review count at entry | 7369.032 | 2089.982 | -5279.050 | 0.000 | 4486.979 | 2334.457 | -2152.522 | 0.000 |
| Positive review share at entry | 0.760 | 0.779 | 0.019 | 0.000 | 0.781 | 0.781 | -0.001 | 0.663 |
| Intra-competition at entry | 1553.213 | 1573.841 | 20.628 | 0.000 | 1652.799 | 1654.579 | 1.780 | 0.655 |
| Game release year | 2014.054 | 2014.640 | 0.586 | 0.000 | 2014.542 | 2014.541 | -0.001 | 0.978 |
| | Unreal | non-Unreal | | | Unreal | non-Unreal | | |
| | Mean | Mean | Diff. | p-value | Mean | Mean | Diff. | p-value |
| Review count at entry | 13024.040 | 3679.883 | -9344.154 | 0.000 | 9271.433 | 4870.863 | -4400.570 | 0.000 |
| Positive review share at entry | 0.796 | 0.771 | -0.025 | 0.000 | 0.813 | 0.815 | 0.002 | 0.423 |
| Intra-competition at entry | 1917.388 | 1554.726 | -362.662 | 0.000 | 1937.382 | 1935.682 | -1.699 | 0.850 |
| Game release year | 2013.341 | 2014.467 | 1.126 | 0.000 | 2013.475 | 2013.475 | 0.000 | 1.000 |

### B.4 Additional analysis: Interdependence between decisions

It may be the case that the decisions to multihome and to continue participating in Steam sales are interdependent. That is, multihoming games may be more or less likely to adjust their responsiveness to orchestration attempts. To test this assertion, we run an additional set of regressions in which we let the probability of sales participation vary between games that multihome and those that do not. In addition, we also analyze how this, in turn, varies between different complementor types. Here, we focus on Indie and multiplayer games, because we did not find evidence that the use of the Unreal engine plays a role in determining sales participation. In addition, estimating the influence of multihoming is subject to endogeneity. Because both decisions are indications of increased incumbent support, the error term is likely correlated with a dummy indicating multihoming games. To address this issue, we use an instrumental variables approach. Specifically, we instrument the multihoming dummy with a dummy indicating Unreal engine use.[36] We deem this sensible because our main analyses show that Unreal engine use is predictive of multihoming, but not sales participation. Moreover, we use an instrument here because it lets us continue to use matching to account for endogeneity in the indie and multiplayer dummies. Table B3 contains the results. Models 1 to 4 are estimated via OLS, without accounting for endogeneity in multihoming, and Models 6 to 8 are estimated via 2SLS. Model 5 reports the first stage. To analyze variation between complementor types, we enter a triple-interaction with an indie dummy in Models 2 and 6, and a multiplayer dummy in Models 3 and 8. Here, we use the same matching strategy as before. Regardless of specification or estimation method, we do not find any evidence that the probability of sales participation varies between games that multihome and those that do not, or that this relationship depends on the complementor type.

[36]We instrument interactions with the multihoming dummy with interactions with the Unreal engine dummy. For example, the term $After \times Multihoming$ is instrumented with $After \times Unreal$.

Table B3: Sales participation analysis: Interdependence with multihoming

| | OLS | | | | 2SLS | | | |
|---|---|---|---|---|---|---|---|---|
| | DV: Participation in sale | | | | First Stage DV: MH | DV: Participation in sale | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| After × Multihoming | -0.0024 | -0.0016 | -0.0161 | -0.0004 | | 0.0020 | -0.0781 | 0.1325 |
| | (0.0096) | (0.0205) | (0.0284) | (0.0218) | | (0.1282) | (0.1730) | (0.1938) |
| After × Indie game | | -0.0211** | | | | | -0.0323* | |
| | | (0.0069) | | | | | (0.0150) | |
| After × MP game | | | 0.0233*** | | | | | 0.0366 |
| | | | (0.0070) | | | | | (0.0250) |
| After × Unreal game | | | | 0.0140 | 0.1046*** | | | |
| | | | | (0.0166) | (0.0082) | | | |
| After × Multihoming × Indie game | | 0.0147 | | | | | 0.2305 | |
| | | (0.0260) | | | | | (0.2523) | |
| After × Multihoming × MP game | | | 0.0418 | | | | | -0.2176 |
| | | | (0.0339) | | | | | (0.4584) |
| After × Multihoming × Unreal game | | | | -0.0038 | | | | |
| | | | | (0.0458) | | | | |
| Game FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Steam sale FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Observations | 76,860 | 54,378 | 55,314 | 55,314 | 76,860 | 76,860 | 54,378 | 55,314 |
| Mean DV | 0.381 | 0.398 | 0.394 | 0.394 | 0.381 | 0.381 | 0.398 | 0.384 |
| Adjusted $R^2$ | 0.574 | 0.579 | 0.572 | 0.571 | 0.599 | -0.059 | -0.061 | -0.061 |

*** $p<0.001$, ** $p<0.01$, * $p<0.05$, + $p<0.1$. Robust standard errors in parentheses. In models 1-4, standard errors are clustered at the game level. The unit of observation is a game-sale. The dependent variable is a dummy indicating that the game participated in a sale. All models include game and sale fixed effects. Models 2, 3, 4, 6, and 7 use matched samples (CEM). Models 1- 4 are estimated via OLS. Model 6-8 are estimated via 2SLS using a dummy indicating Unreal engine use to instrument for multihoming. Model 5 reports the first stage. A constant is included in models 1-4, but not reported.

## B.5 Additional analysis: Minor vs. major sales

We are interested in potential heterogeneity across different types of sales. As pointed out earlier, and shown in Table B1, these sales vary considerably in how many games participate. In particular, some sales seem to be highly popular (e.g. the Winter Sales just before Christmas), and others seem to rather attract specific game types. We therefore re-run our main analysis, but splitting the sample between these "major" and "minor" sales. We make this distinction based on the share of participating games from our sample and classify a sale as "major" if that share is at least 40%. Further, we again use matched samples (akin to Models 5 to 7 of Table 4). We find that the reactions to EGS's launch seem to be entirely driven by minor sales: Indie games are less likely to participate in minor, but not major sales. And multiplayer games are more likely to participate in minor, but not major sales. For Unreal engine games, we again find no statistically significant effects. These results add nuance to the overall picture: evidently, game developers are not willing to forego the high-demand periods generated by major sales. Instead, they react in terms of their responsiveness to more targeted sales periods. In addition, this also puts into perspective our prior assessment of the economic significance of the effects. The average game participates in around 5–6% of minor sales. As a result, the estimated coefficients for Indie (Model 2, $\beta = -0.027$) and multiplayer games (Model 4, $\beta = 0.030$) imply large economic effect sizes.

Table B4: Sales participation analysis: Major vs. minor sales

| | Major Sale (1) | Minor Sale (2) | Major Sale (3) | Minor Sale (4) | Major Sale (5) | Minor Sale (6) |
|---|---|---|---|---|---|---|
| After × Indie game | -0.010 | -0.027*** | | | | |
| | (0.009) | (0.008) | | | | |
| After × MP game | | | -0.010 | 0.030*** | | |
| | | | (0.009) | (0.007) | | |
| After × Unreal | | | | | -0.002 | 0.016 |
| | | | | | (0.020) | (0.018) |
| Game FE | Y | Y | Y | Y | Y | Y |
| Steam sale FE | Y | Y | Y | Y | Y | Y |
| Controls | | | | | | |
| Observations | 30,210 | 24,168 | 30,730 | 24,584 | 8,260 | 6,608 |
| Games | 3021 | 3021 | 3073 | 3073 | 826 | 826 |
| Mean DV | 0.673 | 0.0534 | 0.667 | 0.0527 | 0.688 | 0.0601 |
| Adjusted R-squared | 0.5478 | 0.0542 | 0.5301 | 0.0588 | 0.5390 | 0.0612 |
| Within-R2 | 6.92e-05 | 0.000755 | 6.39e-05 | 0.000971 | 1.95e-06 | 0.000149 |

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1. Robust standard errors in parentheses are clustered at the game level. The unit of observation is a game-sale. The dependent variable is a dummy indicating that the game participated in a sale. All estimations use linear probability models and include game and sale fixed effects. All models use a sample of matched games (CEM). A constant is included but not reported.

## B.6 Additional analysis: Discounts outside sales

We analyze how EGS's launch affected complementors' tendency to offer their product at a discount *outside* Steam's sale promotions. Part of the aim of our study is to show how increased platform competition impacts their responsiveness to orchestration attempts. However, it is possible that complementors generally have less of an incentive to discount their product, which could then offer an alternative explanation for our results. However, if this is the case, then we would also observe a change in their tendency to do so outside Steam sales. To that end, we run a set of regressions using a game-week panel that excludes weeks with an active Steam sale. Similar to our main analysis, we again both use models with time-varying controls and matched samples. Results are presented in Table B5. Across all models, we do not find any significant effects of EGS's launch on complementors discounting their games outside sales promotions. As a result, we take this as evidence that they indeed react in terms of their responsiveness to platform orchestration attempts.

Table B5: Sales participation analysis: Discounts outside sale periods

| | Full Sample | | | | CEM | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| After × Indie game | -0.0030 | | | -0.0033 | 0.0015 | | |
| | (0.0036) | | | (0.0036) | (0.0052) | | |
| After × MP game | | -0.0001 | | -0.0002 | | -0.0038 | |
| | | (0.0039) | | (0.0039) | | (0.0062) | |
| After × Unreal | | | -0.0082 | -0.0089 | | | -0.0240 |
| | | | (0.0139) | (0.0139) | | | (0.0148) |
| Game FE | Y | Y | Y | Y | Y | Y | Y |
| Year-Week FE | Y | Y | Y | Y | Y | Y | Y |
| Controls | Y | Y | Y | Y | | | |
| Observations | 296,696 | 296,696 | 296,696 | 296,696 | 205,078 | 195,681 | 46,658 |
| Games | 3860 | 3860 | 3860 | 3860 | 2668 | 2546 | 606 |
| Mean DV | 0.129 | 0.129 | 0.129 | 0.129 | 0.132 | 0.132 | 0.139 |
| Adjusted R-squared | 0.3529 | 0.3529 | 0.3529 | 0.3529 | 0.3425 | 0.3488 | 0.3532 |
| Within-R2 | 0.0000336 | 0.0000259 | 0.0000336 | 0.0000427 | 0.000106 | 0.0000526 | 0.000548 |

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1. Robust standard errors in parentheses are clustered at the game level. The unit of observation is a game-calendar week. The dependent variable is a dummy indicating that the game is offered at a discount in a week. All estimations use linear probability models and include game and sale fixed effects. Models 1–4 use the full sample of games. Models 5–7 use a sample of matched games (CEM). A constant is included but not reported.

## B.7 Additional analysis: Interaction between games characteristics

Different complementor types are not mutually exclusive. That is, Indie games can include multiplayer functionality. Therefore, as an additional analysis, we are interested in how these two dimensions interact, and which of the two opposing effects dominates. To that end, we run an additional set of regressions in which we define four groups of games: (i) non-Indie and singleplayer ($Indie = 0 \wedge MP = 0$), (ii) Indie and singleplayer ($Indie = 1 \wedge MP = 0$), (iii) non-Indie and multiplayer ($Indie = 0 \wedge MP = 1$), and (iv) Indie and multiplayer ($Indie = 1 \wedge MP = 1$). We then interact dummy variables indicating each group with a dummy indicating sales after EGS's launch. We also include the same set of controls and fixed effects as before. Results are presented in Table B6. Model 1 is run on the full sample of games. The group of "non-Indie-and-singleplayer" games serves as the comparison group. We find that "Indie-and-singleplayer" games are less likely to participate after EGS's launch compared to the baseline ($\beta = -0.0102$). However, the coefficient is estimated with limited precision ($p < 0.1$). In addition, Non-Indie-and-multiplayer games are more likely to ($\beta = 0.0264$, $p < 0.001$). Both are consistent with hypotheses H1b and H2b. For the group of "Indie-and-multiplayer" games, we do not find a significant difference compared to the baseline. This may indicate that the two opposing effects cancel each other out for this group. Next, we run the same regression on a sample of similar games. That means that, while we can stratify the sample along our matching variables, it is not possible to obtain matching weights with multiple "treatment" groups. Therefore, in Model 2, we use a sample of games for which at least one corresponding match can be found, without however weighting to correct for imbalance. This procedure reduces our sample size to roughly one third of the full sample. The coefficients are similar to those obtained in Model 1 but estimated with less precision. As a result, the difference between the baseline and the "Indie-and-singleplayer" group is statistically insignificant. Still, in all, we take this line of inquiry as further support for the predictions of our theoretical framework.

Table B6: Sales participation analysis: Indie-multiplayer interaction

| | (1) Full Sample | (2) Matched Sample |
|---|---|---|
| After × $\mathbb{1}$(Indie = 0 ∧ MP = 0) | Baseline | Baseline |
| After × $\mathbb{1}$(Indie = 1 ∧ MP = 0) | -0.0102+ | -0.0139 |
| | (0.0061) | (0.0120) |
| After × $\mathbb{1}$(Indie = 0 ∧ MP = 1) | 0.0264*** | 0.0338* |
| | (0.0064) | (0.0134) |
| After × $\mathbb{1}$(Indie = 1 ∧ MP = 1) | 0.0122 | 0.0045 |
| | (0.0077) | (0.0132) |
| Game FE | Y | Y |
| Steam sale FE | Y | Y |
| Controls | Y | |
| Observations | 75,179 | 24,138 |
| Games | 4191 | 1341 |
| Mean DV | 0.384 | 0.399 |
| Adjusted R-squared | 0.5769 | 0.5675 |
| Within-R2 | 0.000915 | 0.000708 |

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1. Robust standard errors in parentheses are clustered at the game level. The unit of observation is a game-sale. The dependent variable is a dummy indicating that the game participated in a sale. All estimations use linear probability models and include game and sale fixed effects. Model 1 uses the full sample. Model 2 is run of a sample of games that can be matched via CEM. A constant is included but not reported.

# Appendix C: Additional insights

This appendix provides additional descriptive statistics on the two platforms studied (e.g. composition in terms of price, genres, audience), as well as some additional analyses on the impact of the entry of prices and the number of users.

## C.1 Additional descriptive statistics: Differentiation of platforms

Our original sample consists of 10,748 games. 8,630 games (80.29%) are Steam exclusive, 1,480 are EGS exclusive (13.77%) and 638 (5.94%) are available on both platforms. When available, we compare the characteristics of games available on Steam, on EGS, and on both platforms to comment on the level of differentiation of products available in the two rival markets.

**Prices** Table C1 presents statistics on the prices (list and current prices) on both platforms. List prices are the non-discounted prices of games. While they evolve over time, they tend to be much more stable compared to the current prices which are frequently discounted, for example, during platform-wide sales. We observe that list prices tend to be lower on Steam, on average (15.5 USD compared to 19.82 USD on EGS). The same observation can be made for the current prices (i.e. prices which can be temporally discounted). If we have a look at the distribution of these prices, as presented in Figure C1, we observe differences between our two platforms, with Epic games being more on the expensive side. We also see that games that are available on both platforms (the "multihomers") have a price distribution close to the distribution of the games solely available on each platform.

**Type of games** The composition of catalogs also differs in non-price dimensions, as suggested by Figure C2. For example, the incumbent platform Steam is much more populated by "Indie" games, as compared to EGS. Also, Steam's catalog has a significantly higher share of multiplayer games compared to EGS (29.6% as compared to 4.1%). In terms of the number of developers, which we categorize into different levels, Steam has a vast majority of games developed by very small teams (66% have a team that consists of 1 to 3 developers). Finally, regarding the genres, we observe that Steam offers a large share of Adventure games (about 53% of its portfolio), while EGS offers more predominantly Action games (38% of its portfolio). However, there are two limitations to these comparisons: while we observe a large part of the EGS's catalog, our sample only includes a slice of Steam's complete catalog, and this slice represents the most popular games among all of those present on the platform. Also, the maturity of the two platforms differs significantly. Rietveld & Eggers (2018) highlight the existence of demand heterogeneity over the life cycle of platforms (e.g. in terms of willingness to pay and taste for novelty), which impacts the complementor's success and profitability - what can explain why the platforms appear quite different despite offering very similar services (interface, features that foster network effects, regular sales, etc.)

**Consumer side** To comment on the heterogeneity of users affiliated with both platforms, we collect data from the web-audience tracking tool Similarweb, which provides information on the web traffic of major websites, in particular the socio-demographics of their audiences (age and gender). In our context, these are `Steampowered.com` and `Epicgames.com`. The period of observation is much more recent than the period of analysis in the paper (January to March 2024), but we believe the statistics are still informative. Figure C3 presents the data we retrieved from the tool. We observe that the differences in terms of demographics are rather minimal, suggesting that the audiences are comparable in these dimensions.

Table C1: Average prices on both platforms

| **Variable** | **Mean** | **Std. Dev.** | **Min.** | **Max.** | **N** |
|---|---|---|---|---|---|
| Average list price on Steam | 15.5 | 13.58 | 0 | 149.99 | 8,949 |
| Average current price on Steam | 12.9 | 11.66 | 0 | 145.16 | 8,949 |
| Average list price on EGS | 19.82 | 16.53 | 0.99 | 149.99 | 1,997 |
| Average current price on EGS | 15.72 | 14.81 | 0.21 | 137.7 | 2,001 |

Note: Prices are in US Dollars and are averages computed over the whole period, at the game level.

Figure C1: Distribution of prices on both platforms

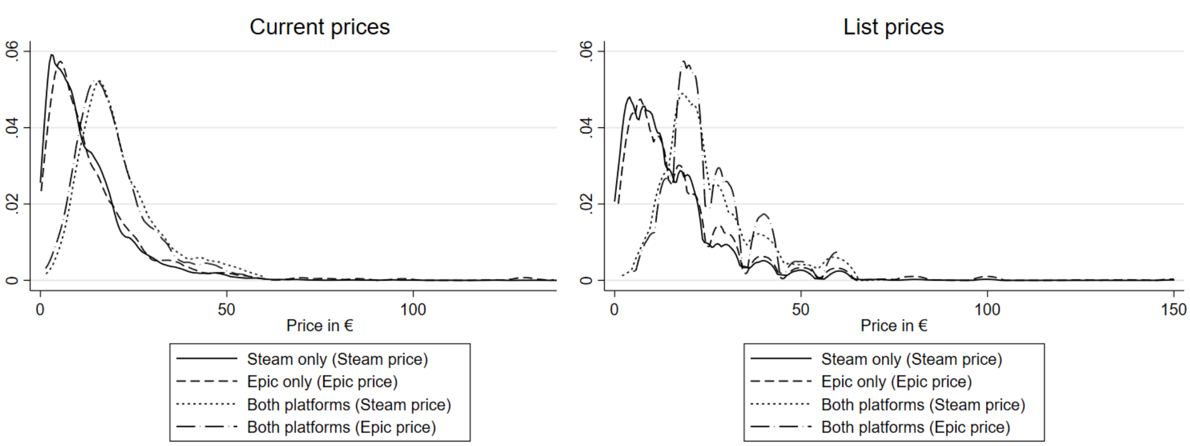


Figure C2: Differentiation of games on both platforms

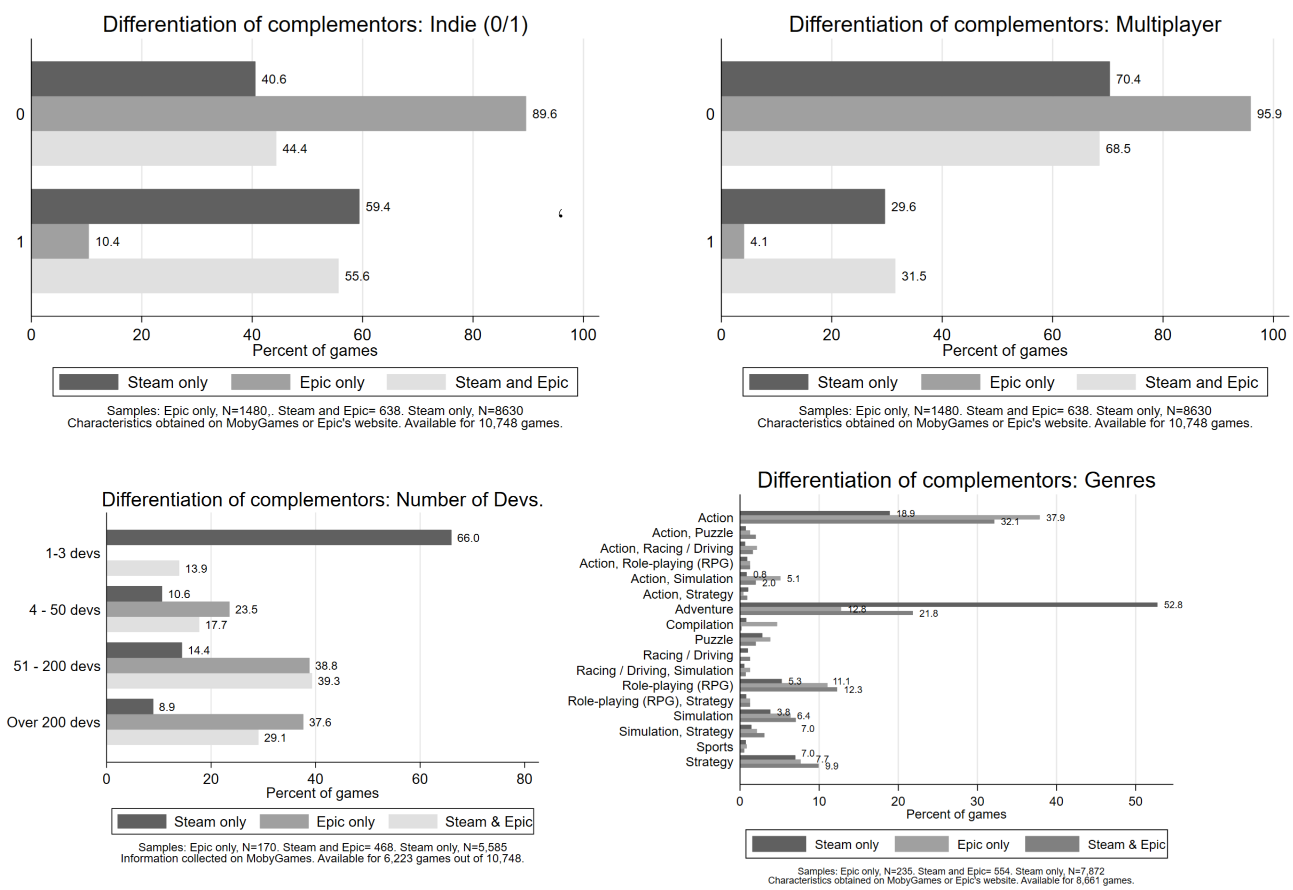
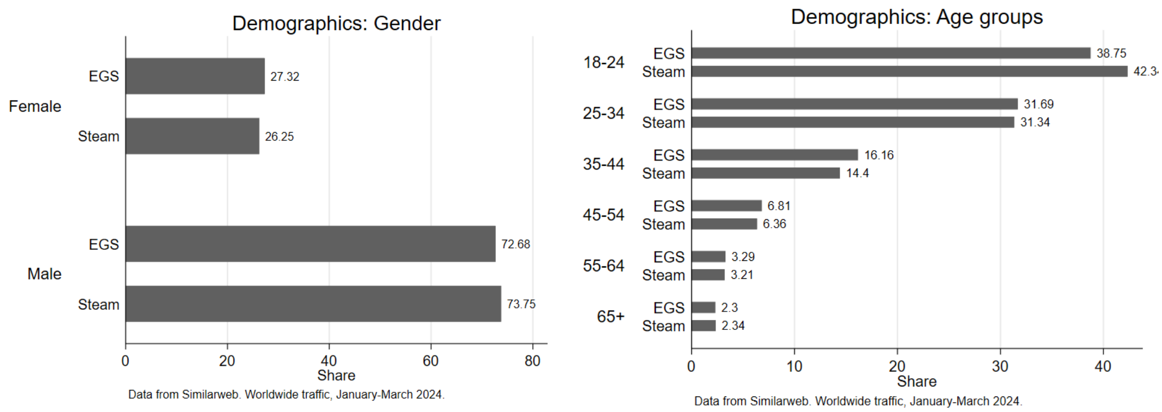


Figure C3: Measures of audience on both platforms




Note: Data from Similarweb. Worldwide traffic. Period: January to March 2024.

## C.2 Additional analysis: Impact of the entry on prices

Our dataset crawled from the website SteamDB allows us to track list prices and discounted prices at the game-day level. We exploit this data to estimate a model similar to the model we estimate for sales, using prices as a dependent variable and interactions between our variables of interest (indie, multiplayer, and unreal engine) with an indicator for the post-entry time periods. We aim to analyze if prices of games on Steam changed after the entry of EGS, with list prices representing the long-term pricing strategies of publishers (adjusted infrequently) while the current prices are subject to short-term strategies, impacted by participation in sales. We restrict the sample in the same fashion as what we do for our sales analysis, 12 months before the shock, and 12 months after. The estimation sample consists of 108,107 observations on 5,536 games observed over 24 months. Results presented in Table C2 suggest that the current prices remain largely unaffected by the entry, while the list prices are affected. In particular, we observe that multiplayer games tend to be less expensive, ceteris paribus, after the shock, while indie games and those using the unreal engine tend to be more expensive. These regressions all include a measure for the age of the game as prices tend to "naturally" decrease over the life cycle of games. Overall, these results indicate that, on top of sales participation, the long-term pricing strategies of complementors were affected by the entry, and the heterogeneity of these effects is what we would expect: the complementors who have incentives to protect the existing ecosystem tend to decrease their (list) prices after the shock, suggesting an intensified effort to stimulate demand. The complementors who find an interesting outside option in the entrant do not make such efforts - to the contrary, they tend to increase their list prices, all things being equal.

Table C2: Impact of the entry on prices

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | All games | | Single-homing games | | Multihoming games | |
| | Current price | List price | Current price | List price | Current price | List price |
| Post=1 × Indie game=1 | 0.063 | $0.310^{***}$ | -0.071 | $0.246^{**}$ | $2.383^{***}$ | $1.426^{*}$ |
| | (0.105) | (0.078) | (0.104) | (0.075) | (0.641) | (0.558) |
| Post=1 × Multiplayer=1 | -0.090 | $-0.254^{**}$ | -0.063 | $-0.313^{***}$ | -0.570 | $0.811^{+}$ |
| | (0.123) | (0.080) | (0.124) | (0.080) | (0.623) | (0.445) |
| Post=1 × Unreal=1 | 0.366 | $0.696^{*}$ | $0.689^{+}$ | 0.444 | -1.199 | $2.600^{*}$ |
| | (0.395) | (0.342) | (0.386) | (0.357) | (1.488) | (1.055) |
| Age in months | $-0.081^{**}$ | $-0.064^{***}$ | $-0.087^{***}$ | $-0.069^{***}$ | 0.040 | 0.005 |
| | (0.025) | (0.017) | (0.026) | (0.018) | (0.121) | (0.092) |
| Age squared | $0.001^{***}$ | $0.000^{***}$ | $0.001^{***}$ | $0.000^{***}$ | $0.001^{***}$ | $0.001^{+}$ |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Controls | Y | Y | Y | Y | Y | Y |
| Month FEs | Y | Y | Y | Y | Y | Y |
| Constant | $12.993^{***}$ | $14.938^{***}$ | $12.024^{***}$ | $14.056^{***}$ | $32.621^{*}$ | $40.264^{***}$ |
| | (0.628) | (0.432) | (0.606) | (0.394) | (13.782) | (11.843) |
| Observations | 98,077 | 98,077 | 92,798 | 92,798 | 5,279 | 5,279 |
| Games | 5,369 | 5,369 | 4,820 | 4,820 | 269 | 269 |
| Within R-squared | 0.064 | 0.009 | 0.063 | 0.009 | 0.112 | 0.037 |

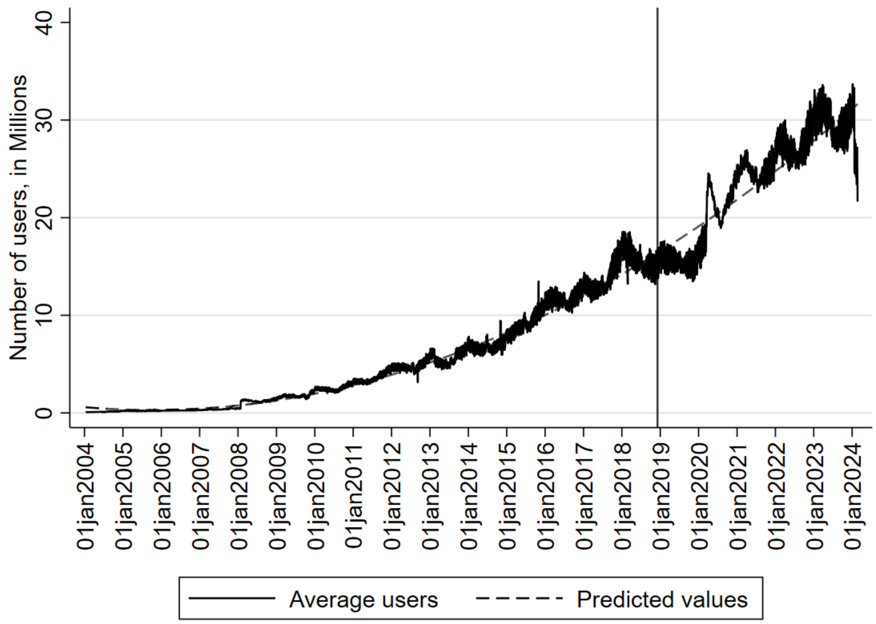
Standard errors in parentheses

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Note: Sample: all games, observed 12 months before and 12 months after the shock. List prices are catalog prices in US Dollars, and current prices are potentially discounted, usually observed for a short period of time (e.g. during sales). Controls are the same as those used in the main sales regression, averaged at the month level. The age of the game is the number of days since its release on Steam.

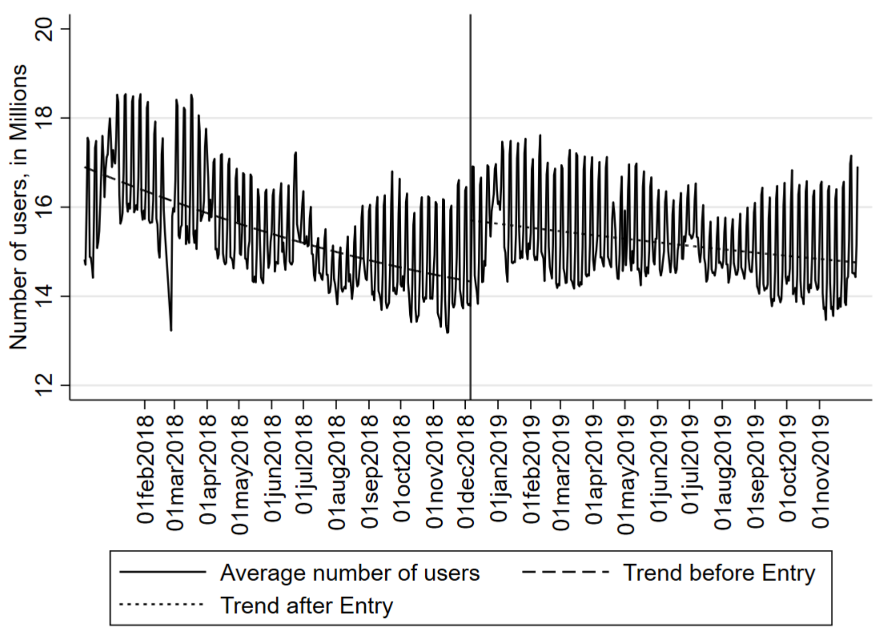
## C.3 Additional analysis: Impact of the entry on the number of users on Steam

Figure C4: Evolution of the number of users on Steam (2004–2024)




Daily data from Steam DB. The vertical line represents the entry of EGS.

Figure C5: Evolution of the number of users on Steam (Pre and Post entry)




Daily data from Steam DB. The vertical line represents the entry of EGS.