UNPAID CROWD COMPLEMENTORS: THE PLATFORM NETWORK EFFECT MIRAGE

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ABSTRACT

Platforms have evolved beyond just being organized as multi-sided markets with complementors selling to users. Complementors are often unpaid, working outside of a price system and driven by heterogeneous sources of motivation—which should affect how they respond to platform growth. Does reliance on network effects and strategies to attract large numbers of complementors remain advisable in such contexts? We test hypotheses related to these issues using data from 85 online multi-player game platforms with unpaid complementors. We find that complementor development responds to platform growth even without sales incentives, but that attracting complementors has a net zero effect on on-going development and fails to stimulate network effects. We discuss conditions under which a strategy of using unpaid crowd complementors remains advantageous.

Keywords: *platforms, innovation, network effects, crowds, heterogeneous motivations, digital innovation*

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INTRODUCTION

Research on network effects and platform strategy has largely conceptualized platforms as multi-sided markets in which producers of complementary goods ('complementors') on one side compete to sell to users on the other side[1] (e.g., Rochet and Tirole, 2003; Shankar and Bayus, 2003; Parker and Van Alstyne, 2005; Adner and Kapoor, 2010; Zhu and Iansiti, 2011; Cennamo and Santaló, 2013). This conceptualization implies that platform owners should pursue strategies for aggressively attracting complementors (subsidies, marketing, etc.), inasmuch as a growing number of complementary goods increases demand from users (and *vice versa*), giving rise to network effects and winner-take-all outcomes (e.g., Garud and Kuramaswamy, 1995; Schilling, 2002; Gawer and Cusumano, 2002).

When a platform's complementors are not regulated by a price system and receive no payments (e.g., Lerner and Tirole, 2002; von Hippel, 2005), however, what then? For example, developers of 'add-on' functions for the Firefox web-browser or specialized programs that run on Stata and R do so in a system in which no payments are made to complementors. Most content contributors to YouTube and contributors of songs and audio mixes to SoundCloud pursue neither sales nor advertising revenues. Members of the general public who contribute to CNN iReports are providing free offerings to users of commercial news platforms. Even with Apple's iPhone, initial third-party producers of complementary software apps were not on the AppStore, but rather 'jailbreak' developers working outside of a price system. As these examples illustrate, complementors in these cases are often

[1] Examples include computer systems, media players, videogames, which allow interactions between users, software developers, hardware developers, and advertisers. Analogously, conferences such as the World Economic Forum enable interactions between a general audience, web users, speakers, influential public leaders and sponsors. Real and virtual shopping malls, such as the Dubai Mall or Amazon.com, bring together consumers, merchants, and advertisers. Other examples include credit cards, academic journals, magazines, directories, portals, etc.

individuals (hobbyists, students, and others working online), frequently referred to as a 'crowd,' rather than traditional enterprises (Howe, 2006; Afuah and Tucci, 2013; Bayus, 2013). Of course, it may be attractive to have complementors making offers to platform users at sub-competitive (zero) charges. However, will network effects be achieved under arrangements in which complementors are motivated by factors other than sales? Will strategies traditionally prescribed for platform growth—rapid, aggressive recruitment of complementors—remain relevant in such contexts?

Regular two-sided network effects work on the assumption that, on one hand, users prefer platforms with many complementors and, on the other, that complementors' incentives and inclination to develop will be higher for a platform with many users (i.e., a larger market). It is this second condition we must reconsider in relation to changing organization and motivations of complementors: when sales incentives are missing, do platform scale and growth continue to generate *mounting* complementor investments of time, effort, and material and increased development (Bresnahan and Greenstein, 1999)?

Our hypotheses, draws on recent advances on heterogeneous sources of motivation of workers on platforms and implications for productivity (e.g., Zhang and Zhu, 2011; Belenzon and Schankerman, 2014). It is important to begin by noting that many of the important sources of motivation of unpaid complementors are, by definition, simply unrelated to platform growth and scale (e.g., intrinsic, learning, own-use motivations, etc.). However, among motivations described in the literature we clarify that signaling and reputational motivations—as when individuals signal capabilities through their work activity, outputs, and accolades (e.g., Lerner and Tirole, 2002)—are a plausible driver of mounting investments and development activity as platforms grow larger. This is because greater numbers of platform participants provide a larger audience to which complementors may signal, and potentially greater incentives to do so. Apart from raising questions regarding the existence and importance of any such effects, we theorize that any such positive responses to platform growth will face an opposing negative effect, as many independent, competing complementors will vie for limited attention and any one signal may degenerate with growing noise and confusion (e.g., Aral and Van Alstyne, 2010).[2]

We study these issues in context representative of modern practices and conditions of online platform development: complementary game modifications ('mods') for online multi-player game engine platforms. We focus on the early 2000s, in which the use of unpaid competing complementors was mature and virtually standard practice and where complementors were restricted by license from charging users. We thus avoid spurious effects of pricing and isolate effects of working outside of a price system (as distinct from, say, 'freemium,' advertising, or 'use now, pay later' approaches). Further, although the design of complementary goods in this instance requires both skill and exertion of effort, rapid development cycles facilitated by platforms enable us to observe meaningful rapid month-to-month variation. With rapid variation in complementary good generation, we can focus our sample on a brief period in which the game engine platforms are themselves not changing. Our focus on this particular context and time period also allows us to devise an instrumental variables approach to measuring key causal relationships.

Despite missing sales incentives in our setting, we find a positive causal response of development rates to growing platform usage and a negative response to growing numbers of complementors. (At the same time, user demand responds positively to growth on the complementor side of the platform, as should be expected.) The patterns are consistent with signaling and reputational motivations palpably responding to platform growth (an inconsistent with alternative mechanisms). However, taken together, the positive response to

[2] As discussed herein, these mechanisms and outcomes related to unpaid competing complementors differ from cases of both paid competing complementors working in multi-sided markets and collaborative platforms.

usage and negative response to growing numbers of complementors effectively cancel one another out with countervailing signs, producing no overall network effect. The overall elasticity of development rates to greater numbers of complementors was -0.03. Findings are robust to alternative specifications, measures, and estimation over subsets of small and large platforms. Although precise magnitudes of countervailing effects should vary from context to context, we argue herein that network effects should tend to similarly break down in a range of similar contexts with competing unpaid complementors—and that these implications should fundamentally differ under different approaches to organizing complementors. Further, we note how outward signs and indications in the industry, although consistent with usual theories of platform network effects and multi-sided markets, are simply a misleading 'mirage' of network effects. Therefore, whereas past theory encourages aggressive and early investment, the findings here urge caution when organizing competing complementors outside of a price system.

Notwithstanding these findings, organizing complementors outside of a price system might nevertheless remain attractive in particular circumstances. Apart from making offers at sub-competitive (zero) prices, unpaid complementors might also avoid chicken-and-egg growth problems (Rochet and Tirole, 2003) at platform launch or in small platforms--precisely because they are less responsive to platform scale and network effects. (Early launch also tends to coincide with a period in which platform owners lack the resources or wherewithal to establish the institutional infrastructure and price system for complementors.) It is only that the findings reported here indicate that unpaid complementors may not be a long-run solution to stimulating self-propelling growth and a mounting platform barrier to entry (Bresnahan, 2002).

THEORY AND HYPOTHESES

Platforms, Network Effects and Aggressive Growth Strategies

Multi-sided platforms, unlike traditional businesses organized with upstream suppliers and downstream buyers, facilitate value-creating interactions among platform participants that might include users on one side and various suppliers of complementary goods and services on the other. The prevailing characterization of platforms in the literature is as a multi-sided *market* in which complementors selling to users can generate cross-platform or 'indirect' network effects (e.g., Rochet and Tirole, 2003; Parker and Van Alstyne, 2005; Rysman, 2009). The logic is that growing the installed base of users increases the size of the market to which to sell and, concomitantly, the motivation for complementors to enter and make platform-specific investments in development. Same-side or 'direct' network effects among users or complementors are also possible (e.g., Economides 1996; Belleflamme and Toulemonde, 2009; Tucker and Zhang, 2010; Boudreau, 2012).

The prospect of lucrative network effects is reflected in the literature's emphasis on aggressive, costly, and ultimately risky growth strategies aimed at attracting large numbers of complementors and generating a wide variety of complementary goods (e.g., Gawer and Cusumano, 2002; Schilling, 2002). The many tactics explored to achieve this end include deeply discounting platform access charges, subsidizing complementors' development and marketing activities, sponsoring complementor gatherings and conferences, launching marketing campaigns to influence complementors' beliefs and expectations and platform preferences, and investing heavily in tools that facilitate the production of complementary goods (e.g., Katz and Shapiro, 1994; Lee and O'Connor, 2003; Clements and Ohashi, 2005). These aggressive strategies, although they incur a significant probability of failure (Noel and Parker 2005), are deemed justifiable owing to the prospect of winner-take-all outcomes. Textbook examples following this conceptualization include the race by JVC in the 1980s to sign up a wide range of hardware manufacturers for its VHS videocassette recorder technology (Cusumano *et al.*, 1992) and rapid growth of IBM's personal computer, spurred largely by the availability of a wide variety of software (Langlois and Robertson, 1992; Bresnahan and Greenstein, 1999).[3]

Boundary conditions for this view, of course, include: the presence of strong network effects, the 'stickiness' and/or switching costs of the installed base (Farrell and Klemperer, 2007), and low and/or declining cost of adding more complementors. Managing large numbers of complementors also requires modularized interfaces (Baldwin and Woodard, 2009) and some ability to govern complementor behavior productively (Boudreau and Hagiu, 2009). Of course, another boundary condition is simply that the returns to attracting complementors is not outweighed by other strategies, such as devoting resources to instead attracting users (Eisenmann and Hagiu, 2008) or innovating direct functionality and product benefits offered by a platform (Zhu and Iansiti, 2011).

Beyond Multi-sided *Markets*: Complementors Working Outside of Price Systems

Most theories of platform strategies and industrial dynamics relate to multi-sided markets, yet the past decade of industrial history finds complementors being organized in a variety of competitive and collaborative arrangements (Boudreau and Lakhani, 2009). Often, as in the context on which we focus here, this takes the form of unpaid competing complementors working outside of a price system to independently develop complementary goods for platform users. Whereas theories of multi-sided markets assume the formation of network effects based on the idea that complementors are motivated by sales and profits, we theorize

[3] Empirical research has found analogous patterns in publishing and advertising platforms (Rysman, 2004), media systems (Dranove and Gandal, 2003), mobile computing (Nair *et al*., 2004), and videogame consoles (Schilling, 2002; Shankar and Bayus, 2003; Venkatraman and Lee, 2004; Clements and Ohashi, 2005; Corts and Lederman, 2009; Zhu and Iansiti, 2011).

the implications for network effects of a different set of motivations for unpaid complementors.

Responses to cross-platform growth. The emergence of a cross-platform network effect depends on (1) whether demand from platform users increases with the number of complementary goods available on the platform, and (2) whether complementors' incentives to develop increases with demand from platform users. For purposes of discussion, we take for granted users' preferences for a wider variety of complementary goods (1) and focus instead on how complementors respond to growth in usage (2), as this most directly relates to the motivations of complementors.

Our hypothesis regarding complementors' response to growth on the user side of the platform draws on a range of earlier studies of collaborative and competitive organization of unpaid complementors. Research conducted in such contexts as open source software development and Wikipedia repeatedly points to a wide range of heterogeneous sources of motivation within and across individuals (e.g., Lakhani and Wolf, 2005). Several stable categories of motivation are regularly identified in this work. A first set of motivational factors is notable precisely because they *do not*, by definition, relate to platform growth. This includes intrinsic motivations derived from work regarded as interesting, challenging, fun, or otherwise stimulating; learning and human capital development; and own-use 'user innovation' motivation (e.g., von Hippel 2005; Roberts *et al.*, 2006; Osterloh and Rota, 2007). A considerably smaller set of papers on unpaid *competing* complementors corroborates the presence of these factors that should be unrelated to platform growth, with survey and descriptive evidence (e.g., Nieborg and Van der Graaf, 2008; Postigo, 2010). A second set of motivational factors identified in collaborative platforms—including motivations based in gaining affiliation and identity through one's work and association with a platform membership, learning through interactions, and prosocial and reciprocating motivations (e.g., von Hippel and von Krogh 2003; Osterloh and Rota, 2007)—would if anything be in response to peer developers rather than to users. In contrast to sales incentives in multi-sided markets, many incentives and motivations here are thus simply not responsive to user-side growth.

Remaining motivations identified in the existing literature relate to 'signaling' and building reputation through the public display of work output, effort, accomplishment, and user adoption of outputs (e.g., Lerner and Tirole, 2002; Zhang and Zhu, 2011; Restivo and Van de Rijt, 2012). This might result in longer-term economic pay-offs in the form, say, of a job offer or such non-economic pay-offs as social status or ego-gratification (e.g., Raymond, 1999; Johnson, 2002; Lerner and Tirole, 2002). The limited existing evidence on unpaid *competing* complementors corroborates the presence of these signaling and reputational sources of motivation (Jeppesen and Frederiksen, 2006; Huberman *et al*., 2009; Wu *et al*., 2010).

Signaling and reputational motivations should have the potential to intensify and stimulate greater complementor development and investments with growing platform usage because it increases the size of the potential audience for signaling one's work activity, outputs and attendant accolades. To have a complement used by a large number of platform users might also constitute a 'trophy' or credential that can be parlayed with third parties such as potential employers. For example, a number of developers making free 'jailbreaking' hacks and apps for the early iPhone (Mollick, 2013) gained became well known and were followed in the press and later hired by leading Silicon Valley firms, as jailbreak hacks and apps gained wider use and popularity.[4] This is analogous to credentials and status that accrue to participation in collaborative (e.g., large open source) projects (Lerner and Tirole, 2002; Roberts *et al*., 2006).

[4] http://www.businessinsider.com/apple-hires-iphone-jailbreak-developer-2011-6.

Existing evidence suggests that signaling incentives do in fact provoke meaningful responses in investment and effort by contributors. Zhang and Zhu (2011) interpreted as signaling motivations the response in the rate of Chinese Wikipedia contributions ('edits') with that platform's usage. Although the precise nature of 'signaling games' in collaborative efforts is surely not the same as that on competitive platforms, the result is nonetheless broadly indicative of an investment response. Also suggestive of a link between signaling and complementor decision-making, Wu *et al.* (2010) find a relationship between the length of time YouTube contributors remain active and their numbers of Youtube users. Given these arguments and past evidence, we hypothesize the following.

> **HYPOTHESIS I (H1).** *With unpaid competing complementors, development rates will increase in response to growing platform usage.*

Apart from testing the hypothesis with unpaid competing complementors, it remains to be seen whether, absent sales incentives, signaling motivations can trigger mounting complementor development. This is especially so given that unpaid competing complementors are motivated by multiple, heterogeneous sources of motivation, most of which do not respond to platform scale and growth. Further, unlike collaborative platforms, in which a marginal contribution might simply constitute an incremental 'edit' or a 'bug fix', in the case of unpaid competing complementors, any effect must be sufficient to motivate the creation of a wholly working complementary good that would not have been developed otherwise.

Responses to same-side growth. The key question with respect to same-side growth is how complementors' motivations to engage in development respond to growing numbers of complementors. Again, there is a first set of motivational factors that should simply be unaffected at all by platform size. Further, the second set of motivational factors described above (e.g., gaining affiliation and identity, learning through interaction, and prosocial and reciprocating interaction) should be far less relevant in contexts in which complementors work independently and the nature of peer interaction is competitive rather than collaborative. Consistent with this point, the early research on unpaid competing complementors' motivations has not reported the presence of these motivations among those identified (Jeppesen and Frederiksen, 2006; Huberman *et al*., 2009; Wu *et al*., 2010). Therefore, as regards same-side effects, we again focus on signaling and reputational mechanisms.

The addition of complementors to a platform might, on one hand, provide a larger audience of peers to which to signal. On the other hand, greater numbers of competing signals diminishes the effectiveness or clarity of any one signal to users, third parties, and peer complementors alike. This is because, growing numbers of complementors—each with distinct and differentiated offerings—can produce issonance, confusion, uncertainty, and 'garbling' of any one signal. (This may contrast with collaborative platforms in which the broader message about a project and its virtues may remain more or less coherent, despite the possibility that individuals within a given project can compete for credit.) For example, the noise and dissonance generated by the glut of game makers for Atari's video console platform caused confusion and ultimately the infamous crash of that platform in the 1980s (Boudreau and Hagiu, 2009).

Apart from degradation of signals, competition in this case is not for sales but rather for limited attention (Davenport and Beck, 2001; Falkinger, 2007; Aral and Van Alstyne, 2010).[5] Economic theory suggests that high numbers of competitors vying for payoffs (in this case, attention and status) will diminish incentives to invest in development (Aghion *et al*., 2005) and any degradation of payoffs with competition will only likely reinforce this point, leading to the following hypothesis:

> **HYPOTHESIS II (H2).** *Development rates will decrease in response to growing numbers of unpaid competing complementors.*

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[5] For example, the reach and readership of content contributors to Facebook has declined as the number of content contributors has increased (see http://techcrunch.com/2014/04/03/the-filtered-feed-problem/).

The larger question raised by these countervailing effects of H1 and H2 is not simply whether signaling motivations are large enough to matter, but whether complementors' responses (and users' reciprocal responses) might work against one another. This leaves open a number of empirical issues, as the weight of any such effects, how these effects respond to growing numbers platform size, and even whether they manifest at all may depend on prevailing structural conditions (e.g., nature of production and signaling technologies, the constitution of complementor motivations, etc.).

EMPIRICAL CONTEXT

The long tradition of unpaid 'modding' in games development

Videogames emerged in the late 1940s and 1950s. They were monochrome and two-dimensional, simplistic by modern standards, and based on various non-standard analogue computing machines (e.g., oscilloscopes).[6] They were also most often the product of informal tinkering in university and government labs by staff who engaged in modifying ('modding') existing systems without any commercial intent or interest in making sales. By the 1960s, digital games had begun to be developed and circulated for general-purpose computers and were being ported by enthusiasts to multiple types of machines.

A commercial tradition of selling games emerged only with the advent of the personal computer industry in the 1970s, when the Apple I, Commodore PET, and Sinclair ZX80 began to bring computer games to a wider, non-specialized consumer audience. Specialized game consoles soon followed, with Intellivision, Colecovision, and especially Atari defining the early industry. By the 1980s, independent third-party publishers became increasingly important sources of games development for these machines. In games consoles, this was

[6] See Kent (2001) and Campbell-Kelly (2004) for industry details.

under especially strict technical and licensing controls that permitted developers to sell to users in exchange for royalty payments. This multi-sided market approach remains today (e.g., X-Box, Wii, and PlayStation). Microcomputer systems also involved third-party development, but offered opportunities for more flexible tinkering and modification. Thus, the longtime tradition of unpaid modding and hacking by individual hobbyists, academics, students, and others continued and grew.

Modern game engine platforms and modding of complementary games

The more open, modifiable microcomputer environment not only attracted development of altogether new games, but also stirred interest in modifying existing games, effectively transforming games to platforms to facilitate further development abetted by their design and architecture. The core of a computer game is a 'game engine platform' (Figure 1) that supports basic functions, such as renderer, which plots the visualization of a game, and a physics engine that prescribes rules of movement. Game engine platforms are sufficiently abstracted that distinct games can be built on the same basic engine. A 'game code' layer establishes an identifiable look and mode of play and defines the features of a game. A 'game environment' layer then determines (drawing on the game code) the sequences, objects, and characters that emerge, and plots the game levels or spatial territories ('maps') in which the game plays out. 'Partial conversion' mods add to an existing game new levels, characters, or objects (e.g., weapons), or effect superficial changes ('skins') by altering or adding to a game engine platform's programming. Our empirical analysis focuses on 'total conversions' mods, which are essentially new games built on game engine platforms.

<Figure 1>

Modding of PC games became a fixture in the early 1980s, employing hacks not sanctioned by the commercial games' developers. An early example was a partial conversion of the immensely popular Castle Wolfenstein game released by Muse Software in 1981.[7] The mod Castle Smurfenstein, released in 1983, was developed by a small team (Andrew Johnson, Preston Nevins, and Rob Romanchu). To hack the game and develop the mod, they used a sector editor (i.e., a low-level machine-code editor), paint program, and an audio editing program.

Unsanctioned mod development continued sporadically into the early 1990s, by which time it had changed qualitatively in sophistication, spiking around such popular games as Duke Nukem, released by Apogee Software/3D Realms. Small teams engaged in modding pioneered many forms of online collaboration and interaction that have become mainstays of complementary development including use of online bulletin boards, online forums, and Internet Relay Chat (IRC) channels. Modders also created and disseminated tools and editors to accelerate the development process. These early hacked mods were distributed informally, without payment, on early dial-up bulletin board systems and diskettes.

The growing popularity and sophistication of mod development in the 1990s coincided with a shift from unsanctioned hacking to development both sanctioned and enabled by commercial game developers. Id Software was a notable pioneer in this respect. With the appeal of its Doom game waning after several years on the market and the release of multiple versions, the company attempted to stimulate mod development by releasing parts of the uncompiled game code in late 1997, without relinquishing control of key game engine platform elements. The code was distributed under the General Public License, a standard open source license. An added condition was that all mods had to be built on a registered

[7] The Nazi guards in the original game became Smurfs, the German voices Smurf voices. The mod entailed creating new title and ending screens and new opening narration and theme, and changed the setting from Germany to Canada (see http://www.evl.uic.edu/aej/smurf.html).

version of the game and that mods had to be made available at no charge[8]. Thus, revenues accrued to the developer of the original commercial game engine platform.

These steps to complementary mod development became a blueprint of sorts, particularly in the first-person-shooter (FPS) genre, in which modding was employed earliest and most widely. By the 2000s, the combination of layered development on the commercial game engine, supporting tools, GPL licensing, and zero payments was virtually standard practice across game engines in the genre. Commercial FPS games, as game engine platforms, became objects of development by thousands of independent developers, complementors operating outside of a price or market system effectively offering substitute or competing offerings to platform users.

DATA SET

Sample

Our data set focuses on full-conversion mods built on online multi-player first-person-shooter game engine platforms (2002–2004). Apart from comments in the Introduction regarding what motivated this choice of context, it should be noted, too, that this is a context in which our key concern of incentives and motivations is plainly important, as complementary development of full-conversion mods required both skill and effort exerted over several months. Further, although it is possible to test H1 and H2 in any platform context with unpaid competing complementors, it is more informative to do so in a context that reflects widely prevailing structural conditions of modern complementary development (e.g., digital online context, modular hierarchical architecture, widely-diffused digital development tools and frameworks, interactions via electronic forums and IRC chat channels, publicly available and readily observable data sources on platform growth for industry

[8] Note: We found five mods among the thousands of mods on the 85 platforms during the sample period that did take donations.

participants, etc.). Sources of motivation in this context also map well to those discussed in the preceding literature review and references to theory (e.g., Nieborg and Van der Graaf, 2008; Postigo, 2010).

The nature of the technology itself assures precise observation of platform usage and complementors for the populations of the relevant game engine platforms. To enable multi-player game play, total-conversion mods had to be loaded on users' personal computers (along with the game engine) and interactions were supported via a publicly observable Web server. The data we study were collected by U.K.-based industry tracker C-Sport.net, the leading global repository of these data at the time. The February 2002 to June 2004 period of the data corresponds to the period during which the firm operated.[9] That these data were collected by crawling publicly available game Web servers enables us to observe the full populations of 3,049 mods and 85 commercial game engine platforms.

We have 2,240 month-platform observations. The panel is unbalanced, with 59 game engine platforms present in 2002, 77 in 2003, and 80 in 2004. Monthly time units provide a period short enough to capture the short development cycles of mods and still more rapid responses of user demand. The distribution of mods across game engines is skewed, 32 having 10 or more mods and 53 with fewer than 10 mods. Eight game engines had just one mod and therefore dropped out of any fixed-effect regression estimates. (Our robustness checks verify results for both big and small platforms.) We identified within the dataset the names (or unique identifying emails) of 535 developers (individuals, teams, and organizations), only 75 (15%) of which were recorded as developing more than one mod during the sample period (the majority of identified developers developed only a single mod).

[9] The company subsequently went out of business, in part, because of the lack of revenue associated with mods at the time. The task of crawling the web to collect relevant data was easily replicated.

Main Variables

We infer variation in the intensity of complementor incentives to invest in development from changes in rates of new complementary development, focusing on the natural logarithm of (one plus) the number of new mods generated for a given platform in a given month (*lnNewComplements*). Taking logarithms usefully re-scales variation to reduce skew, and regressions that use logarithms enable us to interpret coefficients as elasticities. Descriptive statistics are reported in Table 1.

We measure platform usage as the natural logarithm of the total number of minutes played for all mods for a given game engine platform in a given month (*lnPlayerUsage*). This and other platform variables were readily observable by all platform participants at the time, as they were publicly reported by C-Sport.net. (In robustness tests, we also examined sales units of packaged software for each commercial game engine platform, provided by American market research firm NPD.)

The number of complementors in this context is almost precisely the same as the number of complementary mods generated because most individual complementors developed only one mod during the sample period. We therefore measure the size of the complementor side of the platform as the cumulative release of mods over time (*lnNumComplementors*).[10]

Many other imaginable factors could have affected development rates and complementor incentives. Rather than simply control for platform covariates, we exploit the panel structure of the data, using platform and time-period fixed effects to unambiguously control for cross-sectional variation and general macro industry trends.

< Table 1 >

[10] Experimenting with ‘active’ numbers (i.e., those that exceeded some threshold of usage) did not change our results.

Instrumental Variables

To better isolate exogenous variation in our key variables beyond just the use of panel data controls, we exploit instrumental variables. We observed game demand and usage (i.e., *lnPlatformUsage*) to be independently highly influenced by the rapid build out of high-bandwidth Internet connectivity during the period of our study, reflecting the importance of latency and responsiveness in multi-player games. Game development, in contrast, being primarily an off-line activity not dependent on high-bandwidth connectivity, preceded the build-out of high bandwidth links by decades. What supporting online facilities were used (electronic mail, bulletin boards, and Internet Relay Chat (IRC) channels) required only narrowband links. Although game developers were also surely users, they constituted only a small proportion thereof, began usage prior to development, and likely prior to the data set, and the decision to develop using one game engine platform or another could be made quite independently of game play preferences.

We use data on broadband line counts provided by the OECD, defined at the time as those exceeding 256 kilobits-per-second. For every additional million broadband Internet lines in the United States, we find 0.09 million total monthly minutes of usage were added, on average (significant at $p = 1\%$, with robust standard errors). For added lines in the United Kingdom and Germany, we find similar values of 0.07 million and 0.14 million, respectively. As these time series variables are coincident with time fixed effects in our regressions, we implement these instrumental variables by interacting them with platform dummies. Therefore, our estimates exploit the component of platform-specific transitory variation (i.e., controlling for platform and time fixed effects) that projects to the availability of broadband lines. Also note that specifications using instrumental variables reduce variation not just by the estimation procedure itself, but also because these data are available at six-month intervals.

A factor that should have influenced the supply of mod developers, and thus the generation of new mods, was the number of new graduates in computer science, which we measure in thousands as reported by the U.S. Bureau of Labor Statistics (*CompSciGrads*). The United States generated the largest share of complementors during this period. For each graduate (where *CompSciGrads* mean = 53,695; standard deviation = 3,687) we found 0.003 additional mods added on average (significant at $p = 1\%$, with robust standard errors). Again, to avoid having this time series variable simply be coincident with our time fixed effects, we generated instrumental variables by interacting it with platform dummies. This again reduces variation exploited for estimates not just because of the estimation procedure, but because data are available at 12-month intervals. Further, they only capture variation associated with graduates in the United States.

ANALYSIS AND RESULTS

Descriptive patterns and reduced-form estimates of the effect of adding complementors

Before proceeding to estimate individual causal interactions around platforms in our main analysis, we first document reduced-form descriptive relationships in the data. We first regress development rates (*lnNewComplements*) on a constant term and numbers of complementors (*lnNumComplementors*), to examine the simple association between rates of new development and numbers of complementors. We lag number of complementors by three months to reflect that decisions are taken at the beginning of the development cycle. (Results do not depend on specific lag periods, as discussed in robustness checks.) Consistent with the usual network effects hypothesis, we find a strong positive correlation between these variables, 0.021 (significant at $p = 1\%$ based on robust standard errors). However, simply controlling for cross-sectional differences with platform fixed effects leads the estimated correlation to immediately become statistically indistinguishable from zero, at -0.01. Adding time period fixed effects leaves the estimate statistically unchanged. Therefore, the reduced-form evidence strongly suggests the absence of any effect of adding complementors, or a network effect. The analysis to follow investigates the individual causal interactions around the platform that might create this overall (zero) effect.

Estimates of the system of cross-platform and same-side network effects

Here we confirm, as theory would predict, that when complementors work outside of a price system, platform growth does, indeed, provoke a series of causal interactions around the platform. However, the net effect of adding greater numbers of complementors is zero, affirming the above reduced-form estimate.

The system of relationships around platforms might be specified in any number of ways, with greater or lesser degrees of structural specification. Our interest here being to test for the hypothesized relationships with a minimum of econometric manipulation, we estimate a linear system. The relevant relationships are represented in the following expressions.

$$lnNewComplements_{jt} = \alpha + \beta\ lnPlatformUsage_{j(t-3)} + \gamma\ lnNumComplementors_{j(t-3),} + \Theta_{jt} + \varepsilon_{jt} \quad (1)$$

$$lnPlatformUsage_{jt} = \delta + \lambda\ lnNumComplementors_{j(t-1)} + \Omega_{jt} + \zeta_{jt.} \quad (2)$$

H1 and H2 relate to expression (1) as a means of determining how complementors respond to growth on both sides of the platform. However, estimating expression (2), users' response to complementors, enables us to examine the entire set of interactions that could produce platform network effects. Where coefficient estimates can be interpreted causally, a cross-platform network effect exists if both β and λ are positive. A same-side direct network effect exists and is negative if the coefficient γ is negative.

Regressors are lagged to minimize the most mechanical forms of correlation and common shocks between regressors and regressands. As earlier, we lag regressors in expression (1) by three months to reflect decisions being taken at the beginning of the development cycle. We lag the regressor one month in expression (2), given that usage adjustments are far more rapid. (Results do not depend on the precise choice of lag, as we discuss in robustness checks.)

Of course, many factors beyond platform growth, denoted by Θ and Ω, might affect the dependent variables. We address cross-sectional sources of variation (e.g., intrinsic platform attractiveness) and any general macro factors that might affect the industry over time (e.g., industry structure or macro conditions) with platform and time period fixed effects. We further isolate exogenous sources of variation using instrumental variables (as described in Section 6.3).

Model estimates are reported in Table 4. In our estimation, we allow for cross-equation contemporaneous correlations in the error terms (i.e., $E[\varepsilon_{jt}\ \zeta_{jt}\ |X] \neq 0$).[11] Model (1) estimates the model using feasible generalized least squares (FGLS), estimating the error structure in the first-stage and using these estimates in generalized least squares estimates in the second stage. Model (2) of Table 4 estimates the model based on a three-stage procedure that follows the earlier approach, but also projects the (platform-specific transitory) variation of regressors onto the instrumental variables. (See Wooldridge (2010) for point estimate and asymptotic standard error estimate procedures for FGLS and 3SLS.)

Coefficient estimates conform to predictions. The positive cross-platform network effect (β and γ) is reflected in the positive coefficient on *lnPlatformUsage* in models (1.i) and (2.i) and the positive coefficient on *lnNumComplementors* in models (1.ii) and (2.ii). The negative same-side network effect (λ) is reflected in the negative coefficient on *lnNumComplementors* in models (1.i) and (2.i). Given differences in magnitude and significance across models (1) and (2), we regard model (2) as preferred. Noting that the same-side response of rates of

[11] Systems of equations that allow for this error structure are often referred to as 'Seemingly Unrelated Regression Equations.' Although the expressions can be estimated independently, estimating them simultaneously increases efficiency.

development to growth in numbers of complementors is only significant at $p = 10$ percent, we later affirm its significance in a series of robustness checks.

< Table 2 >

Estimated effect of adding complementors

We can use the coefficients of models (2.i) and (2.ii) to estimate the overall effect of increasing numbers of complementors on development rates, with same-side and cross-platform interactions taken into account. This should be comparable to the earlier reduced-form estimate of an elasticity of -0.01. A one percent increase in numbers of complementors will cause usage to grow by 0.09 percent, as in model (2.i). A 0.09 percent increase in usage, in turn, expands new development by 0.27×0.09 percent, or 0.024 percent. If we roughly approximate the remaining 'rippling' back and forth as a geometric series, the estimated overall effect of a one percent addition to the crowd is just 0.025 percent, or an elasticity of about 0.03, all else being equal. This tendency to increase development rates would be met by a -0.06 percent tendency to decrease resulting from the same one percent increase in numbers of complementors, as in model (2.ii). The net of these interactions is therefore approximately -0.03, similar to our -0.01 estimate of net elasticity of development rates from added complementors.

Robustness

We performed several additional tests to assure the robustness of these results, as reported in Table 4. We focused on expression (1), it being most crucial to our theorizing and interpretation. Given the close relationship between platform usage and crowd size, one possible concern is that the negative coefficient on *lnNumComplementors* reflects concavity in the relationship with usage. However, adding a quadratic term does not affect results, as in model (1). Model (2) assesses the suitability of our usage measure by including a measure of numbers of individuals who purchased the game engine platform (i.e., the packaged software for the commercial game).[12] Our findings were not altered. Consistent with our interpretation that complementors were responding to online play, the estimated coefficient (elasticity) on packaged software sales is smaller than that on usage. Models (3) and (4) confirm the pattern of results separately on subsets of larger and smaller platforms (based on below- and above-median sales of packaged software). Model (5), which re-estimated the model in a robust count-model framework (Wooldridge, 1999), further affirmed our results.

< Table 3 >

Given that the coefficient on *lnNumComplementors* was significant in our main estimates at only p = 1% (i.e., model (2.i)), we emphasize here that prior robustness tests each find a significant coefficient. We also reconsidered the possibility that any shocks propagating through time might similarly affect both lagged numbers of complementors and new development rates, and produce an upward bias in the coefficient estimated on *lnNumComplementors*. Here, we exploit the fact that, in principle, more distant lags of *lnNumComplementors* should, in the absence of a bias, produce weaker effects and push estimates closer to zero; however, with upward bias, more distant lags should lead to more negative estimates. In re-estimating the model, we found coefficient estimates on *lnNumComplementors* to become slightly more negative with longer lags. This is consistent with some degree of common shocks and upward bias. However, the effect is small, affecting the estimated coefficient by just one or two percent.

Random Coefficients and Heterogeneity of Responses

We also re-estimated responses to platform growth with a Multinomial Logit model of complementor decisions estimated in our platform-level data, as in model (6). We re-define the right-hand-side arguments in expression (1) from determinants of aggregate development

[12] A preferred approach would be to replace our usage measure with this measure and develop an equivalent instrumental variables estimation strategy. However, this is not possible in these data and context.

rates to factors that determine the benefits or 'utility' derived from developing for one platform or another, or none at all, and allowing for distribution of (i.e., 'random') coefficients across the population of crowd developers. This not only allows us to test predictions using a different model specification, but also enables us to generate estimates of heterogeneity of responses. We use the standard approach of estimating coefficients and asymptotic standard errors using instrumental variable and generalized least squares, as described in detail by Nevo (2000). These estimates confirm a positive incentive response of developers to growing usage, and further indicate that the response was universally positive across the population (mean response to *LnPlatformUsage,* 0.79, and standard deviation, 0.05). This is consistent with positive or at least non-negative responses to signaling motivations with growing usage (H1). Further, these estimates confirm a negative response of developers' incentives to growing numbers of complementors. They also indicate considerable heterogeneity in response across the population, with the possibility that some fraction of individuals in fact responded positively. This is consistent with the degradation of signals and competition with added complementors (H2), but also with some share of participants gaining motivation to signal to a larger audience of peers—a partially positive effect. Coefficients are not directly comparable to earlier estimates. Statistical significance necessarily drops under this specification.[13]

Summary of results

Our main analysis found development rates' elasticity to platform usage to be 0.27, and to growing numbers of complementors to be -0.06, consistent with H1 and H2. Therefore, despite the absence of sales incentives, platform growth does cause a change in

[13] The statistical significance of these estimates is necessarily lower given the way in which the model is estimated. The Multinomial Logit model with random coefficients (Nevo, 2000) uses the logarithm of shares of new complements to estimate coefficients. To minimize instances of zero shares and the inability to calculate defined logarithms, we aggregated the time period to years for this estimate and dropped the few platforms that experienced a year without new releases.

complementors' development rates, and patterns are consistent with responses to signaling motivations, as we theorized. (The estimates of the heterogeneity of responses of complementors, above, are also consistent with signaling motivations.) At the same time, the elasticity of platform usage to increasing numbers of complementors was 0.09. In other words, as expected, users respond positively to an increase in complementors. The *net of these effects* implies that taking actions to attract greater numbers of complementors has a negligible effect on on-going development rates. The overall estimate based on the system of interactions was an elasticity of -0.03. Our estimate based on reduced-form regressions was -0.01. We thus found that, overall, network effects did not materialize.

DISCUSSION AND CONCLUSIONS

Our work contributes to strategy research that has increasingly examined contingencies in the management of platforms and their wider ecosystems (e.g., Gawer and Cusumano, 2002; Adner and Kapoor, 2010; Zhu and Iansiti, 2011; Cennamo and Santaló, 2014), and that which closely examines the workings of network effects (Suarez, 2005; Boudreau, 2012; Casadesus-Masanell and Halaburda, 2014). Here we depart from theory conceptualizing platforms as multi-sided markets in which complementors compete to sell to users. We instead considered contexts in which complementors work outside of a price system and receive no payments. We raised the question of whether, absent sales incentives, network effects and aggressive strategies for attracting complementors remain relevant. We tested our hypotheses in a representative context and found, as predicted, that unpaid competing complementors respond to growth even without sales incentives. The effects, however, were small and effectively cancelled one another out with countervailing signs, producing no overall network effect.

The mechanism: signaling and the elasticity of development to platform growth. As we theorized, responses of complementor development to platform growth are each consistent with signaling and reputation motivations as the underlying mechanism (e.g., Lerner and Tirole, 2002; Roberts *et al.*, 2006), and inconsistent with alternative mechanisms. Because growing platform usage offers a greater audience to observe the work of a complementor (or more broadly increases awareness and relevance to third parties), rewards and motivations to develop can grow as platform usage grows. This interpretation was corroborated in numerous conversations with industry participants in the course of our research. For example, co-creator of the Battlegrounds mod for Half-Life, known as 'Black Panther,' stated: 'Well, it's about website visitor count, download count, server count, people playing […] You get featured in magazines, you get interviews, you get on the gaming websites. It's about seeing your creation's name in lights.' (personal interview, 2003). Most developers we encountered actively monitored usage as an indication of performance.

At the same time, the anecdotal evidence confirms many other sources of motivation that should not be related to platform growth, including 'artistic expression,' 'learning and the joy of creating,' 'fun,' 'articulating my vision,' 'pride of ownership,' and so on. Minh 'Gooseman' Le, developer of Counter-Strike (mod of Half-Life), noted: 'I just wanted to customize the game to fit my vision of what a game should be. First and foremost, it is my vision, not anyone else's. I don't spend 10+ hours a week working on a mod for free just to make a mod that satisfies everyone. I make a mod that I am happy with, and if someone else happens to like it, then that's a bonus' (Minh Le, quoted in Herz (2002)). Heterogeneity of motivations is consistent with the heterogeneity indicated by our random coefficient estimates.

This positive response of development rates to growing usage was met by the negative response to growing numbers of complementors. This might be loosely analogized to negative effects of growing competition and crowding out of incentives documented in cases of paid complementors (e.g., Economides, 1996; Boudreau, 2012). However, the mechanisms and implications for network effects differ a great deal between paid and unpaid situations. Rather than a competition for sales, in an unpaid regime we have competition for the scarce and fixed commodity of *attention* (e.g., Davenport and Beck, 2001; Aral and Van Alstyne, 2010). Moreover, as the number of different complementary goods offered by complementors to platform users grows, the quality of signals can degenerate, giving rise to greater noise, uncertainty, and confusion. In this sense, it is perhaps not surprising that the direct same-side negative effect of added complementors is sufficient to outweigh the indirect cross-platform effect created by interactions between complementors and usage.

General lessons on organizing complementors and network effects. Several conditions separate unpaid competing complementors from traditional multi-sided markets with paid complementors: (i) incentives to make sales to users are simply missing; (ii) absent sales, complementors respond to multiple sources of motivation, most of which do not respond to platform scale and growth; among these heterogeneous factors, (iii) only signaling and reputational motivations might be responsive to platform growth; where (iv) only a subset of complementors may respond to signaling motivations; and (v) any positive responses will be offset by large numbers of complementors competing for a limited audience and creating more noise. Whereas paid complementors can generate network effects that might only be curtailed after extraordinarily high levels of entry (e.g., Economides, 1996; Augereau *et al.*, 2006; Boudreau, 2012), the theory and evidence presented here indicate a diminished scope for network effects with unpaid complementors.

In cases of unpaid competing complementors, precise magnitudes of effects will vary from context to context, depending on prevailing structural conditions (e.g., strength and salience of signals, motivational orientation of complementors, marginal costs of development, signal propagation environment, etc.). For this reason, it was important that we estimate effects in a context representative of modern online development. For network effects to form would requires some combination of: (i) greater positive response of development rates to platform usage, (ii) greater positive response of usage to growing numbers of complementors, or (iii) less negative response of development rates to growing numbers of complementors.

Unpaid competing complementors will differ from collaborative regimes, such as Wikipedia, open source software project contributions, or other systems where complementors make contributions that aggregate to some larger whole (Figure 2). On the one hand, both competing and collaborative complementors respond to platform scale and growth and signaling motivations (e.g. Zhang and Zhu, 2011). On the other hand, competing complementors work independently, therefore motivations must be strong enough to motivate the creation of fully working complementary goods rather than just say an 'edit'. Collaborating complementors might also be driven by additional sources of motivation that respond to platform growth (e.g., motivation to gain affiliation and identity, learning through interaction, and prosocial and reciprocating motivations). Competing complementors will also produce more negative same-side effects, as they each signal their different offerings. These arguments on their own suggest that collaborative arrangements are more likely to produce positive network effects that will unpaid competitive regimes.

< Figure 2 >

The Network Effect 'Mirage'. A first managerial implication of these findings is a note of caution. The breakdown of network effects with unpaid complementors may be difficult to observe and easy to mistake. Positive correlations between platform usage, numbers of complementors, development rates, and such are each consistent with network effects, but can be spurious correlations with platform attributes. Although complementors remain attractive to have, large numbers of complementors no longer produce a self-reinforcing process whereby growth begets growth. Equally, unpaid complementors will lead to weaker entry barriers for platforms than will paid complementors (cf., Bresnahan, 2002). For example, statistical software programs such as Stata, using competing unpaid complementors to build value via a greater library of functions, have so far failed to lock in market dominance with network effects.

When to deploy an unpaid crowd complementor strategy? The findings also offer clues regarding when unpaid competing complementors might best be deployed. Despite not giving rise to network effects, competing unpaid complementors might have certain advantages, such as making offers to platform users at lower than competitive prices (i.e., zero). Unpaid complementors might also be attractive as an approach precisely because they *are* less responsive to platform scale and network effects. This means unpaid complementors might be a useful means of minimizing the usual chicken-and-egg problem[14] (Rochet and Tirole, 2003) when launching a platform. We speculate that unpaid complementors might also be applicable to cases in which complementors are themselves platform users (see von Hippel, 2005). Consistent with these arguments, platforms often launch with unpaid complementors—only later to implement systems that enable complement sales, advertising, and other monetary incentives (e.g., contributors of videos to Youtube and Youku, software and podcasts to iPhone, pictures to Instagram, and content to Facebook) (e.g., Ching, 2014).

Apart from contingent deployment of unpaid complementors where they might have advantages, another management intervention is to attempt to minimize any loss of network effects on the basis of signaling motivations. This might take the form of enhanced complementor reputation systems, increasing openness and feedback and information provision, growing social interactions on platforms and so forth. Platform owners might also take actions to reduce development costs, as with more powerful development tools, or simpler development environments (Katz and von Hippel, 2002)..

[14] The well-known problem relates to the need to attract complementors in order to attract users, but at the same time users are needed to attract complementors.

Limitations and future research. The present study leaves a number of questions for future research. Although our focus was not on sources of motivations *per se*, our findings underline that it is crucial for us to better understand behavioral orientations of complementors in open, creative, innovation systems and platforms. More precisely calibrating motivations can point to how to design platforms intent on harnessing the creative potential of complementors. Our findings, suggesting the importance of heterogeneous motivations, also indicate future research should focus on questions of how complementors sort onto platforms (Belenzon and Schankerman, 2014).

Dealing with many of these questions also requires finer-grained evidence at the level of individual complementors. Given the particular relevance of signaling and reputational motivations discovered here, future research might also attempt to better understand and characterize the nature of the 'signaling game' played by competing complementors and its implications for platform growth. Here, we treated signaling simply as a broad source of motivation affecting platform-level activity. But clearly, in the context of heterogeneous complementors, we might expect important differences across individuals.

Most broadly, the findings presented here underline the importance of continuing to bridge insights between organizational approaches, sources of motivation, and industrial dynamics in platform industries.

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TABLES

Table 1 Descriptive Statistics

	Variable	Mean	StdDev.	Max	Min	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	*lnNewComplements*	0.3	0.7	0.0	4.7	1.00							
(2)	*lnNumComplementors*	1.9	1.5	0.0	6.0	.63	1.00						
(3)	*lnPlatformUsage*	0.2	0.6	0.0	4.2	.52	.50	1.00					
(4)	*lnPackagedSoftwareSales*	7.7	4.4	0.0	13.6	.22	.26	.31	1.00				
(5)	*CompSciGrads*	53.7	3.7	49.1	57.4	-.04	.20	.08	.08	1.00			
(6)	*BroadBandUS*	8.3	1.8	5.7	10.9	.24	.07	.05	.08	.06	1.00		
(7)	*BroadBandGerm*	4.9	1.1	3.2	6.6	.21	.04	.04	.11	.11	.40	1.00	
(8)	*BroadBandUK*	4.0	2.1	1.3	7.4	.29	.06	.04	.18	.03	.17	.42	1.00

Table 2 The System of Relationships that Constitute Cross-platform and Same-Side Network Effects

Dependent Variable:	*lnNewComplements*	*lnPlatformUsage*	*lnNewComplements*	*lnPlatformUsage*
Model:	(1.i)	(1.ii)	(2.i)	(2.ii)
	Response of Complementors	Response of Users	Response of Complementors	Response of Users
lnNumComplementors	-0.02	0.13***	-0.06*	0.09***
	(0.02)	(0.01)	(0.03)	(0.01)
lnPlatformUsage	0.16***		0.27***	
	(0.06)		(0.09)	
Game Platform Dummies	Y	Y	Y	Y
Time Dummies	Y	Y	Y	Y

Notes. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3 Robustness Tests

Dependent Variable:	*lnNewComplements*						
Model:	(1)	(2)	(3)	(4)	(5)		(6)
	Second-Order Usage Term	*Packaged Software Unit Sales*	*Least Popular Game Platforms*	*Most Popular Game Platforms*	*Count-Model Framework*		*Multinomial Logit, Random Coefficients*
lnNumComplementors	-0.07**	-0.08***	-0.08*	-0.26***	-0.53***	mean:	-0.0002
	(0.03)	(0.03)	(0.04)	(0.07)	(0.14)	stddev	0.0038
lnPlatformUsage	0.49**	0.307***	0.33**	0.99***	1.89***	mean:	0.79**
	(0.20)	(0.09)	(0.17)	(0.20)	(0.34)	stddev	0.05
lnPlatformUsage^2	-0.10						
	(0.09)						
PackagedSoftwareSales		0.011***					
		(0.00)					
Game Platform Dummies	Y	Y	Y	Y	Y		Y
Time Dummies	Y	Y	Y	Y	Y		Y

Notes. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

FIGURES

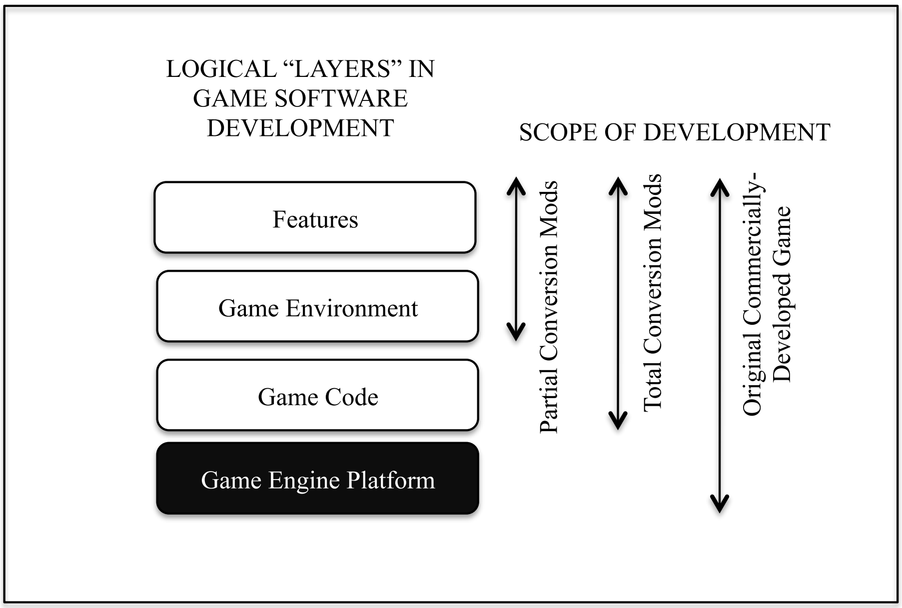

Figure 1 Architecture of Commercial Game Platforms and 'Mods'

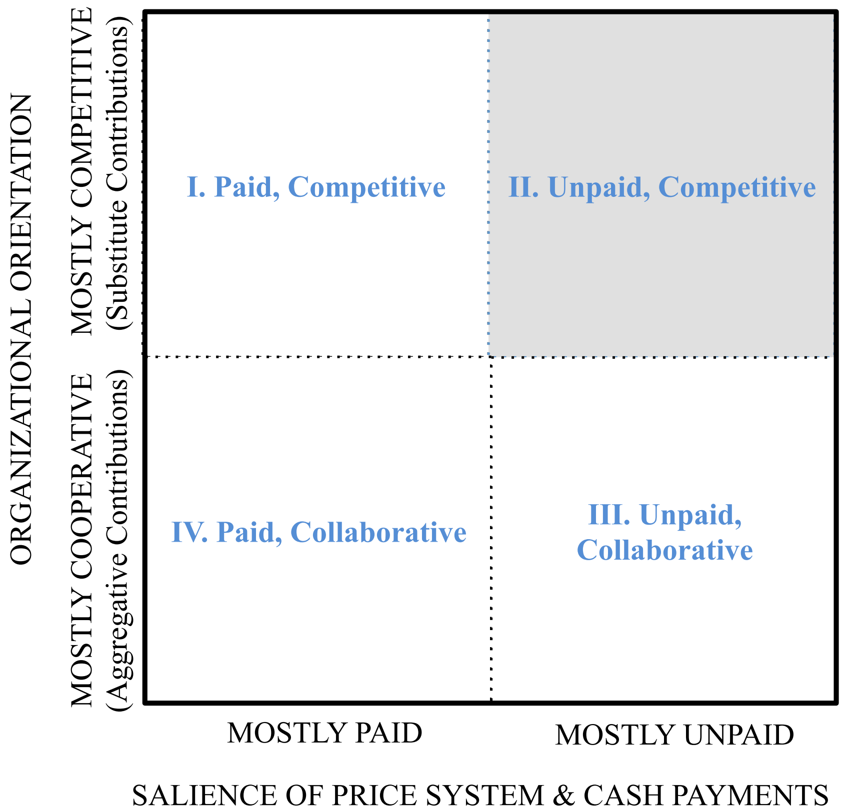

Figure 2 Spectrum of Approaches to Organizing Crowd Complementors