Digital Platform Evolution: The Effect of Stock versus Novelty of Content in Platform Adoption

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Abstract

How digital platform technologies evolve is an important question not just for the design of the platform architecture and the organizational mechanisms governing its evolution, but also importantly for its consequences on value creation for platform users, and accordingly on competitive dynamics. One perspective emphasizes the network effects dynamics and thus the static, inertial trajectory of platform evolution – the platform with a lead in network size will grow larger in network and value through self-reinforcing feedback. Another perspective emphasizes the dynamic evolutionary aspect by stressing the generativity property of digital artifacts. Because a digital platform allows the creation of new, and often unanticipated diverse content by external complementors, its value is continuously (re)shaped by new content, evolving in new directions, attending to new uses and functionalities, and thus meanings to its users. Thus, the network effects logic would suggest that the stock of a platform's content largely defines the value of the platform to prospective users, and thus drives its adoption. The generativity logic would instead suggest that novel content shapes the evolutionary trajectory of the technology and thus its functionalities and value to prospective users; accordingly, it should be the factor driving platform adoption largely. We integrate both perspectives to test the effect of these two (inertial and dynamic) components on platform adoption and evolution, and the implications for platform competition.

Introduction

Digital platform technologies are extensible common technology providing a core functionality upon which third-party firms develop and offer their complementary products to the end-users of the platform (Baldwin and Woodard, 2010; Constantinides *et al.* 2018; Parker *et al.* 2016; Tilson *et al.* 2010; Tiwana *et al.* 2010). An ever-increasing number of companies in various industries such as software operating systems, videogame consoles, smartphone app stores, and ad-supported media portals, are built as digital platforms (Eisenmann *et al.* 2006). Many have highlighted that because digital platforms are generative, in that they evolve in their uses and functionalities by enabling the creation of complementary digital content (complement) that extend the value of the platform in kind, not just in degrees for users (e.g.,Reuver *et al*. 2017; Tilson *et al*. 2010; Yoo *et al.* 2010, 2012), digital platform technologies prove a superior means for creating value. However, when it comes to how platform value evolves over time and its implications for platform competition, we know little about. Which factors affect most platform evolution and value to users?

One perspective emphasizes the so-called indirect network effects (e.g., Eisenmann *et al.* 2006; Parker *et al.* 2016; Song *et al.* 2018); users are attracted to adopt the platforms with high variety of complementary products and, vice versa, third-party developers prefer the platforms with a massive number of users, which represent the potential demand for their offerings. Third-party developers (complementors), hence, play a critical role for the platform success (Parker *et al.* 2017; Yoffie and Kwak, 2006). They generate the extensions (add-ins, apps, modules) to the platform technological foundation (Boudreau, 2012; Tiwana, 2015) and co-create value within the platform ecosystem (Ceccagnoli *et al.* 2012), which in turn allows the platform to exploit the network effect for being adopted by end-users. It is commonly understood that building market momentum around a platform to reach quickly a critical mass of users is paramount for success, as existing users attract new users through a self-reinforcing effect (e.g., Arthur, 1989; Evans, 2009; Hill, 1997; Rysman 2009). Although Arthur (1989), for example, acknowledge that the dynamics of increasing returns and historical events are of much importance to predict the market outcome, much of the focus has remained on the logic that emphasizes the inertial trajectory of platform evolution; the stock of a platform's content largely defines the value of the platform to prospective users, and thus drives its adoption.

However, this perspective misses the dynamic aspect of platform evolution ensuing from its generativity property; as novel, diverse content gets created, it redefines the technological affordances of the platform to users, and thus its value (Constantinides *et al.* 2018; Yoo *et al.* 2010; Tiwana *et al.* 2010). Novel content shapes the evolutionary trajectory of the technology and thus its functionalities and value to prospective users. Accordingly, it must be the main factor driving platform adoption over time. Adner (2004), from a demand-perspective (Priem *et al*. 2012), also note that consumers follow an S-curve trend demand (similar to technology life cycle), accordingly firms need to "rejuvenate" the value added utility to the consumers as they evolve. A platform cannot only rely on its early stages growth in complementary products and the critical mass of users obtained, hence, the network effect raised between the two. It should constantly provide novel offerings and "adapt to evolving user needs" (Tiwana *et al.* 2013: 682).

In this study, we address this shortcoming (of missing the dynamic perspective) conceptually, by decomposing the concept of platform evolution into inertial (i.e., the indirect network effects) *and* dynamic (i.e., the generativity effect) components, and empirically, by estimating the effects of both components on platform adoption by users. We operationalize the inertial component (i.e. stock) as the *cumulative* number of complements available on the platform at a given point in time, and the dynamic component (i.e. novelty) as the *change* in the stock of complements through time. We estimate the effect of both complement (content) stock and novelty on the platform adoption over time by users in the context of videogame industry. We advance that *novelty* has a positive effect on platform adoption, above and beyond the effect of *stock* of complements, and we show that this effect is stronger (in magnitude terms) relative to the effect that stock has on platform adoption. These results are robust to different model specifications and alternative operationalization. We also show that the novelty component has important implications for platform competition. Our findings depict, for example, that 10% increase in the new titles released in the last quarter (novelty) boosts the platform market share (against all other active platforms in the market) by 12.8%. Whereas, 10% increase of the stock all titles until the last year increases the platform market share by only 1.4%, which means the dynamic component has an almost 8.5 times stronger impact on platform market share than of the inertial component. The essential role of the dynamic component on platform success against the rivals has been supported in various models with qualitatively the same pattern, as described later.

Our paper contributes to the growing body of IS literature on digital platforms in several ways. First, coupling the inertial (network effects) and dynamic (generativity) elements of platform evolution can offer a better way to elucidate on the evolutionary trajectory of a digital platform. If one also accounts for the dynamic effect, it becomes apparent, for instance, that enhancing the platform capacity to accumulate a large stock of complements may not be a necessary condition for winning the market: a new platform with a small stock of complements but high rate of new complements creation might soon catch up on the incumbent's user base, or eventually co-exist in the market. By showing that complement novelty impacts platform adoption by users much more than the stock of available complements, we try to advance the discussion beyond the "total size" characterization of network effect, embodying the other critical elements of digital platforms, such as generativity, that make these technologies complex and evolving infrastructure systems (Constantinides *et al.* 2018; Yoo *et al.* 2010, 2012; Tiwana, 2015; Tiwana *et al.* 2010).

Second, we contribute to the emerging view in the IS literature of platforms as digital layered, modular architectural infrastructures (e.g., Cennamo *et al.* 2018; Constandinides *et al.* 2018; Tilson *et al.* 2010; Yoo *et al.* 2010). Embracing this perspective, we advance that digital platforms are first, "market" digital infrastructures enabling value-exchange interactions among distinct groups of users (e.g., complementors and final users) giving rise to the network effects dynamics extensively discussed in the platform economics literature. Second, they are *also* "*generative*" digital infrastructures enabling the creation of unanticipated innovation in platform complements, which extend the reach, uses, and value of the platform to its users. Accounting for this dual nature of digital platforms, we offer an integrated, more holistic view of platform evolution, which couples the evolutionary forces of both the market and innovation dynamics.

Conceptual Framework: Digital Platforms as Digital Infrastructures

Digital Platforms as Market Infrastructures: The Network Effects Evolutionary Logic

The literature on platform economics generally describes digital platforms as "two-sided" markets, with the distinct sides characterized by the presence of positive complementarities (or indirect network effects) between end users on one side and autonomous complement providers on the other (Armstrong 2006; Caillaud and Jullien 2003; Gupta *et al.* 1999; Rochet and Tirole, 2003, 2006). Network effects are reinforcing, so more participation on each side creates more value, with complementor's activities coordinating via market-based feedback mechanism. The majority of studies has thus focused on the initial conditions affecting platform adoption on each side (such as membership rules, pricing, etc.). However, we know little about how platforms evolve. Because of the network effects, it is implicitly assumed that the ensuing positive feedback or self-reinforcing effect enables the platform to grow rapidly and become the market leader—that is, the winner-takes-all. Once a platform gains enough number of users and complements—the *critical mass*—it ignites; that is, it gains momentum until a stable equilibrium (e.g., Evans, 2009; Lee *et al.*, 2003). Conversely, when the critical mass is not reached, momentum fades off and the platform eventually gets locked out the market (Schilling, 2002). Accordingly, the inertial force associated with the cumulative stock of complements on one side of the market will largely determine the evolution of the platform and its adoption by users on the other side.

For example, Nair and coauthors (2014), in the personal digital assistant industry, show empirically the positive (negative) impact of (lack of) third-party applications on the installed base of users. Clements and Ohashi (2005) estimate how the hardware adoption is positively affected by the software provision in the context of videogame industry, the effect of which is stronger at the later stages of platform life cycle. Overall, previous research both analytically (e.g., Church and Gandal, 1992; Hagiu, 2009) and empirically in various platform industries (e.g., Gandal *et al.*, 2000; Gupta et al. 1999; Ohashi, 2003; Rysman, 2004) confirms that complements quantitiy positively impacts the platform adoption by users. We thus consider this *inertial* view as our null, baseline hypothesis.

H0. The greater the stock of complements previously released on a platform, the more the platform adoption by users.

Digital Platforms as Generative Infrastructures: The Generativity Evolutionary Logic

Studies in the platform economics literature largely overlook the *dynamic* aspect of platform evolution and its effect on platform competition (Cennamo 2016; Tiwana, 2015). This is largely an under-explored area: how the change and fluctuation of complements affects the evolutionary dynamics of platform adoption. Most studies limit their lens to the initial phase of the "takeoff" and assumes persistence, stability, and stasis for the rest of the growth. They tend to implicitly conflate the strength of network effect with the actual network size, thus, considering *de facto* only the *inertial* component of platform evolution—that is, the accumulated size of network of complements at each frame of the growth.

Restricting focus to the inertial view of platform evolution prevents us from fully capturing the dynamism of battles among platforms, and explaining, for example, why in some situations new platforms quickly outperform the big and long lasting incumbents. The examples of these *platform dethroners*—late comers, yet key players of the market— are prevalent in different industries (Suarez and Kirtley, 2012). Since the static logic implies that later entrants will lag behind in network size vis-à-vis early entrants and can barely survive, many of the previous studies are mainly concerned with factors affecting first mover dis/advantage at the time of entry, but miss to explore how the temporal development of the market and technology affects this dis/advantage (Suarez and Lanzolla, 2007). Cennamo (2016), for instance, shows that early platform leaders may face strong growth constraints later in the platform market evolution, to the extent that later entrants may catch up with and overcome their network size.

This is so also because "consumers care about new applications to be released in the near future in addition to the currently available ones" Zhu and Iansiti (2012: 95); and it is not necessarily the large, incumbent platform that stimulates greater innovation of novel complements (Cennamo 2016; Zhu and Iansiti 2012). This depends on the extent the digital, platform architecture is *generative* (Anderson *et al.* 2014; Hukal *et al.* 2018) and enables the creation of novel, high-quality complements (Cennamo *et al.* 2018).

Platform architecture has been defined as the "conceptual blueprint that describes how the ecosystem is partitioned into a relatively stable platform and a complementary set of modules that are encouraged to vary, and the design rules binding both" (Tiwana *et al.* 2010, p. 677) (see, e.g., Parker *et al.* 2016, Thomas *et al.* 2014). Both the design of the core technological architecture (e.g., Anderson *et al.* 2014; Cennamo *et al.* 2018) and the rules binding the varying modules and affecting participation of external complementors (e.g. Boudreau 2010; Wareham *et al.* 2014) affect the level of generativity of the platform and its direction, i.e., the particular areas defining platform uses and functionality (e.g., Hukal *et al.* 2018). In fact, although generativity is largely resulting from the participation (into the platform infrastructure) of unfiltered, heterogeneous audience (e.g., Yoo *et al.* 2012; Zittrain 2006), it is recognized that generativity is also a function of purposeful design (Hanseth and Lyytinen 2010). In this regard, platform providers stimulate generativity through different mechanisms, trying to balance the inherent tension between generativity and control (Yoo *et al.* 2012) to achieve the dual goals of being simultaneously "stable and evolvable" (Wareham *et al.* 2014: 1196). According to this generativity logic, platforms evolve through their generative outcome that continuously reshape over time their uses, functionalities and thus value for its users. Greater generativity can then allow more value to be created through the digital platform infrastructure than in traditional infrastructures (e.g., Constantinides *et al.* 2018; Yoo *et al.* 2010) by extending the technology's "affordances" to its users (Majchrzak and Markus 2012; Zammuto *et al.* 2007), and thus the potential consumption benefits they can derive from it. Accordingly, through their participation in the platform infrastructure, complementors constantly reshape the platform's user value through the variety of novel complements they create. This generativity logic suggests that complement novelty of a platform largely characterizes platform evolution and its value to its users. For instance, in the context of an online digital gaming platform, Boudreau and Jeppesen (2015) find that modders' contributions (i.e., the creation of novel variants of games) were positively correlated with additional platform usage. Cennamo and Santalo (2018), in the context of video game platforms, also find that greater generativity (which they operationalized as the variation in novel games launched for a given console) may lead to greater user satisfaction. Thus, we hypothesize that:

H1. The more the number of novel complements available for a platform, the more the platform adoption by users.

Taken together, we can conceive of complement *stock* and complement *novelty* as the two components of platform evolution affecting platform value to users; the inertial (network effects) dimension, and the dynamic (generativity) dimension characterizing the evolution of the platform. The relative significance of the effects of the two components is a matter of context. In some industries, the novelty component can influence to greater extent platform evolution and be largely driving platform adoption by users. In other words, the value and usage of the platform is largely defined by the most recent, novel complements, while the value of complement stock quickly decays over time. Contexts such as digital media, entertainment, and music platforms are clear examples, whereby this decay effect is pronounced, as is in our empirical context, the video game industry. Although gamers care about the library of games available for a console, they are much more interested in newly released games. As is generally the case with entertainment goods, games get played out soon; gamers always look for new titles to satisfy their consumption needs —in other words, game title complements are goods with an accelerated decay effect (Binken and Stremersch, 2009). This renders available titles released in the past less appealing to users with the passing of time relative to novel titles. Moreover, although a wide stock of complements signals that final users might more likely find products that match their preferences and consumption needs, most recent products are generally those making news and creating more buzz around a technology system, typifying the meaning, functionality and use of the console to prospective users. It is on the basis of novel games that users form their perception of the console positioning and expected benefits (Cennamo and Santalo, 2013). For instance, a greater production of novel games with shooting and fighting core-play for a console can signal that the console is mainly designed for action gaming; it might then mainly attract hard-core gamers. Instead, a greater production of novel mind-training, role-playing and fitness games can signal distinct uses and functionalities of the console, which can make it appealing to an enlarged audience of users, including occasional gamers. In fact, it has been found that one newly released high-quality and popular game may on average explain up to fourteen percent increase in platform adoption (Binken and Stremersch, 2009). Being what consumers readily observe, novel platform complements would act as the main reference point in the consumers' decisional process about what technology to adopt. We thus expect the dynamic component (novelty) to outweigh the inertial component (stock) of platform evolution for the adoption of a given console platform.

> *H2. In contexts where platform complements' value decays quickly, the positive impact of novel complements relative to the impact of stock of complements on platform adoption is stronger.*

Data, Method, and Results

Data

Our original dataset contains 910 monthly observations of game console sales and the number of games published for each console from January 1995 to June 2008. These data along with other information such as introduction date of each console and its average selling price are obtained from NPD group. We aggregate this primary dataset to quarter level. Specifically, all *quarterly* variables are computed as the median of that variable in each quarter. Our final sample consists of 293 platform-quarter observations.

Variables

Dependent variables

We have two sets of dependent variables for platform adoption by users. One is the cumulative number of unit sales of the game console until that period which accounts for the overall platform adoption from its launch. The others address the evolutionary nature of platform adoption at each quarter. These second set of variables measure unit sales, market share and market share within generation of the platform at each period. Specifically, the two latter variables account for the platform adoption relative to its rivals, across and within the same console generation. It is worth-noting that platform adoption by users (sale of the videogame console, in our context) actually reflects the value of the platform to users, rooted in the evolutionary trajectory in the content (complements) of the platform, the effect of two components of which are estimated, as follows.

Independent variables

We build two primary independent variables to estimate the effect of game titles´ *stock* vis-à-vis new titles (*novelty*) on a platform adoption, first of which is related to the inertial (indirect network effects) and the latter to the dynamic (generativity effect) components. *Novelty* reflects the number of new titles released for a console from a given quarter(s). In particular, we have four different measures for novelty; number of titles released from last quarter (Q=-1), from last two quarter (Q=-2), from last three quarters (Q=-3), and from last year (Q=-4).The *stock* variable accounts for all titles from the launch of the platform until last year. To check robustness of the results, we build an alternative measure for stock as all titles published on the platform up to the previous quarter(s).

Control variables

We control for the *number of active platform*s in the market to address the competitive dynamics of the market. Moreover, following previous studies we control for the game console's average *price*. Console pricing as a competitive strategy for the platform is an important driver for penetrating the market. Furthermore, it has been established in the literature that platform age has a curvilinear effect on the console adoption by users and on game developers' decision to publish on the platform. More specifically to our study, the trend of new game titles usually decays as the platform approaches the end of its lifecycle. Thus, we control for the *age* of the platform along its squared term. The exact definitions of all variables and pertaining natural logarithm transformations are provided in Table 1. Additionally, we also control for seasonality and platform time-invariant effects by including quarter-of-year and platform dummy variables.

*** Insert Table 1 about here ***

Empirical strategy

We build our estimation model as $Platform\ Adoption_{it} = \Pi_i + \phi_t + \beta X_{it} + \boldsymbol{\epsilon_{it}}$ **;** where Π_i is platform fixed effects to control for unobserved and time-invariant heterogeneities across platforms such as differences in technologies or brand perception by customers. ϕ_t , time fixed effects, accounts for seasonal trend in the game industry. X_{it} is the vector of independent and control variables, and $\boldsymbol{\epsilon_{it}}$ is the error term.

Our independent variables and one of our control variables, price of the console, seem to be endogenous to our model. For instance, there could be some unobservable factors of the console in the error term, such as perceived value of the console by consumers and/or its brand image, which correlate with the willingness to pay, thus price of the console and/or the decision of the game developers for publishing on that platform. Hence, we apply a two-stage least squares (2SLS) model to overcome the violation of OLS assumptions due to the correlation of the endogenous variables with the error term.

Following the previous studies in video game industry (Cennamo and Santalo, 2013; Clements and Ohashi, 2005; Corts and Lederman, 2009) we apply the quarterly exchange rates between the U.S. dollar and the currency of the country where the console is manufactured as an instrument for the price. This variable as a determinant of the production cost should affect the retail price of the console in U.S. but, as an industry aggregate factor, is uncorrelated with the unobserved attributes of each platform, which constitute the error term in our model.

We instrument the number of titles published on the platform, generally, by two instrumental variables. First, the average age of active titles in the market. This variable is a signal for remaining life cycle of the game titles in the market and can alter the game developers' decision about publishing (new) game in the market. Yet, as a market aggregate variable, it is independent of the error term in platform-level adoption model. Second, (the natural logarithm of) the number of television households; this variable as a measure of potential buyers of the video game systems has an impact on developers to enter into the game industry market and publish games but again uncorrelated with individual platform adoption. Particularly, we instrument novelty variable with the former, and stock variable with the latter[1].Both of these variables are used in previous studies on video game as instruments (Cennamo and Santalo, 2013; Clements and Ohashi, 2005; Corts and Lederman, 2009).

As aforementioned, instruments do not change across platforms. Thus, we also interact each of these instruments with dummies for each platform as additional instrumental variables to account for cross-sectional variation (i.e., differences in how platform game titles and price varied to changes in the aging of current titles, size of potential household market, and U.S. dollars' exchange rate).

We use clustered (by platform) robust standard error models in all our analyses to control for the any arbitrary correlation of error terms of the observations that belong to the same platform and for heteroskedasticity. On the other hand, we have many excluded instruments in the first stage of our 2SLS models (as for the interaction terms with platform dummies) which are much more than the number of clusters. In this circumstances, the covariance matrix of orthogonality conditions is not of full rank, and over-identification tests are infeasible. Table 2 depicts the results of all first stages when novelty is defined as the number of titles released from last quarter, and stock as all titles until last year. As it shows, they are consistent with the expectations, and the impacts of instrumental variables on the corresponding endogenous variables are significant. For instance, the number of television household until last year affects positively (β=0.151, $p < 0.001$) the total games title until then; the higher the potential demand for video game system, the more willing are the game developers to publish. The impact of the change in average age of the titles in the market on pace of new titles published on a platform is not clear theoretically: higher average

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[1] The instrumental variables are constructed identically to the time series operators (lag and difference) used for generating novelty and stock variables from all titles.

age may indicate the obsolescence of game titles and at the same time the presence of long-lived "blockbuster" games (Cennamo and Santalo, 2013: 1337). We find a significant negative effect (β=0.517, $p < 0.01$) on new titles released from the last quarter. The impact of the exchange rate on price is also positive and significant (β=256.106, $p < 0.001$).

Moreover, investigating various weak instrument identification tests supports the validity and relevance of our instrumental variables. Following Staiger and Stock (1997), as we have F-statistics above 10 there would be no concern about weak instruments: weak correlation of the instrument with the endogenous regressors. Additionally, Angrist and Pischke test, as a more recent one (Angrist and Pischke, 2009), rejects the null hypothesis of weak and under-identification for each of our instruments. Finally, the joint significance of our instruments is confirmed by Anderson-Rubin Wald test. Here, rejecting the null hypothesis means that our instruments are relevant: they are, in fact, correlated with the endogenous regressors (Stock and Yogo, 2005; Wooldridge, 2002). The output of all above tests are reported in Table 3.

*** Insert Table 2 about here ***

Descriptive statistics

Table 3 shows the descriptive statistics of all variables.

*** Insert Table 3 about here ***

One of the important concerns in our models is the potentially high correlation between new titles (novelty) and all previous titles (stock). However, as Panel A in Table 4 depicts, the correlations between the two sets of variables do not show any evidence of severe multicollinearity issue. We also detrend the previous titles variables to free them up from a linear cumulative trend in Table 4, Panel B. The results are qualitatively the same.

*** Insert Table 4 about here ***

Figure 1 illustrates the median time series (median-spline plots) of dependent and independent variables for platforms altogether. In line with our expectations, especially once the dynamics of competition is taken into account (as shown in unit sales graph, Panel B, and similar to market share measures, not reported here, but available upon request), the fluctuation of platform adoption is much more analogous to the number of recently published titles' pattern (i.e., novelty) rather than total number of titles that are released previously (i.e., stock). To be sure that the stronger one-by-one correspondence between new titles and platform adoption is not merely because of the cumulative essence of accumulated number of previous titles, we plot the graphs after detrending the latter one to see its variation more clearly. Above interpretation still holds in Figure 2.

*** Insert Figure 1 and 2 about here ***

Results

Table 5—the second stage result of the 2SLS model with clustered robust standard errors at platform level—displays the first to fourth quarter models estimate the distinct effect of *novelty*, the number of new titles released since the last Q (Q=-1, -2,-3,-4) quarter(s), and of *stock*, the total number of titles released until last year, on platform adoption. Accordingly, both the stock of titles (inertial component) and new titles (dynamic component) positively affect the platform cumulative sales in all models, in line with indirect network effect and generativity effect, respectively. For instance in model Q=-2, the effect of stock of titles in last year (β=0.240, $p < 0.001$) and new titles released in last two quarters (β=0.157, $p < 0.001$) significantly increase the cumulative sale of the game console. The former supports Hypothesis 0, while the latter corroborates Hypothesis 1.

However, the effect of stock is stronger in all specification but Q=-1(β=0.250, $p < 0.001$). In this case, 10% new titles in the current quarter would increase platform cumulative sales by 2.5%, while a similar expansion of the stock of titles in the previous year would account for 2.4% cumulative sales' increase. Yet, when we consider more than the current quarter for novelty definition, the effect is reversed. For instance, in the "two quarters" model (Q=-2), 10% more titles in the library of the platform until last year would lead to 2.4% higher cumulative sales (β=0.240, $p < 0.001$), while the same amount of new titles released in the last two quarters results in roughly 1.6% increase in the overall adoption (β=0.157, $p < 0.001$), i.e. the cumulative sale of the console until now. However, applying a t-test reveals that in none of these models the coefficients for novelty and stock variables are statistically different from each other (p-value>0.1), as is reported in Table 5. So the interpretation pertaining to the second hypothesis, for this dependent variable, should be considered cautiously.

*** Insert Table 5 about here ***

Elaborating the findings in Table 5, we replace the cumulative sale with the real-time (and evolutionary) indicators of the adoption— unit sale, market share, and market share within generation at each quarter—in Table 6. Both of the new titles and stock of titles still significantly have a positive effect on the platform adoption, supporting Hypothesis 0 and 1. Also, corroborating Hypothesis 2 the impact of new titles (dynamic component) is much stronger than of the stock of titles (inertial component) now in all models (Q=-1, -2, -3, -4). For instance the impact of new titles in the last two quarters on unit sales (β=1.154, $p < 0.001$) is almost 5 times stronger than the effect of all titles until last year (β=0.276, $p < 0.05$), as reported in Table 6. This pattern is similar in all other measures of adoption (market share, and market share within given generation) in Table 7. For example, 10% increase in the new titles released in the last quarter (novelty) boosts the platform market share (against all other active platforms in the market) by 12.8%. Whereas, 10% increase of the stock all titles until the last year increases the platform market share by only 1.4%, which means the dynamic component has an almost 8.5 times stronger impact on platform market share than of the inertial component. As reported in the tables applying a t-test confirms, in all models, the statistical significance for the difference between novelty and stock coefficients.

*** Insert Table 6 and 7 about here ***

Robustness tests

One can argue that our results are likely to suffer from an endogeneity problem. In particular, there could be some (unobserved) variables, such as price promotion, advertisement, and marketing campaign, that affect the platform adoption and could be highly correlated with the new titles released, yet have a weak, if any, correlation with previous titles. That is, the strong coefficient found for novelty, compared to stock, could be driven by these omitted variables. In other words, although we have already controlled for the time-invariant attributes *across platforms* such as brand image, by including platform dummies in the models, there could be *within-platform* factors that vary across time, hence bias our differential impacts of recent versus previous titles released on a given platform. Addressing this concern we take steps to verify the trustworthiness of our findings. First, as illustrated in previously reported results, altering the time frame for novelty definition (i.e. titles released in recent last one, two, three, or four quarters) does not change the findings. Moreover, as mentioned later, running the same models at month level with different time frames results in a qualitatively similar pattern. Although the concern still remains, similar findings for various specifications for recent/previous period to define novelty/stock diminishes the concern about time-dependent bias to some extent. Second, we have already interacted the platform dummies with instrumental variables for stock, novelty, and price variables in the first stage of the 2SLS models to account for time-variant heterogeneity of platforms pertaining to above instrumented variables.

Third, we replace our dependent variable at time *t* by its lead version at time *t+1*. The results (not reported but available upon request) are supportive. Here, the unobserved attributes of the platform at time *t+1* have a weak, if any, correlation with both novelty and stock at previous periods. One can still argue that new games are still *closer* to the dependent variable than the old ones, which means higher correlation and still an upward bias for novelty variable. Nevertheless, in this new specification, at least the potential inflation of novelty coefficient is lessened. Especially, when we lead the dependent variable even to one year (four quarters) ahead, at *t+4*, to be *far* enough from both novelty at time *t* and stock variables, the results are the same.

Fourth, similar to the remedy proposed by Clments and Ohashi (2005), we introduce year-dummy variables and their interaction with platform fixed effects. Doing so, we account for unobserved attributes of each platform in each year, i.e. within-platform heterogeneity across time. Fifth, Following Cort and Lederman (2009), instead of controlling for age of a platform (as a continuous variable) and platform fixed effect separately, we account for both together by defining platform-age (in year) dummy variables. We replace continuous variables for platform´s age and squared age, and platform dummy variables, by these new fixed effects. Again, we control for (unobserved) specific attributes of each platform in each year of its lifecycle.

As the last remedy, we include the lagged version of dependent variable at previous quarter in the model, to absorb the omitted variable bias. Accounting for the autocorrelation between lagged and current version of the dependent variable we applied a generalized method of moments (GMM). Specifically, we instrument lagged dependent variable, stock, novelty, and price in a "difference GMM" approach (Arellano and Bond, 1991; Roodman, 2009). As the most conservative approach, to also deal with the potential concerns about convenience of our instrumental variables for price, novelty, and stock, we exclude all those “external” instrumental variable, described in the empirical strategy earlier, from GMM specifications and assume that only available instruments are “internal” (Roodman, 2009: 100). In particular, all available lagged versions of price, novelty, and stock, and our dependent variable (as its lag is an additional regressor here) are used as instruments for the first differenced endogenous regressors. All other control variables, excluding price, are assumed to be strictly exogenous, so these regressors themselves are used as their own instruments. Results obtained from all above mentioned robustness checks (not reported here, but available upon request).corroborate the reported findings.

Conclusion and Discussion

We revisit the indirect network effect as considered in the extant literature of digital platform evolution and extend the existing theory by disentangling the impact of the evolution of the platform content, on its adoption by users, into an inertial component, which we refer to as *stock*, and a dynamic which we refer to as *novelty*. The focus in prior studies has been prevalently on the inertial component, the mainstream logic being that platform with higher stock of complements becomes attractive for consumers and gain a critical mass of users, enough for a sustained momentum and winning the market.

We estimate both dynamic and inertial components of the platform evolution (in the complementors ´side) and their relative impact on platform adoption (by users), in the context of the U.S. video game industry. We find a positive effect for both yet, with a substantially stronger impact of the dynamic component, i.e. novelty, than of the inertial component, i.e. stock. We should mention that the relative strength of novelty vis-à-vis stock is more evident when the real-time adoption rate is considered as the dependent variable (shown in Tables 6 and 7), rather than the cumulative one (shown in Table 5). This is in line with our aim to reveal the dynamism of platform adoption instead of focusing on a static *frame* of its evolutionary outlook. In particular, cumulative of sales pertain to the inertial consideration, while the current period unit sales (and market share) relates to the dynamic view.

Our findings, while corroborating previous studies on platform adoption highlighting the importance of indirect network effect, emphasizes the generative facet of the platform evolution (e.g., Tilson *et al*. 2010; Yoo *et al*. 2010, 2012). Digital platforms with a large number of complementary products (and installed base of users), via indirect network effect, gain momentum and reach to a stable equilibrium. Yet, beyond this stability, they also need evolvability and variety to be able to meet the expectations of users in a dynamic manner (Wareham *et al.* 2014). What matters for the platform success, is not merely a large network size, but variance in the complements (content) of the platform. A well-managed platform, not only in terms of the sheer quantity but more importantly the novelty in the pool of complements, generates value for the users and benefits from what Parker and coauthors (2016) called as *positive* network effect. Whereas, poorly managing a platform (i.e. failing to embrace the generativity aspect), works at the opposite direction; users switching to the rival platform, causing the network shrinkage, reversing the network effect to a *negative* feedback, and ultimately, platform collapse (Evans, 2013; Parker *et al*. 2016).

Moreover, our study can extend recent works questioning the unconditional dominance of the platform with the largest network (e.g., Lee *et al.*, 2006; Suarez, 2005), the benefits from entering first (e.g., Schilling, 2002, Suarez and Lanzolla 2007; Zhu and Iansiti, 2012), and the winner-take-all outcome (e.g., Cennamo and Santalo, 2013; Lee *et al.*, 2006). Our findings, by emphasizing on the generative aspect of the digital platforms, lend more accuracy in assessing platform evolution and competitive dynamics in markets, which can help explain several instances in the business world from failures of big platforms in the market to the symbiosis of multiple platforms in the market. We try to illustrate these different scenarios, instead of the only winner-takes-all outcome, in a simplified extrapolation, using the relative impacts of inertial and dynamic component obtained from our regression models.

Sectors such as telecommunications (smartphones), videogames (entertainment systems), and social networks have witnessed over the past years drastic changes in leadership, with the rise of newcomers, and the fall of dominant firms' technologies despite their huge existing installed user base and complements. The smartphone sector is a paramount example. The pioneer and dominant player in the industry, Nokia, the first to assemble a network of apps developers around Symbian (the operating system powering its devices), has soon lost leadership of the premium segment of the market in favor of BlackBerry, a startup that very quickly gained momentum and the mass of corporate users. Yet, despite this dominance, a new player, Apple, has been able to overcome the disadvantage associated with the lack of installed user base, and quickly erode market share from incumbent players, but only to then see yet another new player, Google, gaining about 80% of the whole market. Despite the predictions of existing theory on positive feedback loop of the indirect network effect (e.g., Arthur, 1983; 1989; Evans, 2003, 2009; Schilling, 2002, 2003) according to which the large network of complements and users would act a self-reinforcing isolating mechanism and limit room in the market for late comers, we observe "dethroners" in a range of contexts (Suarez and Kirtley, 2012). We find that our empirical context is more consistent with the "dethroning" scenario given the relative prominence of generativity logic (the dynamic component of platform evolution), according to which the late entrants might grow their network faster, despite their initial network disadvantage and take over the incumbent platform (Suarez and Lanzolla, 2007).

Anecdotal evidence suggests that provision of novel content crucially affects users' adoption and usage of the platform in many other platform contexts, including social networks, mobile app industry, media and entertainment platforms, and retailing portals among others. For instance, in a C2C portal such as Airbnb, renters value the up-to-date rental ads rather than a diverse number of *abandoned* ones. A full list of diverse, yet idle, rental ads, is not enough to invite customers to adopt/use the platform's services. The same applies to other platforms such as Youtube (novel videos catch generally more attention from viewers) or Groupon (users are much more interested in novel offerings than "dated" ones). Assessing the weight of indirect network effect and generativity effect (i.e. the inertial and dynamic components of platform evolution) in different contexts might shed light on important overlooked contingencies that improve our understanding of platform competition *and* evolution dynamics. Our analysis, though not directly testing different scenarios of platform competition, is a starting point towards this direction, which we hope will stimulate further work.

Limitations and further research

Despite the fact that we find a much stronger impact of novelty than stock on platform adoption, we should acknowledge that this high asymmetry pertains to our specific context. Although we expect to find a similar pattern in other contexts related to entertainment, media and even retailing industries as exemplified earlier, in some other contexts productivity/functionality aspects might be more important (such as in Operating Systems) than the novelty of content. Further studies should assess to which extent this is the case by analyzing the effects in other industries. Moreover, we assumed that game titles are goods with a strong decay effect. However, we did not explicitly model this aspect; we tried to capture it by estimating various distinct lags in our analysis. Developing a formal model while considering a discount factor value of complements (based on Clements and Ohashi, 2005) is a worthwhile opportunity to accurately estimate the relative strength of inertial versus dynamic effects in different contexts. Moreover, we did not account for the different policies that platform sponsors deploy to attract complementors and stimulate the production of novel complements. We just control empirically for differences across platforms through fixed effects; yet, how precisely these differences contribute to shape the inertial and dynamic component of momentum is an interesting area to investigate. Finally, although we tried to deal with the aforementioned endogeneity concern (stock versus novelty coefficients) with several remedies, future analyses with other available instrumental variables is called for increasing the robustness of our results.

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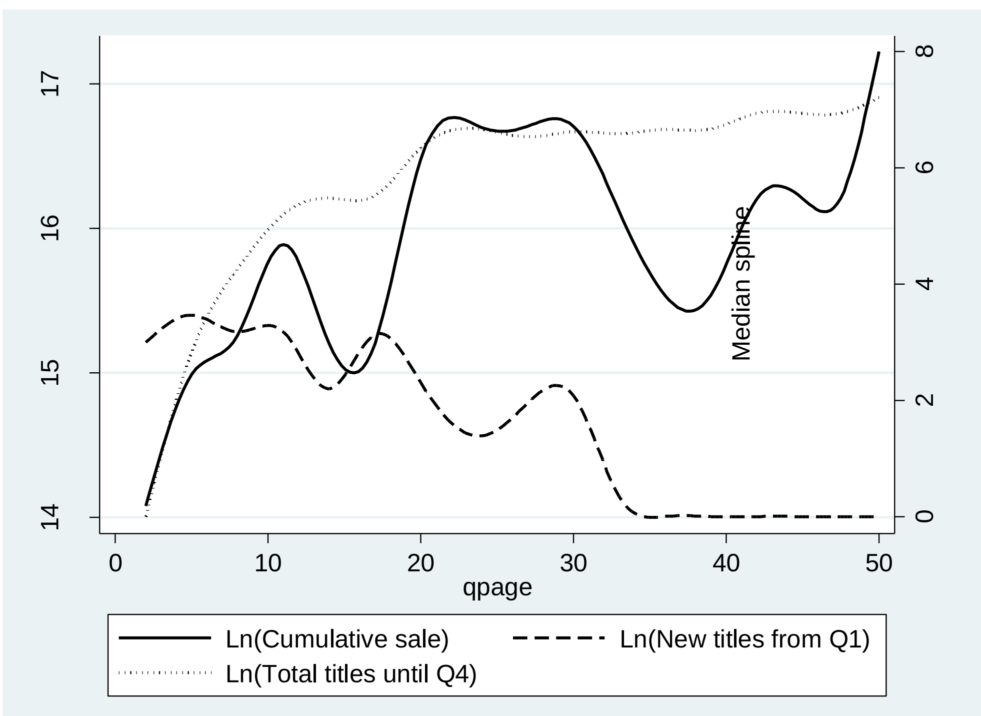
FIGURE 1
Median time series of new and total title variables vs. sales and cumulative sales
Panel A



Panel B

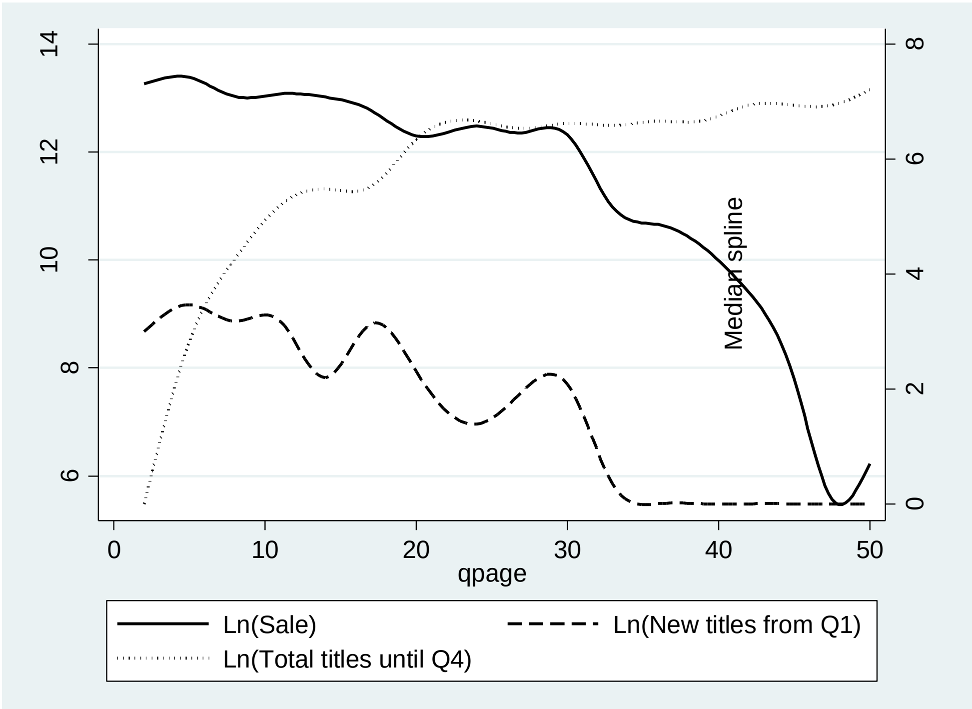
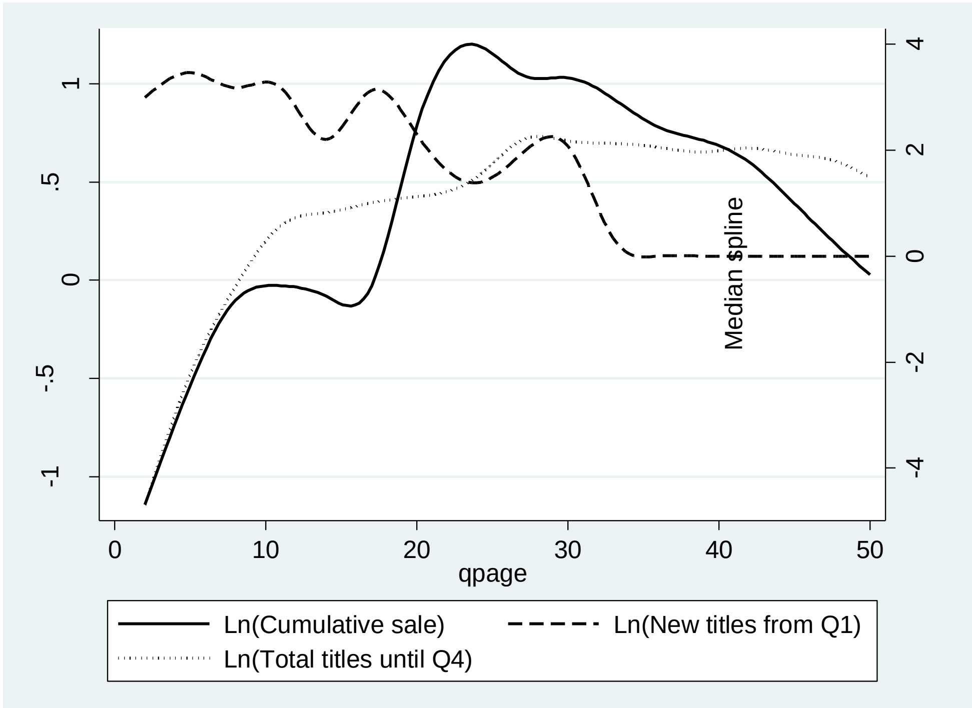


FIGURE 2
Median time series of new and (detrended) total title variables vs. sales and (detrended) cumulative sales
Panel A



1
.5
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-.5
-1
4
2
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-2
-4
Median spline
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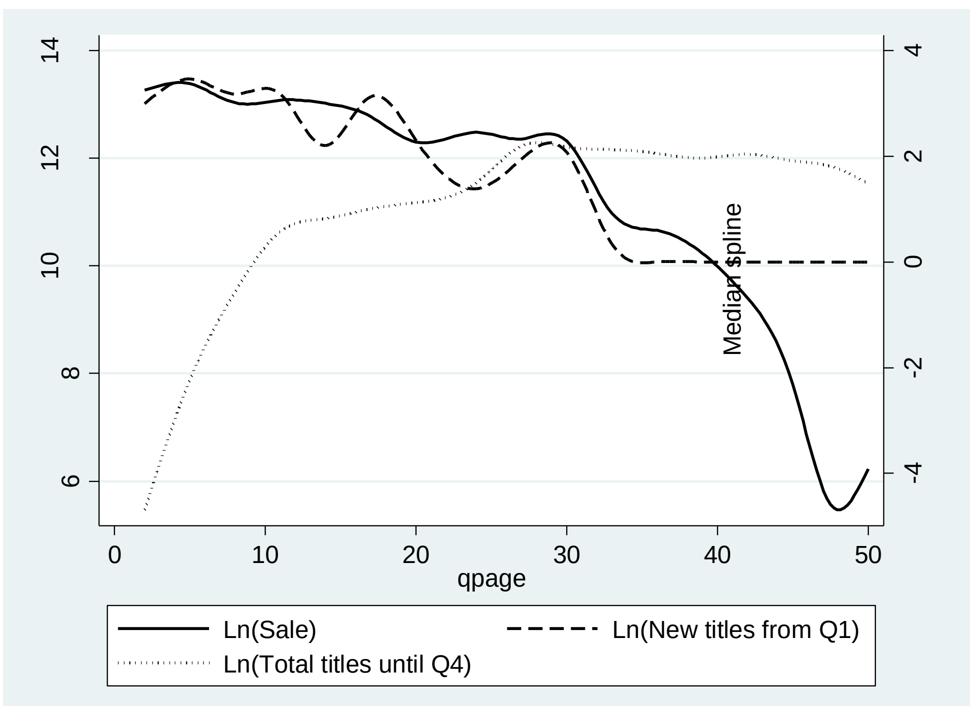
10
20
30
40
50
qpage
Ln(Cumulative sale)
Ln(New titles from Q1)
Ln(Total titles until Q4)

Panel B



14
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Median spline
0
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qpage
Ln(Sale)
Ln(New titles from Q1)
Ln(Total titles until Q4)

TABLE 1
Variables definition

Variables		***Definition***	***Transformation method***
Cumulative sale	*Dependent variables*	Cumulative unit sales of the console until end of each quarter	Ln(x)
Sale		Unit sales of the console at each quarter	Ln(x)
Market share		unit sales of game consoles divided by all sold consoles of active platforms at each quarter	Ln(x)
Market share within generation		Unit sales of consoles divided by all sold consoles of active platforms in the same technology(console) generation at each quarter	Ln(x)
Novelty: New titles from Qi	*Independent variables*	Number of new titles published on the platform in last i quarters	Ln(x+1)
Stock: Total titles until last year (Q=-4)		Number of all titles published on the platform until last year	Ln(x+1)
Price	*Control variable*	Quarterly retail price of the game console in U.S. dollars	Ln(x)
Age		Number of quarters since the launch of the platform	-
Active platforms		Quarterly number of active platforms at each quarter	-
Exchange rate	*Instrumental variables*	Quarterly exchange rates between the U.S. Dollar and the currency of the country where the console is manufactured	-
Average titles age in the market		Quarterly average age of active titles in the market	-
Television household		Quarterly number of television household	Ln(x)

TABLE 2
First stage of 2SLS regression and post estimation tests

Variables	*Ln(New titles from Q=-1)*	*Ln(Total titles until Q=-4)*	*Ln(Price)*
Ln(Television household until Q=-4)	-.050*	0. .151***	-.040***
	(0. 022)	(0. .017)	(0.008)
Average titles age in the market (from Q=-1)	-0.517**	-0.751***	-0.063
	(0. 116)	(0.105)	(0.042)
Exchange rate	462.758***	252.547***	256.106***
	(76.994)	(45.668)	(29.951)
Age	-.050+	0.128***	-0.054***
	(0. .027)	(0. .014)	(0.011)
Age^2	-.001**	-0.003***	0.000
	(0. .000)	(0.000)	(0.000)
Active platforms	-.053	0. 175	-0.106
	(0. 167)	(0. 178)	(0.067)
Platform fixed effects	YES	YES	YES
Platform fixed effects × Ln(Television household until Q=-4)	YES	YES	YES

Platform fixed effects × Average titles age in the market from Q=-1	YES	YES	YES
Platform fixed effects × Ln(Exchange rate)	YES	YES	YES
Seasonal fixed effects	YES	YES	YES
Constant	-1.604*	1.327*	3.221***
	(0. .638)	(0. .591)	(0. 257)
Observations	293	293	293
R^2	0.90	0.95	0.93
Instrumented Variable	F test of excluded instruments	Angrist-Pischke under-indented instrument test	Angrist-Pischke weak instruments test
Ln(New titles from Q=-1)	F(42,13)=66.55 p=0.000	F(40,13)= 9.9e+09 p=0.000	F(40,13)= 1.8e+08 p=0.000
Ln(Total titles until Q=-4)	F(42,13)= 27.25 p=0.000	F(40,13)= 178.59 p=0.000	F(40,13)= 3.28 p=0.012
Ln(Price)	F(42,13)= 290.05 p=0.000	F(40,13)= 9847.41 p=0.000	F(40,13)= 180.85 p=0.000
Anderson-Rubin Wald test	F(6,13)= 2174.26 p=0.000	Chi-square(6)= 17759.02 p=0.000	

Standard errors in parentheses, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All models are the first stages of 2SLS regressions with clustered (by platform) robust standard errors.

TABLE 3
Descriptive statistics

Variables	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
Ln(Cumulative sale)	293	15.135	1.888	8.761	17.547
Ln(Sale)	293	11.169	3.104	0.693	15.317
Ln(Market share)	293	-3.451	3.070	-13.732	-0.377
Ln(Market share within generation)	293	-2.044	2.791	-13.641	0
Ln(All titles)	293	5.677	1.258	0.693	7.449
Ln(New titles from Q=-1)	293	2.127	1.609	0	4.700
Ln(New titles from Q=-2)	293	2.733	1.820	0	6.507
Ln(New titles from Q=-3)	293	3.116	1.912	0	6.534
Ln(New titles from Q=-4)	293	3.406	1.943	0	6.572
Ln(Total titles until Q=-4)	293	4.659	2.463	0	7.344
Ln(Price)	293	4.696	0.774	2.754	6.394
Age	293	18.447	12.807	1	52

Active platforms	293	2.812	1.118	1	5
Exchange rate	293	0.009	0.001	0.007	0.012
Average titles age	293	15.135	1.888	8.761	17.547
Ln(Television households)	293	11.169	3.104	0.693	15.317

TABLE 4

Panel A- Correlation matrix for novelty and stock variables

Variables		**1**	**2**	**3**	**4**
1.Ln(New titles from Q=-1)	*Novelty*	1			
2.Ln(New titles from Q=-2)		0.912*			
3.Ln(New titles from Q=-3)		0.886*	0.969*		
4.Ln(New titles from Q=-4)		0.865*	0.946*	0.980*	
5.Ln(Total titles until Q=-4)	*Stock*	-0.237*	-0.261*	-0.241*	-0.215*

All correlations with asterisk are significant at the .05 level.

Panel B- Correlation matrix for novelty and (detrended) stock variables

Variables		**1**	**2**	**3**	**4**
1.Ln(New titles from Q=-1)	*Novelty*	1			
2.Ln(New titles from Q=-2)		0.912*			
3.Ln(New titles from Q=-3)		0.886*	0.969*		
4.Ln(New titles from Q=-4)		0.865*	0.946*	0.980*	
5.Ln(Total titles until Q=-4)	*Stock*	-0.288*	-0.294*	-0.266*	-0.232*

All correlations with asterisk are significant at the .05 level.

TABLE 5

Ln(Cumulative sale)

Variables	***Q=-1***	***Q=-2***	***Q=-3***	***Q=-4***
Ln(Total titles until Q=-4)	0.204***	0.240***	0.246***	0.240***
	(0.028)	(0.028)	(0.027)	(0.026)
Ln(New titles from Q=-1)	0.250***			
	(0.046)			
Ln(New titles from Q=-2)		0.157***		
		(0.047)		
Ln(New titles from Q=-3)			0.161***	
			(0.044)	

Ln(New titles from Q=-4)				0.173***
				(0.047)
Ln(Price)	-0.105	-0.081	-0.137+	-0.184*
	(0.080)	(0.078)	(0.073)	(0.083)
Age	0.066***	0.054***	0.049***	0.048***
	(0.014)	(0.012)	(0.010)	(0.008)
Age^2	-0.001**	-0.000*	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Active platforms	0.043	0.034	0.026	0.023
	(0.035)	(0.043)	(0.045)	(0.048)
Platform fixed effect	YES	YES	YES	YES
Seasonal fixed effect	YES	YES	YES	YES
Constant	11.070***	10.657***	10.845***	11.023***
	(0.398)	(0.416)	(0.386)	(0.419)
Observations	293	293	293	293
R^2	0.98	0.98	0.98	0.98
Adjusted R^2	0.98	0.98	0.98	0.98
Novelty vs. Stock effect t-test (null: no difference)	p= 0.460	p= 0.180	p= 0.136	p= 0.234

Standard errors in parentheses, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All models are second stages of 2SLS regressions with clustered (by platform) robust standard errors.

TABLE 6
Ln(Sale)

Variables	***Q=-1***	***Q=-2***	***Q=-3***	***Q=-4***
Ln(Total titles until Q=-4)	0.172*	0.276**	0.314**	0.301**
	(0.086)	(0.101)	(0.104)	(0.103)
Ln(New titles from Q=-1)	1.271***			
	(0.305)			
Ln(New titles from Q=-2)		1.154***		
		(0.299)		
Ln(New titles from Q=-3)			1.144***	
			(0.296)	

Ln(New titles from Q=-4)				1.139***
				(0.308)
Ln(Price)	0.222	-0.225	-0.424	-0.480
	(0.640)	(0.753)	(0.822)	(0.878)
Age	-0.118	-0.156*	-0.177**	-0.187**
	(0.074)	(0.070)	(0.067)	(0.068)
Age^2	0.001	0.002	0.003*	0.004*
	(0.001)	(0.002)	(0.002)	(0.002)
Active platforms	-0.354*	-0.325+	-0.352	-0.371
	(0.168)	(0.198)	(0.223)	(0.260)
Platform fixed effects	YES	YES	YES	YES
Seasonal fixed effects	YES	YES	YES	YES
Constant	5.781+	5.833+	6.236+	6.288
	(3.150)	(3.355)	(3.629)	(3.876)
Observations	293	293	293	293
R^2	0.83	0.85	0.85	0.85
Adjusted R^2	0.81	0.83	0.83	0.84
Novelty vs. Stock effect t-test (null: no difference)	*p= 0.001*	*p= 0.014*	*p=0.020*	*p=0.021*

Standard errors in parentheses, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All models are second stages of 2SLS regressions with clustered (by platform) robust standard errors.

TABLE 7
Ln(Market share) and Ln(Market share within generation)

	Ln(Market share)				***Ln(Market share within generation)***			
Variables	***Q=-1***	***Q=-2***	***Q=-3***	***Q=-4***	***Q=-1***	***Q=-2***	***Q=-3***	***Q=-4***
Ln(Total titles until Q=-4)	0.140+	0.245*	0.285**	0.275**	0.227***	0.338***	0.361***	0.341***
	(0.083)	(0.097)	(0.102)	(0.101)	(0.068)	(0.085)	(0.092)	(0.094)
Ln(New titles from Q=-1)	1.288***				1.219***			
	(0.310)				(0.282)			
Ln(New titles from Q=-2)		1.167***				1.058***		
		(0.301)				(0.287)		
Ln(New titles from Q=-3)			1.159***				1.052***	
			(0.295)				(0.277)	
Ln(New titles from				1.162***				1.055***

Q=-4)								
				(0.307)				(0.289)
Ln(Price)	0.530	0.041	-0.190	-0.304	1.276+	0.906	0.664	0.520
	(0.727)	(0.821)	(0.875)	(0.924)	(0.653)	(0.756)	(0.790)	(0.839)
Age	-0.115	-0.157*	-0.180*	-0.194**	-0.040	-0.082	-0.102+	-0.114+
	(0.077)	(0.075)	(0.073)	(0.073)	(0.061)	(0.060)	(0.060)	(0.062)
Age^2	0.000	0.002	0.003+	0.004+	0.007***	0.009***	0.010***	0.011***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Active platforms	-0.422*	-0.401*	-0.433+	-0.462+	-0.707***	-0.694***	-0.721***	-0.747**
	(0.173)	(0.198)	(0.222)	(0.256)	(0.170)	(0.177)	(0.198)	(0.229)
Platform fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Seasonal fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Constant	-9.335**	-9.088*	-8.532*	-8.220*	-11.083***	-11.225***	-10.526**	-10.005**
	(3.523)	(3.585)	(3.783)	(3.994)	(3.128)	(3.259)	(3.404)	(3.640)
Observations	293	293	293	293	293	293	293	293
R^2	0.83	0.85	0.85	0.85	0.83	0.85	0.85	0.85
Adjusted R^2	0.81	0.83	0.83	0.83	0.82	0.84	0.84	0.84
Novelty vs. Stock effect t-test (null: no difference)	*p= 0.000*	*p= 0.006*	*p= 0.008*	*p= 0.010*	*p= 0.000*	*p= 0.024*	*p= 0.027*	*p= 0.029*

Standard errors in parentheses, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All models are second stages of 2SLS regressions with clustered (by platform) robust standard errors.