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Adoption Dynamics of Increasing-Return Technologies in Systemic Contexts

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Abstract
Many systemic, complex technologies have been suggested to exhibit increasing returns to adoption, whereby the initial increase in adoption leads to increasing experience with the technology, which drives technological improvements and use, subsequently leading to further adoption. In addition, in the systemic context, mimetic behavior may lend support to increasing returns as technology adoption is witnessed among other agents in the systemic context. Finally, inter-dependencies in the systemic context also sensitize the adoption behavior to fundamental changes in technology provisioning, and this may lend support for the increasing returns type of dynamics in adoption. Our empirical study examines the dynamics of organizational technology adoption when technology is provisioned by organizations in another sub-system in a systemic context. We hypothesize that innovation, imitation, and technological change effects are present in creating increasing returns in the systemic context. Our empirical setting considers 24 technologies represented by 2282 data points in the computer industry. Our results provide support for our prediction that imitation effects are present in creating increasing returns to adoption. We further discuss the managerial and research implications of our results.

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1. Introduction

This paper explores the dynamics of technological innovation adoption at the firm level and subsequent resource allocation under increasing returns conditions. Namely, we study firms' adoption of technologies that displays increasing returns and hypothesize the more the technologies are adopted the more they will be adopted due to the accumulating experiences and positive feedback loops (following [1]), learning by using [2], learning by imitating [3], and influence by demand-side increasing returns [4]. Specifically, we study the dynamics of technology provisioning and adoption of these technologies in a systemic, high-technology context.

1.1 Adoption of innovations and increasing returns

Technological innovation adoption has been applied to thousands of empirical studies concerning an individual's innovation adoption and organizations' innovation adoption [see e.g. 5, 6, 7, 8, 9, 10]. These studies have found that resource allocation and technology adoption at the firm level are influenced by a number of factors, for example, ease of use, performance in relation to other technological alternatives, and end-users' market preferences. Subsequently, many firms lending support and using a technology lead to customers being encouraged to buy that technology, and this behavior leads more firms to adopt and use the technology in question [11]. This positive feedback loop creates an increasing returns type of dynamics between the firm's adoption and the end-user's use.

At the same time, competition takes place not only between companies producing technologies, or adopting these technologies, but also at the level of technologies competing for end-users' attention and adoption [12]. Competition between technologies is determined, at least partially, with a group of products that follow the same technological paradigm [13] following a compatible design path. Further, this competition is also determined by the organizational support this design gains as it is adopted, which is influenced by the positive feedback loops from the demand side (the organizations using the design and the end-users who prefer it). Competition between technologies is due to the existence of multiple organizations using and supporting compatible products that suggest to the market a possible industry standard [11], at least for a brief duration. This support further gives customers confidence that future products will be based on this technology, and therefore increases the likelihood of customers adopting the technology in question.

1.2 Technological systems

Technological systems are complex by nature, consisting of various nested levels [14] and comprising various technical and social components [15]. In the PC (personal computer) technological system, for example, we identify technical elements such as hard disks, processors, monitor screens, application software, and operating system programs [16, 12, 17, 18]. In turn, the social components of this system constitute the organizations that nurture the aforementioned artifacts, the employees and managers in these organizations, as well as government, institutional, and legal bodies that directly or indirectly guide technological development. In this manner, we view the technological system as a socio-technical system [e.g., 15, 19, 20].

The literature studying technological systems identifies different types of socio-technical systems, including complex product systems (CoPS), large technical systems (LTS), systems of innovation, and modular systems. As technological systems, all of these systems exhibit a common set of properties [21, 22]. First, technological systems have a hierarchically nested structure, whereby a given system is seen as a composition of smaller sub-systems that are themselves systems comprising further sub-systems [e.g., 23, 14]. In this system structure, some organizations specialize in producing particular sub-systems, while other organizations specialize in integrating sub-systems into holistic technical systems [24, 25]. Second, technical sub-systems, which are specialized in delivering particular functions, are interdependent within the same as well as across different levels of the system hierarchy [e.g., 23]. This fundamental property of all technological systems also links organizations whereby the performance of any systemic organization depends on the performance of other organizations. And, third, technological systems are goal-seeking [e.g., 15, 19, 26] at the sub-system and holistic system levels. Driven by objective orientation, holistic technological systems evolve over time to attain higher performance levels.

Within the hierarchical structure, this system-level evolution depends on the reciprocated and interdependent cause-and-effect processes taking place among all technical and social sub-systems [15]. In this light, this paper focuses on the decisions made by organizations (i.e., social actors) to adopt technological innovations made available by other organizations within the same evolving system. Specifically, as one organization delivers a higher level of performance in a technical sub-system, the organization creates the potential for organizations producing interdependent sub-systems to adopt and use this performance in their own offering [27, 28]. The rate and pattern of adoption of these new technological innovations, within the systemic context, are therefore important to study, because they affect the evolution of the socio-technical system, in which organizations are embedded.

1.3 Adoption of innovations in technological systems

In the systemic context, positive feedback loops emerge, ranging from technology development to adoption of the technology and use of its potential, and finally to the end-user's preference for the technology due to the initial support for the technology through organizational adoption. This leads us to consider the adoption process at the firm level within a systemic context, namely, the diffusion of innovations in socio-technical systems.

Following Bass [29], the adoption of innovations can be formally modeled with the diffusion model as

$$\frac{dF}{dt}(t) = \big(p + qF(t)\big)\big(1 - F(t)\big),$$

where $F(t)$ is the installed base fraction. Following established definitions, p is the coefficient of innovation, and q is the coefficient of imitation. The closed-form solution is [see 29]

$$F(t; p, q) = \frac{1 - e^{-(p+q)t}}{\left(\frac{q}{p}\right) e^{-(p+q)t} + 1},$$

where time $t>0$.

Adoption of technological innovations by organizations in socio-technical systems may be viewed as technological learning at multiple levels [3], and the learning can take place as learning by doing and learning by studying and developing (i.e., R&D), as well as learning by imitating. The imitation process has been found in empirical studies on adoption of technological innovation in firms [30], especially when firms have information on the behavior of their counterparts and the firms are able to imitate their counterparts' behavior [31]. In particular, the interconnectivity and standardized nature of technologies and infrastructure motivate information dissemination since experiences are relatively fast and transparent, leading to increasing returns [32]. Naturally, as companies face new technologies, the organizations are burdened by ambiguous and risky decision-making situations with a limited amount of information concerning the output and performance implications of innovative behavior and, as a result, prefer imitative behavior that poses a risk-reducing alternative.

Therefore, following the above discussion, organizational adoption of technological innovations, namely, the final population of adopting entities, *m,* in a systemic context would be influenced by both coefficients of innovation adoption, *p* and *q*, and by the technological leap taking place between successive technology launches. In this paper, we build hypotheses that establish relationships between these parameters since we maintain the *post-hoc* setting of our research. Additionally, we follow recent calls for increasing our understanding of the various aspects of organizational technology and innovation adoption, use and integration of theories of technology, and market evolution [e.g., 42] by extending the Bass model to the technology adoption context.

The positive feedback loops and time pressures in the industry to use a winning technology as fast as possible encourage companies to imitate as fast as possible, and subsequently follow innovations. In addition, later adoptions use technology that has already been successful, since the learning has been accumulating, thereby increasing adoption. At the same time, to anticipate the influence of the positive feedback loops we may hypothesize that *p* and *q* are related to the final population adopting the technological innovation. However, *p* (the innovation coefficient) and *q* (the imitation coefficient) represent different mechanisms of increasing returns leading to an increased number of companies adopting a particular technology. The imitation factor relates directly to observation and learning by imitating type-increasing returns. On the other hand, the coefficient of innovation is indirect in the sense that the company needs to come up with the use scenarios and utilitarian adoption decisions based on external market and technological information, and this leads to learning by using. Therefore, learning by using is expected to be influenced by increasing returns in that the more companies use the technology the more adoption we witness in the marketplace. Additionally, technological change inevitably forces companies to face uncertainties in adoption decisions. Technological changes present companies with the need for new or revised sets of technical skills [e.g., 17]. Similarly, the speed of technological change influences companies' decisions to adopt technologies. Therefore, positive feedback loops and the resulting increasing returns would be expected to result in the following hypotheses.

First, we hypothesize that learning by using influences the increasing returns in technology adoption in the sense that the more companies use technology, the higher the final population of companies adopting the technology will be. Therefore, we arrive at

Hypothesis 1 (H1):

When m is high, the innovation coefficient, p, dominates; i.e., p is high.

Second, we hypothesize that learning by imitation influences increasing returns in technology adoption as the more companies witness other companies adopt a certain technology and the imitation process proceeds fast, the lower the final population of companies adopting the technology will be as imitation rapidly consumes its momentum given the constant innovation process. Additionally, with short life cycles successive technology launches from the provisioning side become options for adopting innovator firms starting the innovation-imitation cycle again. Therefore, we arrive at

Hypothesis 2 (H2):

When m is low, the imitation coefficient, q, dominates; i.e., q is high.

Third, as new technologies require new sets of skills or upgraded existing ones, we may expect that if successive technologies vary greatly in their technological performance, companies will face increasing difficulties in using the new technology, and therefore, adoption of the new technology will decrease. Therefore, we arrive at

Hypothesis 3 (H3):

The lower the performance disparity between successive technology adoptions, the higher the m.

Finally, as the speed of technological changes increases, companies have less time to adopt successive technologies, whether the companies attempt to learn by using or imitating, and therefore, we hypothesize that

Hypothesis 4 (H4)*:*

The higher the speed of technological change in adoption, the lower the m.

2. Data and methodology

This paper reports the results of a study on a PC technological system, specifically focusing on the function of the PC system as a computer gaming platform. The PC system forms an ideal context for our empirical study because of the recognized and documented systemic nature of PCs [33, 34, 35], and the highly dynamic nature of the PC and its sub-systems [36, 37]. Nevertheless, the PC is a large and hierarchically complex system, which hinders its entire analysis. Thus, we have limited our empirical analysis by concentrating on only two technical sub-systems, which are crucial to the gaming performance delivered by the PC as a gaming platform. We analyzed PC game software as one of the technical sub-systems, focusing on its co-evolution with an important and interdependent hardware sub-system: the CPU (central processing unit). The co-evolutionary relationship between these technical sub-systems is marked by CPU manufacturers (e.g., Intel and AMD) providing successively higher levels of processor performance over time, which PC game developers and publishers (e.g., EA Games and Activision) adopt and implement in their software products.

To study the technology provisioning and adoption dynamics in our PC system context, we selected and analyzed the technological performance indicators that are among those highly relevant for computer gaming. For the CPU sub-system, we selected the performance indicator of processing speed, measured in Hertz (Hz), which indicates the CPU's speed of operation, governing the computational performance of the PC through its interaction with software programs such as PC games. Higher speeds mean faster data manipulation and increased computer performance. For the PC game sub-system, we considered the software is designed to use a certain level of hardware performance such that the intended game qualities can materialize through the PC. Therefore, software developers stipulate a set of minimum hardware performance requirements with which the software will function as designed. Hence, in our study we used the minimum processor speed requirements stipulated by the PC game software as its technological performance indicator [following 27]. In this manner, we deemed that a higher level of technological performance is embedded in the software when it stipulates a higher minimum processor speed requirement, and therefore carries more capacity to deliver a higher level of functional performance.

To collect data on technology provisioning in the CPU industry, we first gathered launch specifications and dates for CPUs commercialized by the two most influential manufacturers, namely, Intel and AMD, in PCs starting from 1996 and ending in 2008 from the companies' corporate websites. Second, we collected game specifications stipulating the minimum requirements and launch dates from GameSpot.com and publishers' websites between 1996 and 2008. From this data, we included in our analysis only those games that specified as minimum requirements the type of CPU and the required speed in MHz, leaving us initially with 77 different technologies in the computer industry. We also considered only Intel processors since AMD processors were mentioned only in recent years as minimum requirements. If we did not find both specifications (CPU type and speed) unambiguously stated on the publishers' websites, we discarded the game from our consideration. With these procedures, we arrived at an initial sample of 3064 games that stipulate specific minimum technology specifications. Therefore, our data reveals the adoption time series considering the number of game launches based on using a certain technology. For each technology, we fitted the Bass diffusion curve and estimated the diffusion parameters *p, q,* and *m*. To estimate the diffusion parameter, we considered only time series that had more than 10 data points in certain technologies [following suggestions e.g. from 38, 39, 40].

We also calculated the disparity of technological performance between successive CPU technology launches, that is, the difference between successive technological processor speed performance parameters as measured with MHz (*dMHz*) and the speed of technological change (the time lag between successive technology adoption data points as measured in months [*dMHzmnth*]). These reflected the amount of technological leap and the speed of technology change in adoption, respectively. In calculating the *dMHzmnth*, if subsequent technology adoption dates were the same for two or more technologies, we calculated the *dMHzmnth* values compared to the earlier technology adoption date. We also removed from our data set all the adoption time series that had negative *dMHz*, that is, the previous adoption time series had higher clockspeed than the earlier one. Therefore, our study concentrated only on the forefront of technology adoption at the frontier of technology evolution [13]. Therefore, after these controls, our final data set included 24 time series with 2282 data points composed in detail of 4 time series with 425 data points at the technology family level (Pentium generations) and 20 time series with 1857 data points at the technology level (variations in type of CPU and clockspeeds).

However, in the present study we did not consider repeat adoption, that is, a certain company launching multiple products based on the same technology.[1] The data is therefore biased to the upper side of the adoption. We obtained the diffusion parameters by fitting the diffusion model with a nonlinear least-squares (NLS) fitting procedure in MATLAB to the adoption data. In particular, we denote the observed total number purchased up to time $t_i > 0$ as $Y(t_i)$, and apply NLS to

$$Y(t_i) = mF(t_i; p, q) + u(t_i)$$

where *m* is the total number of adopters and *u* is an additive error term with variance σ^2. Nonlinear least-squares estimation chooses parameter values that minimize the sum of the squared residuals, $\sum_i (u(t_i))^2$. The NLS approach has been widely used in innovation diffusions [e.g., in 41].

Our methodology for testing the hypotheses is rather straightforward. Namely, we used multiple regression with OLS (ordinary least-squares) fitting looking at whether *p, q, dMHz*, and/or *dMHzmnth* predict the behavior of *m*. We emphasize that the main goal here is to explore statistical dependencies between the parameters, search for linear function with optimal solution, and as a result, explore the post hoc relationships between parameters.

3. Revealed dynamics of adoption

Table 1 presents the summary of our fitting of the diffusion model parameters.

Table 1. Summary of the study's fitting results.

	p	q	m	R2	n	dMHz	dMHZmnth
min	0,000	0,057	14	0,896	25	10	3
max	0,027	0,256	1093	0,998	153	700	550

Therefore, we conclude the fitting results represent the dynamics of technology adoption well, since the explanatory power, R^2, is at 90% or well above. This lends confidence to the next phases of the study in which we conducted regression analysis based on these fitting results.

Figure 1 presents an example of our fitting procedure results.

[1] We assume, following most of the existing literature, that each adopter launches only one unit.

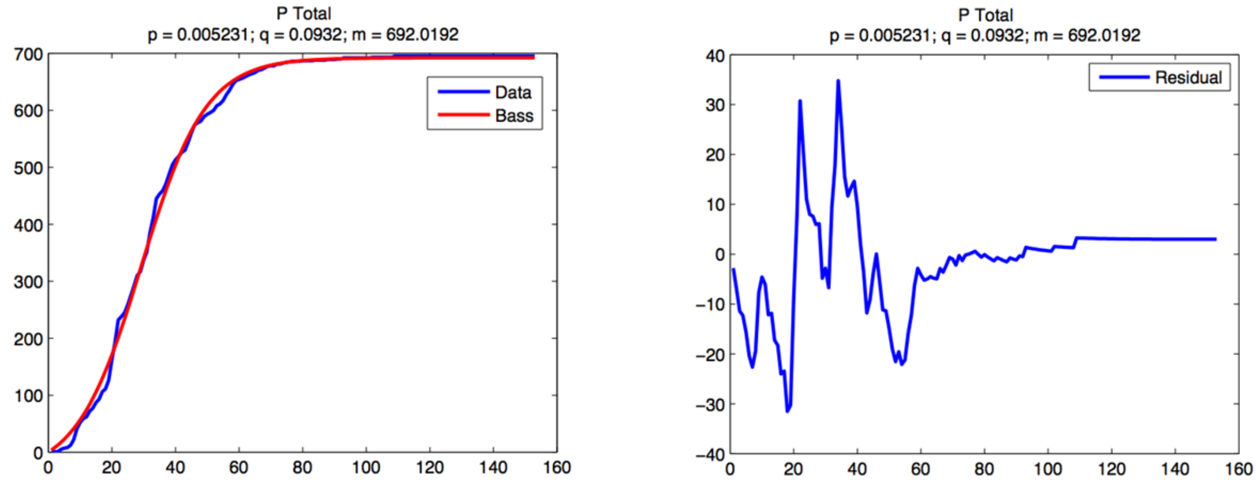

Figure 1. Example of our fitting results with residuals.

Table 2 outlines the correlation details of the time series used in our study to shed light on the variables.

Table 2. Correlation table of variables used in our analysis.

	p	q	m	dMHz	dMHZmnth
p	1				
q	-0,22	1			
m	-0,23	-0,52***	1		
dMHz	-0,43*	-0,10	0,33	1	
dMHZmnth	-0,12	-0,19	0,01	0,52**	1

* significant at the 0.10 level (2-tailed)
** significant at the 0.05 level (2-tailed)
*** significant at the 0.01 level (2-tailed)

In Table 2, *dMHz* and *p* have a statistically significant negative correlation; in other words, the higher the *p*, the lower the *dMHz*. Similarly, the relationship between *q* and *m* is significant and negative. Finally, there is a significant positive correlation between *dMHz* and *dMHzmnth*.

We present the results of our hypotheses testing with regression analysis in Table 3.

Table 3. Regression results for testing our hypotheses (unstandardized coefficients presented and their standard errors in parentheses).

Hypotheses	H1	H2	H3	H4	
Dependent	m	m	m	m	m
Predictor					
p	-8806,22 (7923,12)				-8751,09 (7819,92)
q		-2757,40*** (956,42)			-2567,56** (1036,04)
dMHz			0,324 (0,219)		0,309 (0,260)
dMHZmnth				0,012 (0,461)	-0,577 (0,468)
R^2	0,053	0,274***	0,108	0	0,396*
F	1,235	8,312	2,187	0,001	2,461

* significant at the 0.10 level (2-tailed)

** significant at the 0.05 level (2-tailed)

*** significant at the 0.01 level (2-tailed)

Hypotheses H1, H3, and H4 received no support, whether all the independent variables were included or not. However, for hypothesis 2, namely, the final adopting organizational population is low and the imitation coefficient *q* dominates and is high, we found strong support. Thus, according to the Bass diffusion parameter estimations, companies imitate the behavior of other organizations in adopting technology rather than innovating and learning by using.

4. Conclusions

Our results lend support to imitation effects in creating increasing returns to adoption in a systemic context. This finding might be due to the fast-paced, transparent nature of the systemic context. CPU manufacturers introduce new technologies frequently, and these introductions are expected by PC game developers and publishers. At the same time, increasing returns to adoption on the game developers' supply side mostly makes sense when large numbers of competing game developers adopt the technology as a minimum requirement. Therefore, beneficial behavior involves imitating rather than innovating and being early in adopting technology in the minimum requirements. In addition, the transparency of the industry may lend support to mimetic effects as the PC gaming industry launches products and new technologies frequently, competitive moves can be monitored, and imitative behavior can be sustained.

Theoretically, these exploratory results suggest that innovating and learning by using are not significant drivers of increasing returns to adoption. This finding further suggests it may not be beneficial to a company be among the first movers when considering raising the bar in minimum requirements. The companies may see minimum requirements as risky, as being among the first to impose increased performance requirements on end-users is economically less beneficial than sticking with the lower, already established performance levels. However, since first movers adopt higher minimum requirements, the more competitors do so, the more others have propensities to follow suit; that is, positive bandwagon effects are created through imitation. These results call for further theoretical validation.

Managerially, these preliminary results raise concerns about technology use and managerial practices in launching technologies that present substantial improvements to existing technological base. Especially in systemic contexts, companies using these technologies with large performance improvements need supporting activities, educating use in operations to lower the risks associated with learning by doing a type of increasing returns, i.e., lowering their production costs and risk. However, at the same time the market side (end-users) needs support for the installed base to be increased rapidly. This starts the positive feedback loop that increases adoption of the technology among companies, creating learning by imitation and further enhancing end-user adoption due to increases in the supply of products based on the new technology. This way companies may be able to instill the seeds of the increasing returns type of dynamics in the process of adopting technologically superior technology that substantially increases performance delivery.

There are a number of reasons why we did not find support for these hypotheses, which, at least partially, may be due to the limitations of our study. First, our data selection procedure filtered a number of launches in the timeframe of our study. Especially, our stringent data selection procedure of including only games that have explicitly stated minimum requirements specifications on publishers' websites limited our data set. Thus, our data set may not be representative of the whole population of PC games in the considered timeframe. However, this limitation increases the replicability of the research and enhances the reliability of the data with a price on the coverage of our sample. This may have skewed and biased our results, and future studies may want to extend the data set to minimize the possibility of non-representativeness and replicate the analysis. In addition, we assumed that each adopter launches only one product (no "repeat purchase"). There may be multiple launches by the same company in our data set, and this presents a fruitful avenue for future research to examine the influence of first vs. repeat adoptions on the results. Our hypothesis testing procedure also ignored the pure time dummy and temporal variables such as seasonality, and these variables may be significant in representing the industrial dynamics and the temporal changes that the industry as a whole has gone through during the last fifteen years. Finally, a number of different products, namely, different genres of games, may differ from one another in significant ways. This issue may also be included in the analysis of the time series data and may improve the results substantially. Therefore, the results of our study should be treated as initial and exploratory. These limitations, therefore, leave ample avenues for future research in studying the prediction of increasing returns to adoption. Namely, increasing the data coverage of the industry would be the obvious, logical next step. Additionally, including company-level analysis and studying individual organizations' adoption decisions would add significantly to our understanding of the dynamics of increasing returns to adoption. Finally, considering other independent and control variables would significantly increase our understanding of the technology adoption dynamics.

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