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Technological host-parasites co-evolution

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Abctract. The fundamental problem in the field of technology studies is how technology evolves and sustains economic change in human society. This study confronts the problem here by proposing the theory of technological host-parasites coevolution, an approach that may be useful for bringing a new perspective to explain and generalize, whenever possible, the evolution of technology in human societies. Technological host-parasites coevolution is a mutual symbiotic relationship between a host technology and associated technologies directed to satisfy needs and/or to solve problems of human beings. To explore the potential of adopting a theory of technological host-parasites coevolution and to predict which technologies are likeliest to evolve rapidly, this study implements an empirical test based on historical data on the evolution of four example technologies (aircraft, tractor, locomotive and bicycle technology) to substantiate the theoretical framework. Empirical evidence is broadly consistent with the theoretical expectation that host technologies with many associated parasitic technologies advance rapidly, whereas host technologies with fewer parasitic technologies improve slowly. This study begins the process of clarifying and generalizing, as far as possible, the role of long-run coevolution between technologies in complex systems of technology. The proposed theoretical framework also lays a foundation for the development of more sophisticated concepts to explain technological and economic change in human society. The evolution of technology plays an important role in economic and social change of human society. However, little is known about how technologies evolve and sustain human progress, despite being a crucial process in socio-ecological systems for millennia. This study proposes, for the first time to our knowledge, a concept of technological host-parasites coevolution that may be useful for bringing a new perspective to explain the evolution of technology. Statistical results suggest that host technologies with many associated parasitic technologies have a higher rate of evolution than technologies with fewer associated parasitic systems and sub-systems. The mutual symbiotic relationship between a host and parasitic technologies seems to be an invariant property driving the evolution of technology in human society.

Keywords. Evolution of technology, Technological parasitism, Technological host-parasites coevolution, Technological interaction, Technological evolution, Coevolution, Nature of technology, Technological change, Host technology, Technological innovation.

JEL. B50, B52, O31, O32, O33, O39.

1. Introduction

The evolution of technology plays an important role in the economic and social change of human societies (Basalla, 1988; Freeman & Soete, 1987; Hosler, 1994; Nelson & Winter, 1982). In 2009, Brian Arthur claimed that one of the most important problems to understand regarding technology is to explain how it evolves (p.15ff). In this context, technological evolution has been compared to biological evolution by many

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scholars (Arthur, 2009; Basalla, 1988; Solé *et al.*, 2013; Wagner, 2011). The similarities between biological and technological evolution have generated a considerable literature (see reviews in Erwin & Krakauer, 2004; Solé *et al.*, 2011). Wagner & Rosen (2014) argued that biological thinking has reduced the distance between life sciences and social sciences (cf., Nelson & Winter, 1982; Dosi, 1988; Solé *et al.*, 2013, 2011). Basalla (1988) suggested that the history of technology can profitably be seen as analogous to biological evolution. Technological evolution, alongside biological evolution, displays radiations, stasis, extinctions, and novelty (Valverde *et al.*, 2007). In general, patterns of technological innovation emerge and evolve with technological paradigms and trajectories in specific economic, institutional and social environments (Dosi, 1988). Hosler (1994, p.3, original italics) argues that the development of technology is, at least to some extent, influenced by "technical *choices*", which express social and political factors, and "technical *requirements*", imposed by material properties. Arthur & Polak (2006, p.23) claim that: "Technology … evolves by constructing new devices and methods from ones that previously exist, and in turn offering these as possible components—building blocks—for the construction of further new devices and elements". In particular, Arthur (2009, pp.18-19) argues that the evolution of technology is due to combinatorial evolution: "Technologies somehow must come into being as fresh combinations of what already exists."This combination of components and assemblies is organized into systems or modules to some human purpose and has a hierarchical and recursive structure: "technologies … consist of component building blocks that are also technologies, and these consist of subparts that are also technologies, in a repeating (or recurring) pattern" (Arthur, 2009, p.38). In addition, Arthur (2009) claims that technology evolution is based on "supply" of new technologies assembling existing components and on "demand for means to fulfill purposes, the need for novel technologies."

Other scholars suggest that technological evolution is driven by solving consequential problems during the engineering process (Coccia, 2014e, 2016, 2017e; Dosi, 1988; Usher, 1954) andby supporting leadership of distinct purposeful organizations -for instance firms- to achieve the prospect of a (temporary) profit monopoly and/or competitive advantage (Coccia, 2015, 2017a)[1]. However, it is clear that there are at least some aspects of the evolution of technology that these studies have trouble explaining. In particular, little is known about how technologies interact and create systems in which each component (sub-system) and overall

[1] For other studies concerning source, diffusion and evolution of technology and science, cf., Calabrese *et al.*, 2005; Coccia, 2003, 2005, 2005a, 2005b, 2005c, 2005d, 2006, 2006a, 2007, 2008, 2008a, 2008b, 2008c, 2009, 2010, 2010a, 2012, 2013, 2013a, 2014, 2014a, 2014b, 2014c, 2014d, 2014e, 2015, 2015a, 2015b, 2015c, 2016, 2016a, 2016b, 2017, 2017a, 2017b, 2017c, 2017e, 2017f, 2018, 2018a, 2018b, 2018c, 2018d, 2018e, 2018g, 2018h, 2018i, 2018l, 2018m, 2018n, 2018o, 2018p, 2019, 2019a, 2019b, 2019c, 2019d, 2019e, 2019f, 2019g, 2019h; Coccia & Cadario, 2014; Coccia *et al.*, 2015; Coccia & Finardi, 2012, 2013; Coccia & Rolfo, 2009, 2010, 2013; Coccia & Wang, 2015, 2016.

system can continue to evolve in socio-ecological environments. In this research context, our study has two goals. The first is to define the concept of technological host-parasites coevolution, a new perspective that may explain and generalize aspects of technological evolution in human societies. The second is to provide an empirical test based on historical data of the evolution of four example technologies to substantiate the theoretical framework. Statistical evidence hint at general properties of technological evolution, and, in particular, provide some insights into which technologies have greater potential to advance rapidly. This new theoretical framework of technological host-parasites coevolution lays a foundation for the development of more sophisticated concepts and theories to predict technological coevolution and explain economic change in human society.

2. Theoretical framework

2.1. Basic concepts

This study analyzes the interaction between technological breakthroughs in host-parasite systems, in a broad analogy with ecology. Parasites (from Greek para = near; sitos = food) are defined as any life form that finds their ecological niche in another living form. Host–parasite interactions can be of different types. Under certain conditions, a host–parasite relationship results in commensalism (a class of relationships between two organisms where one organism benefits from the other without affecting it), in mutualism (two organisms of different species exist in a relationship in which each individual benefits from the activity of the other) orin symbiosis (long-term interaction between two different biological species that live and evolve together). In other conditions, the relationship may result in parasitism. Mutualism, commensalism, and symbiosis represent a spectrum of interactions without clear cut-offs that distinguish them from parasitism, and each relationship represents an end-point of an evolutionary development (Poulin, 2006). In particular, parasitism is an interaction that evolves over time towards commensalism, mutualism and symbiosis (Price, 1991). The symbiosis is also increasingly recognized as an important selective force behind interdependent coevolution (Smith, 1991). Some scholars argue that the host-parasite interaction tends to generate stepwise coevolutionary processes within systems (cf., Price, 1991; Coccia, 2018).

2.2. Philosophical foundations of the theory of technological parasitism

Although models of technological evolution exist to explain the patterns of technological innovations (Sahal, 1981), there is no unified theory of coevolution that can explain the emergence of complex interaction patterns of different technologies. Interactions between technologies have profound effects on technological evolution, but despite their importance, little is known on the general structure and properties of this process. An important step towards explaining the fundamental interactions between and within systems of technology with technological host-parasites coevolution or technological parasitism is to first clarify the concept of complexity and complex systems. Simon (1962, p.468) states that: "a complex system [is]… one made up of a large number of parts that interact in a non simple way …. complexity frequently takes the form of hierarchy, and …. a hierarchic system … is composed of interrelated subsystems, each of the latter being, in turn, hierarchic in structure until we reach some lowest level of elementary subsystem." McNerney *et al.* (2011, p.9008) argue that: "The technology can be decomposed into *n* components, each of which interacts with a cluster of $d-1$ other components." This modularity can be one of the most important features of complex adaptive systems (cf., Arthur, 2009). Another characteristic of complex systems is the interaction between systems and sub-systems such that the hierarchy can be defined in terms of the intensity of interaction of the elements of the system. A distinction in hierarchic systems is the interactions between systems and the interactions within systems—i.e., among the parts of those systems. In this context, Simon (1962, p.474) points out that hierarchies have the property of nearly decomposable systems: "(a) in a nearly decomposable system, the short run behavior of each of the component subsystems is approximately independent of the short-run behavior of the other components; (b) in the long run, the behavior of any one of the components depends in only an aggregate way on the behavior of the other components."

The primary goal of this study, based on theoretical background discussed above, is to define the concept of technological host-parasites coevolution or technological parasitism; and that definition should meet the conditions of independence, generality, epistemological applicability and empirical correctness.

3. A proposed definition of technological host-parasites coevolution

Suppose that:

a) Technology is defined as a complex system that is composed of more than one component and a relationship that holds between each component and at least one other element in the system. The technology is selected and adapted in the Environment *E* to satisfy needs, achieve goals, and/or solve problems in human society.

b) Interaction between technologies is a reciprocal adaptation between technologies with interrelationship of information/resources/energy and other physical phenomena to satisfy needs, achieve goals, and/or solve problems in human society.

c) Coevolution of technologies *is* the evolution of reciprocal adaptations in a complex system that generates innovation—i.e., a modification and/or improvement of technologies that interact and adapt in a complex system to satisfy needs, achieve goals, and/or solve problems of human society over space and time.

d) The simplest possible case involves only two technologies; of course, the concept can be generalized for a complex system including a finite number of technologies.

Definition of the technological host-parasites coevolution ('iff' is shorthand for 'if and only if'):

P is a parasitic technology in **H** (host or master technology) iff during its life cycle ***P*** is able to interact and adapt into the complex system of ***H***, generating coevolutionary processes to satisfy needs, achieve goals, and/or solve problems in human society.

Remark: if host or master technology H*i* can fulfill needs and purposes in society without P*j*, and P*j* can fulfill purposes if and only if it interacts with other technological systems *Hi*, then P*j* is a parasitic technology ($\forall i$=1, …, n; $\forall j$=1, …, m).

Parasitic technologies P*j* are often sub-systems embedded within and primarily functional in the ecological system of host (or master) technologies H*i*. For instance, the dynamo (electric generator) is a parasitic technology when installed as an accessory to bicycles and other machines. Audio headphones are parasitic technologies of many electronic/audio devices. Technology *Pj*can be a parasite of different technologies *Hi*; technology *Hi* can be a host of different parasitic technologies *Pj* (e.g., mobile devices are host of software applications, headphones, Bluetooth technology, etc.). A technological innovation with many parasitic technologies can be considered a complex system with a high hierarchy (as defined by Simon, 1962) in comparison to a technological innovation with low number of parasitic technologies (i.e., less associated sub-systems of technology). To put it differently, a technology with a high hierarchy is associated with a higher number of technological parasites than technologies with less hierarchy in their system, such as aircraft vs. bicycle technology. In general, many technologies P*j* do not function as independent systems themselves, but *de facto* they depend on other technologies H*i* to form a complex system of parts that interact in a non-simple way (cf., Coccia, 2018m). Moreover, the diffusion and adaptation of parasitic technologies as complex adaptive systems depend on market forces, social networks, institutions, technical choices, and technical requirements over time and space (cf., Anadon *et al.*, 2016; Coccia, 2010, 2017; Dosi, 1988; Kreindler & Peyton Young, 2014; Hosler, 1994). Figure 1 visualizes a technological host-parasite system.

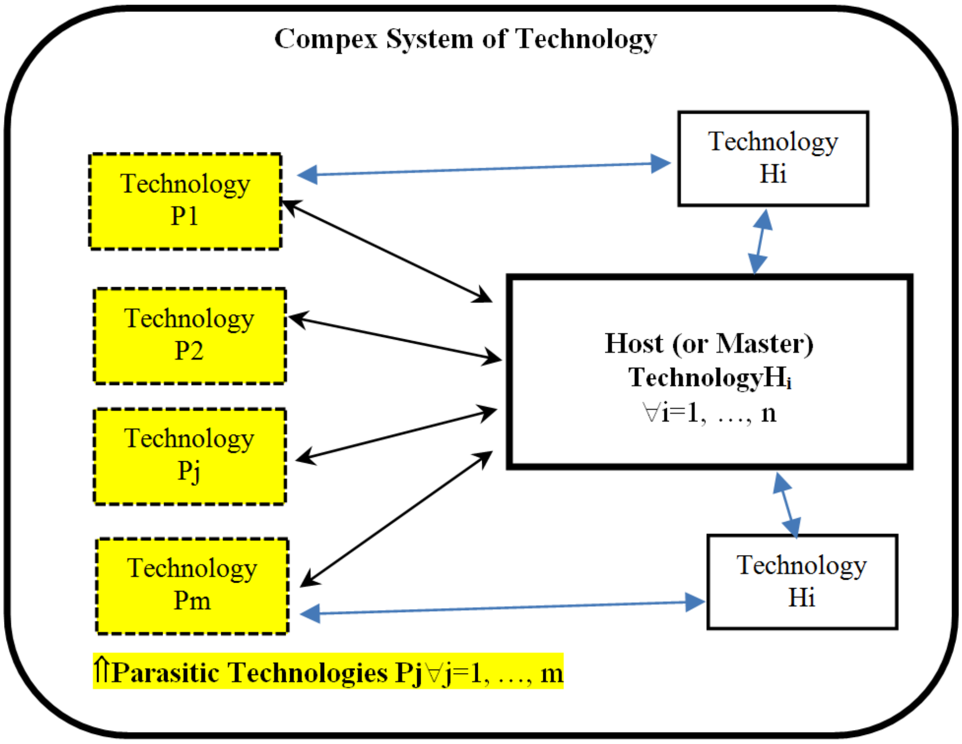

Figure 1. *Atechnological host-parasite system*

4. Study design

The statistical evidence here offers a preliminary assessment of the theory of technological host-parasites coevolution, considering historical data from the developmental trajectory of four technologies:

- Passenger aircraft, 1932-1965 CE (Current Era) and 2014-2017 CE
- Farm tractors, 1920-1968 CE
- Freight locomotives, 1904-1967 CE
- Road racing bicycles, 1901-2017 CE

Sources of aircraft, tractor, and locomotive data are tables published by Sahal (1981, pp.341-346; cf. also pp.321-330, originally sourced from trade literature; additional data for aircraft technology are from Lufthansa magazine, 2014; 2017. These data are also documented in supporting information here). The cycling data were archived by McGann & McGann (2006; Bicycle race data, 2017). In particular, this study compares aircraft technology (that is assumed to be a complex technological system with many interactions intra- and inter- parasitic technologies within a host technology) to other less complex technological innovations, such as the racing bicycle, farm tractor and freights locomotive. In particular, the high complexity of aircraft technology is due to the integration of many technology components and interaction between parasitic technologies necessary to safely meet the requirements—i.e., meet human needs or solve problems—of manned heavier-than-air flight. In fact, aircraft are characterized by several subsystems and associated air-to-air and air-to-ground systems of technology with intra- and inter-component interaction to be able to fly and satisfy human needs (main component technologies in aircraft are: jet engine, cockpit, slats, spoiler, aileron, flaps, elevator, rudder, radar, vertical and horizontal stabilizer, etc.; cf., NASA, 2017). Moreover, in the initial stage of development many of the components, particularly electronics, were not essential to tractor and locomotive technology (cf., Sahal, 1981). Evolution of these technologies is measured with Functional Measures of Technology (FMT) over time to take into account both major and minor innovations supporting technical performance and efficiency of technology (Sahal, 1981, pp.27-29). FMTs applied here are:

1. for passenger aircraft: maximum sustained airspeed in miles per hour over 1932-1965 CE and 2014-2017 CE
2. for farm tractors: mechanical efficiency (ratio of drawbar horsepower to belt or power take-off –PTO- horsepower) over 1920-1968 CE
3. for freight locomotives: tractive effort in pounds over 1904-1967 CE
4. for road racing bicycles: the increase in efficiency[2], over 1901-2017 CE (cf., Appendix)

The Functional Measures of Technology *i* in *t* (FMT*i*, *t*) are systematized in a comparable framework by applying the following standardization formula for the technology *i* in *t*:

$$\varphi_{it} = \frac{FMT_{it} - \mu_t}{\sigma_t} \tag{1}$$

where:

φ_{it} = standardized FMT_{it} (Functional Measures of Technology *i* at *t*=time)

FMT_{it}= Functional Measures of Technology*i* at the year *t*

μ_t = arithmetic mean of the FMT over a period *t*

σ_t = standard deviation of the FMT over *t*

Remark: φ_{it} is negative when the raw score is below the arithmetic mean, positive when it is above. A zero value of φ_{it} indicates that the raw value is equal to the arithmetic mean.

This approach compares the technologies described above considering similar patterns of technological development from the initial stage for each technology. Aircraft data are 34 years (1932-1965 CE), and for the purpose of comparing these different technologies, we have focused our statistical analysis on trends of the first 34 years available for the other three datasets.

[2] Efficiency is a metric of how much power generated by the cyclist is translated to forward motion. Because the bicycle is the only example of human-powered equipment discussed here, and because of improvements in athletes' training (and performance-enhancing drugs) it was necessary to try and isolate the innovation in racing bicycles from the performance of the rider. A detailed explanation of the bicycle FMT is offered in the additional materials (supporting information) section, but briefly this measure is derived from average speeds of world-class races while using data from contemporaneous running events (marathons) to control for rider performance improvement.

The statistical analysis also presents a comparison of aircraft *vs.* bicycle technology for a long run represented by 117 years for bicycle technology and 85 years for aircraft technology (data sparse after 1967 for latter technology; long-run data for freight locomotive and farm tractor were not available). Note that in all of these examples, the first year represented is not the year of invention; instead these data all come from a time period approximately thirty years after the original invention, when data from established (but nascent) industries and FMT metrics are available (cf., Sahal, 1981).

The time series of each technology are estimated with a simple regression analysis to assess the coefficients of regression of the evolution of these technologies under study here.

Specification of the linear model is:

$$y_{i,t} = \beta_0 + \beta_1 t + \varepsilon_{i,t} \qquad (2)$$

$y_{i,t}$= Standardized FMT_{it} Functional Measures of Technology *i*, *t*
t = Time
$\varepsilon_{i,t}$=error term
i=technology=1, 2, 3, 4

In the presence of a specific scatter of empirical data for a technology, the study design here estimates the most appropriate relation, such as cubic, power, compound or exponential model. These models of simple regression are estimated with Ordinary Least Squares (OLS). Statistical analyses are performed with the Statistics Software SPSS® version 24. The expectation here (per the theory and the computational model introduced) is that aircraft technology, as a complex technology with many parasitic technologies, will show more technological development than the other technologies with less parasitic technologies.

5. Results

The second priority of this study is to explore empirical, historical data on the evolution of four example technologies. In particular, the results of the historical data for the development of four technologies data assess the theory of technological host-parasites coevolution. The results of this study, based on aircraft, tractor, locomotive, and bicycle technologies are shown in Figure 2. In particular, the results reveal that the passenger aircraft technology, a more complex technology with many parasitic technologies and considerable interaction between associated technologies, has the fastest rate of evolution. This empirical finding of faster evolution of technology associated with high number of parasitic technologies is also confirmed in the long run when aircraft technology is compared with bicycle technology (Figure 3)[3].

[3]Data of bicycle technology are from 1901 to 2017, whereas data of aircraft technology are from 1932-1965. In order to analyze the long-run evolution of these two technologies with

The statistical evidence here suggests that host (or master) technologies with more technological parasites (and technological interactions, e.g., aircraft technology) have a rapid evolution of technology in the long run. Technologies with fewer parasitic technologies and a low level of interaction with associated technologies improve more slowly, such as racing bicycles (Fig. 2 and 3). Overall, this empirical evidence is consistent with the theory of technological host-parasites coevolution. Properties and predictions of the evolution of technology with technological parasitism are as follows.

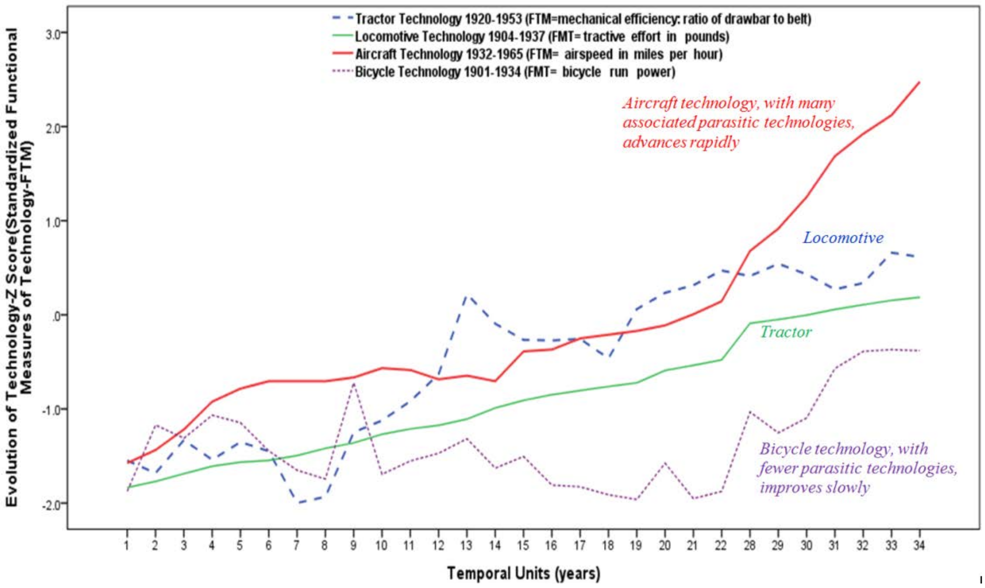

Figure 2. *Evolution of racing bicycle, farm tractor, freight locomotive and passenger aircraft technology over medium run (based on empirical data).*

Note: The bicycle is a less complex technology with fewer parasitic technologies than aircraft technology. The temporal units (years) on *x*-axis are from *1* to *m*, where *1* is the initial year of data of the technology (i.e., 1920 for tractor technology; 1904 for locomotive technology, 1901 for bicycle and 1932 for aircraft technology). Period under study here is 34 years for having a similar time span of data between technologies. *y*-axis indicates the Functional Measures of Technology standardized. For the tractor, locomotive and bicycle technologies, the estimated relationships of linear models ($y_{i,t}= \beta_0+ \beta_1 \times t + \varepsilon_{i,t}$), based on empirical data, reveal: for farm tractor technology (1920-1953) unstandardized coefficient beta is $\beta_1=0.71$, standardized coefficient is 0.899 (*p-value* < 0.001, $F=114.10$, *sig*.=0.001, Adjusted $R^2=0.80$); for freight locomotive technology (1904-1937), unstandardized $\beta_1=840.11$, standardized coefficient = 0.998 (*p-value*< 0.001, $F=9444.85$, *sig*.= 0.001, Adjusted $R^2=0.997$); for racing bicycle technology (1901-1934) unstandardized $\beta_1=1.35$, standardized coefficient is 0.392 (*p-value* < 0.05, $F=5.82$, *sig*.= 0.022, Adjusted $R^2=0.13$). The trend of passenger aircraft technology (1932-1965), a complex technology with many parasitic and associated technologies, fits a compound model ($\ln y_{i,t}= \ln \beta_0+ \beta_1 \ln \text{time} + \varepsilon_{i,t}$). Results of the estimated relation of aircraft technology are: unstandardized $\beta_1=1.03$ (*p-value* < 0.001, $F=457.66$, *sig*.= 0.001, Adjusted $R^2=0.93$). Aircraft technology has also a standardized coefficient beta higher than other technologies: $\beta_1=2.629$. Empirical evidence here shows the rapid evolution of aircraft technology compared to other technologies. This result in aircraft technology can be explained by the high number of parasitic technologies (and interaction) within and between this specific system of technology.

a higher (aircraft) and lower (bicycle) complexity and number of parasitic technologies, data of aircraft technology are integrated with cruising speed of Lufthansa Fleet of Airbus, Boing, Boing BBJ, Embraer and Bombardier from 2014 to 2017 (Lufthansa magazine n. 12/2014; p. 88; n. 05/2017, p. 74).

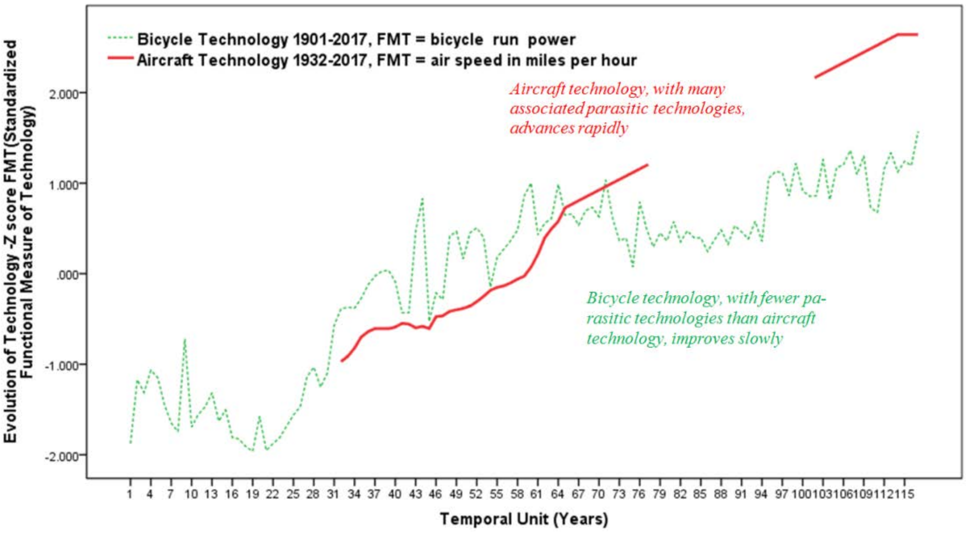

Figure 3. *Long-run evolution of racing bicycle and passenger aircraft technology based on empirical data*

Note: The racing bicycle is a less complex technology with fewer parasitic technologies than aircraft technology. The temporal units on *x*-axis are years. Period under study is 117 years for bicycle technology (1901-2017) and 85 years for aircraft technology (1932-2017). *y*-axis indicates the Functional Measures of Technology standardized. For the aircraft and bicycle technologies, the estimated relationships of linear models reveal: for passenger aircraft technology, unstandardized coefficient beta β_1=0.99, standardized coefficient is β_1=5.23 (*p-value* < 0.001, *F*=1855.24, *sig*.=0.001, Adjusted R^2=0.98); for racing bicycle technology, unstandardized coefficient is β_1=0.89, standardized coefficient is β_1=1.92 (*p-value* < 0.001, *F*=429.72, *sig*.= 0.001, Adjusted R^2=0.79). Empirical evidence here also confirms the faster long-run evolution of aircraft technology than bicycle technology. Note that in 1932 aircraft is an emerging technology in comparison to bicycle that had a higher technological evolution started in 1901 and in a growing phase. Subsequently, the higher number of parasitic technologies and technological interaction in aircraft technology than bicycle technology explains the high long-run rate of evolution of aircraft technology: i.e., $\beta_{\text{passenger aircraft technology}}$=5.23 >$\beta_{\text{racing bicycle technology}}$=1.92

6. Predictions of the theory

Technologies are complex systems composed of interrelated sub-systems of technology until the lowest level of technological unit (cf., Oswalt, 1976; Coccia, 2018; 2019g). Our study of technological host-parasites coevolution, starting with theory that was further refined with a computational model, and finally compared to empirical data and statistical analyses, suggests the following predictions:

1. Higher-level host technologies with many parasitic technologies advance rapidly. Technologies with fewer parasitic technologies and a low level of interaction with associated technologies improve slowly.

2. The long-run evolution of a technology depends on the behaviorand evolution of associated parasitic technologies; the long-run evolution of any technology is *not* independent of the other technologies (*technological symbiosis*). To put it differently, long-run evolution of a specific technology is due to interaction with new parasitic technologies. In brief, technological innovation is enhanced by the integration of two or more parasitic technologies that generateco-evolution of system innovations (cf., Theorem of not independence of any technological innovation by Coccia, 2018m).

7. Discussion and conclusion

Scholars argue that technologies and technological change display numerous life-like features, suggesting a deep connection with biological evolution (Basalla, 1988; Coccia, 2018, 2019g; Erwin & Krakauer, 2004; Solé *et al.*, 2011; Wagner & Rosen, 2014). We extend the broad analogy between technological and biological evolution to more specifically focus onthe potential of technological parasitism, but fully acknowledge it is not a perfect analogy; of course there are differences (Ziman, 2000). For studying technical change, though, the analogy with parasite biology and ecology is a source of inspiration and ideas because it has been studied in such depth and provides a logical structure of scientific inquiry.

The study here proposes that the interactions between technologies in complex systems are similar to the biological interaction of host-parasite dynamics. In particular, technological host-parasites coevolution is a dynamic process that can predict evolutionary pathways of interactive technologies in complex systems.

On the basis of statistical evidence presented in this study, technological host-parasites coevolution can explain and generalize, whenever possible, some characteristics of the evolution of technology in human society. In particular, the results of the analyses here suggest:

1. Technological host systems with many parasitic technologies generate a rapid stepwise evolution of technological host-parasite systems not seen in technologies with fewer associated parasitic technologies and a low level of technological interaction.
2. The long-run behavior and evolution of any technology is *not* independent of the other associated parasitic technologies (cf., Coccia, 2018m).
3. Studying inter-related or more symbiotic technologies as complex systems can help explain aspects of technological and economic change in human societies.

The study documented here makes a unique contribution, for the first time to our knowledge, by showing how technologies co-evolve by interacting in complex systems of devices and artifacts in a context of host-parasitic dynamic process. In particular, the theory here suggests a general prediction that it may be possible to influence (improve) the long-term evolution of technical change by increasing the fundamental interactions between parasitic and host technologies. This finding could aid technology policy and management of technology to design best practices to support mutual symbiotic relationships between a specific host technology and associated parasitic technologies directed to enhance the technological progress in human society.

Hence, the analogy of the study here provides an appropriate theoretical framework to explain one of the characteristics of the evolution of technology. However, the concept of technological evolution departs from biological evolution in fundamental ways. In general, technological innovations and their evolution are due to entrepreneurs that seek optimality, typically under economic criteria, such as minimization of cost, maximization of profit, etc. to achieve the prospect of a monopoly power and/or sustain a competitive advantage of firms in markets (cf., Coccia, 2017e; McNerney *et al.*, 2011; Solé *et al.*, 2013). In contrast to technology, living organisms are the result of tinkering that is undirected mutation plus a widespread reuse and combination of available elements to build new structures (Jacob, 1977).

In this research context, Valverde (2016, p.5) states that: "Technological progress is associated with more complex human-machine interactions." As a matter of fact, humans act as ecosystem engineers, able to change the socioeconomic environment and support progress (cf., Solé *et al.*, 2013).

The idea of a "technological parasitism" or in general of technological host-parasites coevolution presented in the study here should not necessarily be considered as a general behavior, because it is adequate in some cases but less in others because of the vast diversity of technological innovations and their interaction in complex systems and socioeconomic environments. Nevertheless, the analogy keeps its validity in explaining several phenomena of the coevolution of technology in human society. The theory of technological host-parasites coevolution suggests some properties that are a reasonable starting point for understanding the universal features of the coevolution of technologies that leads to technological and economic change, though the model of course cannot predict any given paths and characteristics of the evolution of technologies with precision. We know, *de facto*, that other things are often not equal over time and space in the domain of technology

Overall, then, the proposed theory here—technological parasitism based on the ecology-like interaction between technologies and innovations—may lay the foundation for development of more sophisticated concepts and theoretical frameworks. Future efforts in this study will be directed to provide further empirical evidence to better evaluate this new approach and to refine the computational model. However, identifying generalizable theory at the intersection of engineering, economics, sociology, anthropology, and perhaps biology is a non-trivial exercise. Wright (1997, p.1562) properly claims that: "In the world of technological change, bounded rationality is the rule."

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Appendix

Bicycle innovation data and calculation of the Functional Measure of Technology FMT in racing bicycle technology (bicycle efficiency)

The raw data underlying the assessment of bicycle efficiency improvements is the average speeds of several long-running top-level races. Specifically, we have included data from eight races: the three grand tours (Giro d'Italia, Tour de France, Vuelta a España), and the five one-day classics (Milano-San Remo, Flanders, Paris-Roubaix, Liege-Baston-Liege, Tour de Romandie). The oldest of these races was first held in 1892, but recognizably modern formats and rules were not used until the early 20th century. Also, the grand tours consist of multiple stages (over 20 stages in recent decades), different formats (e.g., individual time trials, team time trials, and regular road races), and courses that vary significantly over the years (e.g., some years include more climbing). Taken altogether though, the average speeds of the winners across the three grand tours (and the one-day classics, which are raced on consistent courses) minimizes any effect of year-to-year course and weather variations. Note that data from the earliest years and also the war years are sparse. Average speeds have improved in the years since 1901 (about 64% faster) due to improvements in rider training, faster bicycles –new materials (e.g., carbon fiber) for components– (and yes, in some cases, performance-enhancing drugs; Bicycle race data, 2017).

Our intent with this data was to isolate insofar as possible the technological development of the bicycle. Importantly, though, average speeds of race winners are the outcome of many, many factors—and some of those factors that may contribute to faster racing through time (such as team tactics) are difficult or impossible to quantify. But it is possible to largely control for the most relevant parameter other than the bicycle itself: the athlete. For comparison, we also collected data on winning speeds of the Boston Marathon data (2017), a running event held since the late 19th century. Marathon speeds have also improved, but much more modestly compared to cycling (15% for running). Weighting the cycling race speeds by removing the effect of the athlete (using the running data) provides a much cleaner assessment of the innovations in bicycle technology.

Because cycling speeds are generally 2.5-3 times faster than marathon runners, further transformation of the speed data was necessary to compare the two sports. First, the power generated by the athlete to either run or pedal a bicycle can be reduced to a function of the oxygen metabolized to generate that power. If you can calculate the power necessary to run a certain speed, you can likewise calculate the speed of a cyclist generating the same power (assuming slope and winds are non-factors; those other parameters can be accounted for in the math, but it is much more complicated). For example, in 2016, winning cyclists averaged 40.4 km/h, and a simplified estimate of the power required to maintain that speed is 355 watts (equation below, note the non-linear relationship between power and speed; because of air resistance, large gains in power are necessary for even modest gains in speed). Alternately, in that same year the marathon winner ran 19.1 km/h and generated power around 339 watts.

For the early years, cycling speeds and related power estimates were low (e.g., 26 km/h, or less than 100 w). Importantly, early 20th century cyclists were not pushing much lower power compared to modern cyclists (perhaps 15% less, not almost four times less!). Instead, their bikes were less efficient. The difference in power generated by the marathon runner and the cyclist any given year provides a reasonable assessment of the efficiency of the bicycle. To that end, to generate our metric of bike innovations, we simply subtracted the running power from cycling power each year 1901-2017 as follows.

How to transform bicycle race speeds into Functional Measures of Technology FMT (bicycle efficiency):

Bicycle Speed	Average km/h of the 3 grand tours and 5 one-day Classics (*Giro d'Italia, Tour de France, Vuelta a España; Milano-San Remo, Flanders, Paris-Roubaix, Liege-Baston-Liege, Tour de Romandie*).Note: data sparse during war years.
Bicycle Power	Power (watts) needed to maintain speed given drag coefficient of 0.25
Calculated:	$$P_b = C \times s^3$$ where: P_b= Bicyclepower (watts) C = drag coefficient, set to 0.25 s= speed converted to meters per second (simplified from Puget, 2015)
Run Speed	km/h of *Boston Marathon* winner
Run Power	Pace converted to watts for 150 lb (68.2 kg) athlete
Calculated:	$$P_r = \frac{210}{p} \times \frac{W}{1000} \times 75$$ where: P_r= run power (watts) p = pace in minutes/km W= weight in kg *Note*: given economy numbers of 75W/L on the Bicycle and 210ml/kg/km on the run (O_2 consumption). Converts running pace to O_2 consumption, then O_2 to Bicycle power (Hawley and Noakes, 1992).

Hence, the difference between $P_b - P_r$ = FMT and indicates the bicycle efficiency, i.e. the evolution of bicycle technology, without the human improvements.

Data of technologies and their sources for empirical analyses

Year Tractor *	Farm Tractor (mechanical efficiency) *	Year Locomotive *	Freight locomotive tractive effort in pounds *	Year Aircraft *	Passenger aircraft airspeed in miles per hour *	Year Bicycle/ Marathon ♦†	Racing bicycle speed (km/h) ♦	Run speed Boston Marathon (km/h) †
1920	52.17	1904	22804	1932	109	1901	25.862	16.94767
1921	50.95	1905	23666	1933	116	1902	28.088	15.51287
1922	54.19	1906	24741	1934	127	1903	27.3915	15.67778
1923	52.25	1907	25781	1935	142	1904	28.8915	16.01666
1924	53.99	1908	26356	1936	149	1905	28.43767	15.98127
1925	53.09	1909	26601	1937	153	1906	25.96567	15.27421
1926	48.03	1910	27282	1938	153	1907	28.01275	17.53255
1927	48.62	1911	28291	1939	153	1908	27.252	17.37413
1928	54.95	1912	29049	1940	155	1909	29.26617	14.58353
1929	56.1	1913	30258	1941	160	1910	26.9586	17.00649
1930	57.99	1914	31006	1942	159	1911	29.03783	17.87293
1931	60.64	1915	31501	1943	154	1912	29.561	17.9172
1932	68.49	1916	32380	1944	156	1913	29.47467	17.43195
1933	65.58	1917	33932	1945	153	1914	27.85083	17.43195
1934	63.99	1918	34995	1946	169	1915	27.795	16.69069
1935	63.94	1919	35789	1947	170	1916	26.69	17.19126
1936	64.09	1920	36365	1948	176	1917	25.89	17.0351
1937	62.19	1921	36935	1949	178	1918	25.46	16.89114
1938	67.01	1922	37441	1950	180	1919	25.22757	16.9666
1939	68.61	1923	39177	1951	183	1920	27.49457	16.93256
1940	69.35	1924	39891	1952	189	1921	27.21343	18.22022
1941	70.79	1925	40666	1953	196	1922	27.68514	18.32352
1942		1926	41886	1954	204	1923	27.18371	17.60774
1943		1927	42798	1955	208	1924	26.924	16.91559
1944		1928	43838	1956	210	1925	27.17057	16.54706
1945		1929	44801	1957	214	1926	28.47829	17.38009
1946		1930	45225	1958	219	1927	28.56157	15.78695
1947	70.25	1931	45764	1959	223	1928	29.32543	16.1135
1948	71.45	1932	46299	1960	235	1929	28.90957	16.53265
1949	70.42	1933	46916	1961	252	1930	29.49114	16.35465
1950	68.95	1934	47712	1962	274	1931	30.54386	15.18261
1951	69.56	1935	48367	1963	286	1932	32.81586	16.48242
1952	72.54	1936	48972	1964	296	1933	33.22914	16.76437
1953	72.12	1937	49412	1965	314	1934	33.02329	16.55969
1954	69.57	1938	49803			1935	33.42913	16.64315
1955	71.77	1939	50395			1936	33.86475	16.47527
1956	72.54	1940	50905			1937	34.38257	16.51109
1957	74.22	1941	51217			1938	34.30471	16.27405
1958	74.08	1942	51811			1939	35.11286	17.0084
1959	73.12	1943	52451			1940	34.7425	17.05231
1960	74.55	1944	52822			1941	32.742	16.80704
1961	79.55	1945	53217			1942	33.29125	17.24004

Table of the data and their sources of technologies (continued from previous page)

Year Tractor *	Farm Tractor (mechanical efficiency) *	Year Locomotive *	Freight locomotive tractive effort in pounds *	Year Aircraft *	Passenger aircraft airspeed in miles per hour *	Year Bicycle/ Marathon ♦†	Racing bicycle speed (km/h) ♦	Run speed Boston Marathon (km/h) †
1962	75.41	1946	53735			1943	36.493	17.05806
1963	76.03	1947	54506			1944	37.4935	16.6742
1964	82.26	1948	55170			1945	32.538	16.80332
1965	83.09	1949	56333			1946	33.97471	16.94011
1966	75.34	1950	57075			1947	34.07475	17.38208
1967	66.06	1951	58476			1948	35.70538	16.76252
1968	73.97	1952	59966			1949	36.22757	16.6742
1969		1953	61339			1950	34.99938	16.585
1970		1954	63152			1951	36.62014	17.13503
1971		1955	65005			1952	36.33157	16.66872
1972		1956	68745			1953	37.15643	18.23335
1973		1957	61515			1954	35.276	18
1974		1958	61312			1955	36.63963	18.29704
1975		1959	61408			1956	37.3525	18.86044
1976		1960	61314			1957	37.07075	18.07281
1977		1961	61969			1958	36.83288	17.3523
1978		1962	61415			1959	38.35038	17.74142
1979		1963	61533			1960	38.93425	17.96806
1980		1964	62311			1961	36.99463	17.62409
1981		1965	63096			1962	37.34988	17.6057
		1966	70900			1963	38.02814	18.21804
		1967	65267			1964	38.827	18.08572
		1968				1965	38.30375	18.54046
		1969				1966	38.31588	18.45487
						1967	37.998	18.64972

Note. Sources of data.
*Sahal (1981, pp. 341-346; cf. also originally sourced from trade literature pp. 321-330)
♦Bicycle race data (2017). [Retrieved from].
†Boston Marathon data (2017) from the race organizer's Boston Athletic Association website [Retrieved from].
For complete dataset see sources of data above.

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