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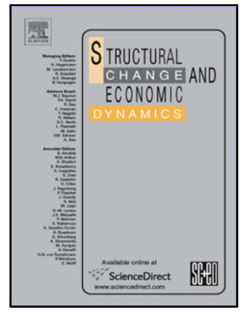

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Pervasive Technologies and Industrial Linkages: Modeling Acquired Purposes

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Abstract

What makes an industry a *dominant filière* and a particular technology a so–called General Purpose Technology (GPT)? The paper contributes to a microeconomics of vertically related and networked industries by framing GPTs as a peculiar case of technological connectivity between sectors and provides a simple model that accounts for the endogenous success (failure) of GPT–based industries in a competing technologies setting. In a nutshell, we explore the process potentially leading to technological pervasiveness and dissect it in its structural elements. The model takes into consideration several conditions under which an upstream technology increases its pervasiveness in the economy or remains constrained as a component used by a small subset of downstream applications only. Hence, the model shows how 'purposes' are acquired by a technology struggling to dominate the downstream market. Policy implications of the analysis are highlighted, and dynamic implications of the model are discussed. Two main features of the study are that i) we go beyond the a priori assumption that a pervasive GPT–like technology already exists in the economy and ii) we bring GPT theorizing under the umbrella of studies of structural change through the dynamics of industries' linkages.

Keywords: general purpose technology; industrial linkages; pervasiveness; star economy; competing technologies.

JEL Classification: C63, D24, L14, O32.

1 Introduction

The pervasiveness (or generality of purpose) of technologies is a feature that economic theory usually disregards or assumes *a priori*. In this paper, we posit that the process through which a technology gains pervasiveness matters: The evolution of a technology can result in a broad diffusion or in a failure to spread. The main question to be answered is: how are purposes 'acquired'? Purposes are meant here in the sense of 'applications', or uses for a given technology that can serve as a component, or input, to other technologies or economic activities. Relatedly, we define *purpose acquisition process* the dynamics leading a technology — developed to deploy specific functions or to solve specific problems — to identify further purposes and uses beyond the ones the technology was originally planned or designed for. We focus on a particular setting in which the protagonists are general purpose technologies (hereinafter GPTs), upstream technologies (input) characterized by a spectrum of application ranging beyond a single industry or sector and by the capacity to induce economy–wide transformational effects (Bresnahan and Trajtenberg, 1995; Bresnahan, 2010; Lipsey et al., 2005). The relation between GPTs and their applications is a particular case of linked markets, that in which an upstream industry serves multiple downstream industries. Relatedly, pervasiveness can be thought as some function of the installed base of downstream user industries; thus, in a sense, this paper establishes a link between GPT theory and network externalities literature (Shy, 2011). This conceptual 'bridge' is not the only one we perform in this study. In fact, by shifting GPT theory to a theory of linked markets whose structure evolves in time, we bring GPT literature under the umbrella of studies on structural change (Pasinetti, 1983). In a nutshell, we answer the question 'how are purposes acquired' by filling a gap in the literature concerned with the nature of pervasive technological change; we do that providing a microeconomic formulation of the purpose acquisition process and the factors influencing it.

The study of the process of purposes acquisition is relevant because it captures the multilevel nature of the determinants shaping technological trajectories (Dosi, 1982) and the configuration of technological systems. A contemporary example useful to make clear the issue at stake is that related to the energy–storage and battery sector. As Crabtree recalls,

> In 1991, the year that the lithium–ion battery was commercially released, no one foresaw the disruption that it would cause in personal electronics. After initially being used in portable music players and camcorders, lithium–ion batteries later found their way into, and spurred the development of, laptops, tablets and mobile phones — technologies that have permanently changed how much of society works. Yet there is an even bigger revolution on the horizon. In the same way that telephones had a rotary dial for most of their existence, the electricity grid and cars have mostly existed in a single, unchanged format. But as we move beyond lithium–ion technology, a new generation of cheaper and more powerful batteries will completely rejig the power grid and usher in an age of electrically powered transportation. (Crabtree, 2015)

The example mentioned above is a case in point that allows to capture at least two deeper pieces of evidence regarding technological pervasiveness. First, input technologies are usually introduced for specific purposes and gain pervasiveness later on; second, the pervasiveness of an upstream incumbent input can be challenged by entrant technologies that try to increase their downstream market share of applications. Furthermore, as argued in a more general argument by Stephan et al. (2017), the pattern of change of a given technological system is affected by its sectoral configuration (namely the number and types of sector linked in a technological system value chain); this suggests that the structural relations in an economy — industries' vertical relations for what concerns this paper — influences the dynamics of purposes acquisition. This paper takes these stylized facts as the point of departure to develop a general microeconomic approach to describe the process of purposes acquisition.

We propose a model of technological competition in a setting featuring vertically–linked markets. A set of downstream industries can adopt one of the possible alternative upstream input technologies that struggle for pervasiveness. The competition among those technologies can result either in the establishment of a new pervasive GPT or in the persistence of the existing GPT as the dominant one. To understand this dynamics, we extend the Schumpeterian concept of 'competition for the market' (Geroski, 2003) to the case of vertically related industries, introducing a 'competition for the downstream market'. As the competition for the downstream market unfolds, the process of acquisition of purposes might take place if the new upstream technology prevails on the established one.

We borrow a simple analytical framework used in the literature on international trade to model acquired purposes and to offer a description of how, in a setting featuring linked markets and upstream technological competition, a newly introduced specific purpose technology can become pervasive and, hence, general purpose. The factors affecting the 'specialization' of the downstream industries in one of the alternative upstream technologies are identified and discussed. To summarize our argument, two main features of this study are that using our framework i) we go beyond the a priori assumption that a pervasive GPT–like technology already exists in the economy and ii) we bring GPT theorizing under the broad umbrella of studies of structural change through the dynamics of industries' linkages.

In a nutshell, the issue at stake for our study is the representation of the process leading to technological pervasiveness. To uncover such process, we build on and extend the theory of general purpose technologies filling a main gap of this body of literature: the microeconomic modeling of general purpose technologies as a special case of technological competition displaying vertically–linked payoffs. Furthermore, we combine different strands of literature to offer a contribution encompassing a handful of issues in innovation economics.

The paper proceeds as follows: Section 2 defines the building blocks used to intersect theories of linked markets, GPTs, technology evolution, and structural change. Section 3 set up a simple Ricardian model in the spirit of Dornbusch et al. (1977) and Cantner and Hanusch (1993), and outlines a static and dynamic analysis. Section 4 concludes discussing the results and suggesting directions for further research.

2 Connectivity and General Purpose Technologies

We consider the study of the process of purposes acquisition part of a more general investigation into the nature of economic connectivity and structural changes therein. To support this claim, we now show how different phenomena taken up in seemingly unrelated strands of literature share similar conceptual features and, therefore, can be used to setup a broad framework linking industrial organization, general purpose technologies, and appreciative theorizing in the spirit of Neo–Schumpeterian economics.

First, input–output theorists and development scholars have always been interested in the inner structure of connections and bottlenecks (Hirschman, 1958) shaping economies, in order to fine–tune public intervention and to identify the best routes for industrialization processes to escape a handful of 'traps'; on the contrary, standard economic modeling mostly focused its attention either on aggregate dynamics or on industry level structural features.

Second, the analysis of the linkages between industries is recently experiencing a silent resurgence. We outline three main (not mutually exclusive) reasons for that: i) New Growth Theory and Schumpeterian Growth Theory fail to explain complex market dynamics; this induces scholars to investigate beyond the surface of aggregation and to frame macroeconomic issues (e.g. fluctuations) as phenomena emerging from localized and micro–level shocks (Acemoglu et al., 2012); ii) network models developed in the context of complexity sciences made their way into economic theorizing, revamping the input–output view of economic activities as a fruitful way to understand and represent production relations, industrial transformations (Carvalho and Voigtländer, 2014; Contreras and Fagiolo, 2014; McNerney et al., 2013), specialization and international trade (Hausmann and Hidalgo, 2011) and the dispersion of manufacturing in global value chains (Timmer et al., 2014); iii) the economic crisis and a timely rediscovery of the role of the public sector in the economy boosted a novel discussion on the aims and tools of industrial policy (Cimoli et al., 2009; Hausmann and Rodrik, 2006; Mazzucato, 2013; Stiglitz et al., 2013) and on the intertwined channels transmitting policy impulses to firms and markets. The idea that ties matter in influencing economic behaviors is certainly not new in innovation economics: The literature on open innovation, collective invention, R&D collaborations and patent networks (Cantner and Graf, 2006) is well developed. Also, the very idea at the basis of the Pavitt taxonomy (Pavitt, 1984) is to highlight industries' external sources of technical change — hence the role played by the connectivity with suppliers, an exercise further developed by a rich literature on rent and knowledge spillovers (Verspagen and De Loo, 1999) and technology flows analysis (Scherer, 1982).

Third, the diffusion of a network–inspired theorizing due to reasons described above allows for an increased use of concepts that were confined until recently to niches of the economic discipline as evolutionary, innovation and development economics. Concepts such as multiple equilibria (Hoff, 2000; Stiglitz, 1987; Stiglitz and Greenwald, 2014), learning, ergodic and out–of–equilibrium processes (Arthur, 2013), positive feedbacks, linkages (Hirschman, 1958), all blossom again in the economic literature. These building blocks are helpful to reformulate economic stylized facts as dependent on linked payoffs. More specifically, stating that economic outcomes depend on connectivity — that is on the strength and distribution of linkages among the units of analysis — has consequences for the study of industry dynamics, especially for what concerns some unresolved puzzles. For example, the known technological and economic drivers of market selection (Cantner et al., 2012, 2016), market turbulence (Cantner and Krüger, 2004) and industry life cycles (Klepper and Graddy, 1990; Klepper, 1996) may just be a part of a larger story: connectivity may affect the speed of selection and survival probabilities, the rate and pace of technological change, and the duration of the phases of the industry life cycle. External effects originating in linked markets may play a much broader role in innovation and economic activities than it is usually accounted for.

In this paper, connectivity is accounted for by studying how the technological specialization of downstream industries (their 'upgrading', in the language of development economics) and the pervasiveness of upstream technologies (input) are related. The most stylized case of connectivity one can study is that of an upstream–downstream relation between a single supplier and a single customer industry. The literature focuses mainly on incentives and constraints for vertical integration (transaction cost economics being prominent in such type of analysis; see also Arrow (1975) and Bresnahan and Levin (2012)) and on the effects of different market structures on the performance of vertically related markets, for example in the case of double marginalization (Spengler, 1950; Bresnahan and Reiss, 1985). What is interesting the endogenous determination of payoffs, when decisions on one side of the relation affect the returns of some activities (for example, innovative activities) on the other side, and vice versa. This is the case, for example, of two–sided markets and platforms (standards) formation (Rysman, 2009; Weyl, 2010) driven by network effects and of organizational ecologies' densities interdependencies (De Figueiredo and Silverman, 2012).

In what follows, we focus on a very specific case of connectivity structure, that stands in–between a singular upstream–downstream connection and a complex network structure with multiple upstream–downstream ties. We consider a production structure featuring vertical (that is, hierarchical) relations between one upstream technology and a set of downstream applications and analyze the effects of the introduction of incoming upstream technologies. This structure is similar to what Carvalho (2014) calls a *star economy* (that is, a hub–and–spoke network), with the difference that here the upstream vertex features a handful of technologies competing for prevalence in use in the downstream industries. A star economy–like structure is the most straightforward representation of the linkages between a GPT (at the center) and its downstream applications (in the surrounding periphery). On this rather general basis, GPT theory has been developed in several economic fields, such as industrial organization (Bresnahan and Trajtenberg, 1995), new growth theory (Helpman, 1998), and evolutionary economics (Carlaw and Lipsey, 2011).

However, the 'generality' of the phenomenon it describes has not yet been exploited to sketch a fully–fledged theory of economic connectivity and linked payoffs in the context of vertically related industries. We fill this gap by extending the GPT setting to the case in which the incoming technology striving for pervasiveness is not yet a GPT. When the establishment of a GPT is not assumed a priori, the resulting prevailing and pervasive upstream technology has to emerge from the competition between upstream technologies for the downstream industries. The reason to look at GPTs from this perspective lies in the definitional underpinnings of the very GPT concept (Field, 2008), which 'has come under growing attack' (Ristuccia and Solomou, 2014) recently. To the authors' knowledge, only the paper by Thoma (2009) takes the same viewpoint as the one suggested in this paper. The paper studies how potential GPTs 'strive for a large market'. Thoma's analysis focuses on a specific case (Echelon's *LonWorks* control technology) and highlights the different strategies experimented by the company Echelon to foster a pervasive use of its product. These strategies were ranging from value chain integration and collaborations to open sourcing of the product software in order to create a community of loyal users. Eventually, it has been the role played by a big public demander to create the conditions for an increasing pervasive use of the technology. This goes in line with the result of classic GPT models, according to which public procurement can lead the GPT diffusion to higher equilibria (Bresnahan and Trajtenberg, 1995). Our contribution goes in the same direction but provides an abstract framework, rather than a case study, to understand how incoming candidate GPTs succeed or fail while striving for a large market. It goes without saying that our extended framework to address the dynamics leading the establishment of a GPT among competing potential alternatives remains a simplification of the complex array of interwoven factors influencing technological pervasiveness. While aware of the partial explanatory power of our model, we nevertheless consider it a step forward in the research agenda dealing with the understanding of radical and general purpose technologies from a microeconomic perspective.

In existing GPT models vertical connectivity is key for economic performances and most importantly for innovation performances, given the existence of the so–called 'dual inducement' of innovational complementarities between the single upstream GPT technology and downstream applications. The problem in that context is to determine and solve the coordination issue arising between downstream applications and a pre–determined upstream technology. Market outcomes can be lower than socially desirable, however, there, coordination is about the intensity, rather than the direction of innovative activities. In our paper, also the direction matters, in the sense that the incoming upstream technology is not aware of its potential GPT 'status'; it learns it through its (successful or not) dynamics toward prevalence, persistence, and pervasiveness (Cantner and Vannuccini, 2012). User industries can choose the upstream technology to which to be tied; the outcome of this dynamics in terms of which upstream technology prevails decides the direction of innovative activities.

The modeling of a star economy in the making can be related to several strands of literature: First, there are similarities with models dealing with infant industries and early stages of industrialization (Hausmann and Rodrik, 2003; Hoff, 1997). In fact, one may think of the process leading to the establishment of a GPT as a case of 'infant technology' development. Second, modeling the problem of 'acquired purposes' closely resembles the phenomena on which studies on competing technologies (Arthur, 1989) focus on, namely dynamic increasing returns to adoption. Third, modeling the switch between upstream technologies by downstream industries can be framed as a standard topic in industry dynamics, that of entry/exit patterns. In this case those entering are not firms; it is an entire application industry that, by adopting one of the upstream competing technologies, enters in one of the potential GPT sectors. Fourth, our model is conceptually and analytically close to models of network externalities — in particular those employing Hotelling–style frameworks — as, next to technological features, the installed base of user industries influences the dynamics of purposes acquisition. Fifth, a model of pervasiveness in the making is intuitively a model of structural change in which the economy re–structures its working logic around competing GPT–like core technologies.

Our model builds upon the classic (Bresnahan and Trajtenberg, 1995, hereinafter BT) model.[1] There, the authors explore the simple 'star economy' case. The basic structure of the model is a 'hierarchical pattern' of technological interdependence between a single GPT industry and many downstream application industries/sectors (hereinafter AS). BT define an AS an industry/sector 'that (i) is an actual or potential user of the GPT as an input; (ii) can earn positive returns by engaging in R&D of its own; and (iii) the rents it earns increase monotonically with the "quality" of the GPT' (Bresnahan and Trajtenberg, 1992, p. 11). In short, the BT model features a coordination game in innovative activities with one–to–many upstream–downstream linked payoffs. These generate on the one hand a potential positive feedback process in innovation (a so–called dual inducement mechanism) and, on the other hand, suboptimal equilibria due to a vertical and a horizontal externality. The vertical externality emerges from the linked payoffs between GPT and AS — it is a bilateral moral hazard problem; the horizontal externality results from the linked payoffs between the many ASs given their indirect connection through the GPT. The main variables affecting the two types of sectors' optimal decision making with regards to innovative activities (the objective functions to be maximized being the expected gross returns on innovative activities for the AS and the expected profits for the GPT) are a scalar for the GPT technical 'quality' (z), the price of the GPT input (w) and the constant marginal cost of production of the GPT–embodying commodity for the GPT sector (c). This set of variables proxy both economic and technological explanations affecting the GPT–AS coordination game. We explicit here the BT model specification as our model maintains the same notation while extending its reach to more than one upstream GPT.

Besides the rationales derived from the relevance of studies on economic connectivity and from the received IO–based GPT theory, the paper's main question is also justified by a further theoretical argument that has to do with the representation of the process of technological takeover. This process is usually related to the phenomenon of 'disruption' (Gans, 2016).[2] Adner and Zemsky (2005) offer a formal discussion of the conditions for technological disruption to occur. The authors explore the economic conditions and the timing under which a novel technology either invades a mainstream market or remains confined in a niche, for the case featuring two competing technologies and heterogeneously distributed firms' willingness to pay. Even if the argument is not made explicit there, the model can be framed as one of firms' choice among alternative upstream competing technologies and goes in the same direction taken by this paper — namely, to show that multiple equilibria and, therefore, alternative economic structures, are viable outcomes in a vertically related market with linked payoffs and more than one potential pervasive technology available. Adner and Levinthal (2002) bring the analysis of purposes acquisition on the terrain of evolutionary theory by comparing the pervasiveness in the making of a technology with the phenomenon of speciation. Speciation in the economy is *the application of existing technologies to a new domain of application* (Adner and Levinthal, 2002, p. 51), and it resembles the mechanisms through which a candidate GPT gains shares in the downstream application domain. A close — though distinct — similitude is that with the

[1] In what follows we refer to the journal version of the study, dated 1995. In case the contents of interest are available only in the extended working paper version we refer to the source dated 1992.

[2] Despite the similarity of the concepts of generic technological change and disruption, the two have only a partial overlap. The progressive establishment of a GPT may or may not produce disruption. Its establishment as an emerging pervasive input can be characterized by re–domaining (Arthur, 2009) of existing activities around new physical principles and by the generation of complementarities, rather than substitution.

concept of exaptation (Andriani and Cohen, 2013; Dew et al., 2004). Exaptation occurs *when traits get co–opted for use in unintended ways* (Andriani and Cohen, 2013). Speciation and exaptation processes are conceptually proximate with what is labeled technological upgrading in development economics, re–domaining in complexity economics (Arthur, 2009) and technological convergence in the economics of technical change (Rosenberg, 1963). In a broad sense, the core idea is that in the struggle for pervasiveness, the more downstream applications switch to one of the upstream inputs so that it starts to be used in new domains, the more the economy experiences a technological structural change.[3]

Finally, as already mentioned, the study of pervasive technologies in the making is strongly embedded into structural change theorizing (Pasinetti, 1983; Silva and Teixeira, 2008). In fact, our model captures in the most stylized way the change in the underlying structure of an economy between alternative technological infrastructures. By adopting new upstream technologies the structure of industries' interdependencies changes. However, our Ricardian model displays only one type of linkage — that between upstream potential GPTs and downstream GPT–user industries — in order to study the dynamics leading to technological pervasiveness. In this sense, we focus only incidentally on the composition of the economy, and in doing that we distance ourselves from classic studies of structural change. Nonetheless, ours is a study of the shift in structure of a given economy from a prevailing core technology to a new, competing one, in the style of the literature on Long Waves and Techno–economic paradigms (Freeman and Louçã, 2001; Perez, 2010; Silverberg, 2003), where the process of pervasiveness in the making through purposes acquisition captures the formation of a new paradigmatic technological 'envelop' driving the re–domaining of the whole set of downstream industries.

Taking stock of the discussion so far, we can highlight some propositions to be used in the remainder of the analysis: i) technology adoption and technological competition depend both on economic and non–economic (technological) determinants, that can be considered independently from each other; ii) the adoption/diffusion of an incoming upstream technology is function of the change in the economic and technological determinants across all the relevant alternatives; iii) an incoming upstream technology striving for pervasiveness can encounter resistance from the established GPT; iv) purposes are acquired in an evolutionary manner, either co–opting functions for use in unintended ways or applying existing functions to new domains. In what follows, these premises are used to set up a toy model capturing how an upstream potential GPT can succeed or fail to acquire purposes in the downstream market.

3 A Model of Purposes Acquisition and Structural Change

We propose a simple model representing the dynamics of purposes acquisition when more than one upstream technology is available in the market and, hence, a 'competition' to gain pervasiveness in linkages with the downstream economy takes place. The outcome in terms of upstream–downstream connectivity structure varies according to the state and change of the economic and technological variables at work. We distinguish three broad outcomes of the model: i) in the competition between an established and a new upstream technology, the new

[3]With technological structural change we mean here a transformation of the technological base of industries rather than — as usually meant for structural change — a shift in employment allocation through macro–sectors.

upstream technology gains pervasiveness in the market and in the limit takes over and serves the whole downstream economy; ii) in the competition between an established and a new upstream technology, the established upstream technology maintains its pervasiveness in the economy and a novel one occupies only a niche (it is adopted by none or a limited amount of downstream sectors); iii) in the competition between an established, a new and a third, *newer*, upstream technology, the newer upstream technology displaces the new one, making the former a sort of 'failed GPT'.

The model is a simplified version of the Dornbusch et al. (1977) assignment model of international specialization in line with Cantner and Hanusch (1993), Acemoglu and Autor (2011); Cimoli (1988); Dosi and Soete (1983) and, more recently, Costinot (2009) and Costinot and Vogel (2015).[4] In our version the matching occurs between upstream technologies (industries) and downstream industries, rather than countries and products as in Cantner and Hanusch (1993) and skills/labor and tasks as in Acemoglu and Autor (2011). The units of analysis of the model are generic individual industries; firms' behavior is not explicitly taken into account. We assume homogeneity between firms and heterogeneity between industries; while barely realistic (stylized facts regarding the persistent 'fractal' nature of economic characteristics the more disaggregation is deepened are well–known, see Dosi and Nelson (2010)) the introduction of firms heterogeneity would only magnify a phenomenon already emerging under more simplifying restrictions. For the sake of generality, hereinafter instead of the term 'downstream industries' we use the term 'downstream applications', in order to take into account a more disaggregated and richer set of economic activities.

The next sub–section describes a baseline case featuring two–upstream industries — one established and a new upstream technology. We illustrate this case in detail as it provides the main gist of our contribution: shifting from a setting featuring a one–to–many relationship between a GPT and downstream industries to a two–to–many relationship between alternative upstream (GPT–like) technologies and downstream industries is enough to shed light on the process leading to technological pervasiveness (or failure in achieving it). Later on, we extend the analysis to a three–upstream industries scenario in order to highlight the robustness of our argument when the setting complexity increases.

3.1 The Case of Two Competing Upstream Industries

We assume that each upstream industry produces a single, recognizable, technology.[5] The upstream technology is in turn used as a single component in downstream applications. The economy broad structure is that of a linear value chain with two layers: upstream, that of the supplier industries; downstream, that of the user industries. Upstream industries are labeled with the index E (for the established technology) and N (for the new technology). Technology N is a potential 'entrant' in the upstream market; furthermore, it is reasonable to assume that N is, from its 'birth', associated to a limited set of specific downstream industries initiated thanks to the very discovery or invention of N. Given that downstream applications' production technologies depend only on the upstream product, they can be characterized by their valuation

[4] The model itself can be conceived as a case of exaptation, given that a framework developed for a specific purpose is imported into another field of economic theorizing.

[5] By doing so the use of the terms upstream industry and upstream technology in the paper is indifferent.

of the specific upstream technologies and ordered in a continuous and closed interval $[0; I_n]$, where I indicates a generic downstream application and n is an ordered index.[6]

In Dornbusch et al. (1977) and Cantner and Hanusch (1993) goods are characterized by a scalar, the labor requirement (the inverse of labor productivity) needed to produce them. A decrease in labor requirement capturing in this context an increase in production efficiency. In our model we look at industries or downstream applications (instead of goods) and we assume that — due to strong complementarities — the upstream components quantity requirement is constant (and normalize it to one unit) and what changes are just the benefit of using one or the other upstream technology. In BT, this is captured by the 'quality' characteristic of the GPT. The ranking over the continuum of downstream applications, which is assumed to be invariant over time, distributes the downstream application according to the *relative* benefit of using the new upstream technology. Relative benefit measures the advantage or the disadvantage for a downstream application to 'attach' to the new upstream industry compared with the choice of staying with the established one. This is a measure that proxies in a scalar a number of innovation determinants that are well known in the literature, such as technological intensity or performance gap (Cantner and Hanusch, 1993, p. 220), technological opportunities (Klevorick et al., 1995), price/performance sensitivity (Almudi et al., 2013; Dosi and Nelson, 2010; Pavitt, 1984) or relative willingness to pay for the upstream technologies. In turn, all these concepts are potential proxies for the easiness of technology switch from an established to a new upstream technology, and capture the core of the technological side of our model.

In order to keep a degree of consistency with the previous literature, the model uses the same set of explanatory variables and a similar notation to that outlined in Section 2. The measures of benefit just described can be interpreted as functions of the perceived *usefulness* of (one of) the (potential) GPTs. We call $z_j(I)$ such application–dependent usefulness, where $j = \{E, N\}$, E is the established and N the novel upstream technology and z varies in I. The novel feature of our model is that we are discussing *relative* rather than *absolute* usefulness — that is a measure for 'comparative advantage' of technology N with respect to technology E. Therefore, our variable of interest is $\zeta(I) = \frac{z_N(I)}{z_E(I)}$, the relative technological usefulness (attractiveness) of upstream technologies. It is important to highlight here that while in Bresnahan and Trajtenberg (1995) model z is a single scaler value (the GPT 'quality') known to all the AS, in our case z is a downstream application's valuation of the upstream technology quality. The model is deterministic, that is we do not interpret z as an 'expected' usefulness but as a source of heterogeneity between applications. In this way, heterogeneity is introduced in the model via a continuous distribution of downstream propensities to choose the performance of N relatively to E and the model can be considered belonging to the class of *probit or threshold models of diffusion* (Geroski, 2000).

Given that it is defined over the interval of downstream applications, $\zeta(I)$ is a function

[6] As for the microfoundations of the model: following Balan and Deltas (2013), downstream industries can be considered as customers. Analytically, they can be thought as being represented by a value function of the type $v(0) + u(I)$ where v is a degenerate function and equals zero. However, in this paper we are not interested in a optimal decision given the maximization of the value function but in the structural effects at the economy level due to the shifts in the threshold of 'specialization' of downstream industries between competing upstream core technologies. Hence, we can leave the microfoundations on the background; by doing that, our model becomes a simplified version of an Hotelling setting based on relative valuations.

— the relative (upstream) technology usefulness (performance) curve. Following Dornbusch et al. (1977) we make the following assumptions on the shape of $\zeta(I)$: i) it is continuous and differentiable in $[0; I_n]$; ii) it is monotonically increasing in I due to the downstream applications' ordering, with $\zeta' > 0$; iii) it is reversible ($\zeta^{-1}(I)$ does exist). In short, $\zeta(I)$ represents the comparative increasing rewards obtained from purchasing the new upstream component rather than using the established one. At this point, it has to be remarked that downstream sector size does not play a role in the model; each downstream application, defined over an infinite continuum, has an infinitesimal size with respect to the whole economy. Theoretically speaking, sub–intervals of technologically proximate (in the comparative advantage space) applications can be identified and aggregated in order to model different industries sizes and to provide a more realistic representation of the unequal weight of downstream economic sectors in the economy. Such a refinement is left aside in this version of the model, even if downstream sector size may play a role when mutual feedbacks and linked payoffs are explicitly formalized and taken into account.

In order to have an upstream–downstream markets assignment, technological relationships have to be confronted with economic ones. More precisely, the technology relative usefulness (performance) curve has to be coupled with a relative cost curve. In Dornbusch et al. (1977) and in Cantner and Hanusch (1993) the corresponding curve is a demand curve that integrates consumption shares over the continuum of goods given Cobb–Douglas preferences of consumers. Here we simplify the object of analysis by displaying only the relative cost for downstream sectors to acquire upstream technologies. If each downstream application purchases a constant amount of upstream component (we assumed only one unit), then no demand curve exists to determine the pricing of the potential GPTs. What matters is the relation between the two costs. Again consistently with Bresnahan and Trajtenberg (1995) we define $w_j(I)$ as the cost of the upstream technology, where $j = \{E, N\}$, E is the established and N the novel upstream technology. We do not deal with price–cost margins (profits) in the upstream market, because the change in the downstream shares using one or the other upstream technology is completely driven by downstream applications' adoption decisions.[7] The ratio $\omega(I) = \frac{w_N(I)}{w_E(I)}$ represents the relative cost (downstream expenditure) curve. Regarding the shape of $\omega(I)$ the assumptions we made on $\zeta(I)$ on continuity and differentiability hold. Concerning the slope of $\omega(I)$, there are three possibilities: i) *ceteris paribus* the downstream applications' ranking, the novel upstream technology will be relatively more (less) costly for downstream applications with a comparative disadvantage (advantage) in switching: $\omega(I)$ is monotonically decreasing in I; ii) $\omega(I)$ is constant over the whole distribution of downstream application because either $w_N(I)$ and $w_E(I)$ are constant for all I or are monotonically decreasing at the same rate over I; iii) $\omega(I)$ is non–monotone. Formulation i) and ii) are more straightforward for comparative statics purposes, while iii) may produce multiple equilibria. In the remainder of this Section, we assume that cases i) or ii) apply.[8]

[7]However, price–cost margins may be quite relevant in affecting the magnitude of vertical externalities (Bresnahan and Trajtenberg, 1995).

[8]One may discuss if to identify a single 'net benefit' curve by defining a function $\nu(I) = \zeta(I) - \omega(I)$ could be an equivalent modeling strategy. Working with $\nu(I)$ would bring our analysis into a standard Hotelling setting; instead, we prefer to distinguish the two functions to highlight the role played by both technological and economic determinants.

Given the shapes of $\zeta(I)$ and $\omega(I)$, the model determines a downstream industry I_e that separates the market between applications using upstream technology E and applications using upstream technology N. To determine I_e, over the interval $[0; I_n]$ we can set into relation the relative usefulness and the relative cost of the upstream technologies for each downstream application I

$$\frac{z_N(I)}{z_E(I)} \lesseqgtr \frac{w_N(I)}{w_E(I)} \rightarrow \frac{z_E(I)}{w_E(I)} \lesseqgtr \frac{z_N(I)}{w_N(I)}$$

which transforms in a usefulness/cost ratio $\frac{z_j(I)}{w_j(I)}$. By the properties of the ζ– and the ω–functions there is a downstream application I_e for which the following holds:

$$\frac{z_N(I)}{z_E(I)} = \frac{w_N(I)}{w_E(I)} \rightarrow \frac{z_E(I)}{w_E(I)} = \frac{z_N(I)}{w_N(I)}$$

A downstream application adopts N if $\frac{z_E(I)}{w_E(I)} < \frac{z_N(I)}{w_N(I)}$. In I_e equality holds and the model yields the unique threshold or borderline downstream application that is indifferent in the choice of upstream technology. In addition to the identification of I_e the model simultaneously provides the size of intervals $]0, I_e]$ and $]I_e, I_n]$, which are the shares of the downstream market specialized either in E or N. A measure or a metric can be derived for the length of the $]0, I_e]$ and $]I_e, I_n]$ intervals, and used to assess the pervasiveness and thus the 'GPT nature' of the upstream technologies and to track the dynamics of the purposes acquisition process. The latter point suggests an insight contributing to the debate on the definitional drawbacks of GPTs (Field, 2008). In fact, while GPT theory tends to adopt a discrete distinction between GPT and non–GPT technologies, the empirical identification of GPTs has come to terms with the more continuous nature of pervasiveness indicators (see for example the distribution of patents' generality index in Hall and Trajtenberg (2004)). What our model does is to import the non–discrete approach to GPTs identification into modeling. We suggest that the share of downstream market served by a given upstream technology embodies information on its GPT–nature and on its trajectory of purposes acquisition.

The endogeneity of $\zeta(I)$ and $\omega(I)$ curves' determination is — for the moment — purposefully avoided in the model, in order to distinguish the effect of purely technological and pure economic determinants of the downstream establishing a linkage to one or the other upstream industry. The feedback effects both on the demand and supply side can be already detected by fractioning the dynamic adjustment process of specialization in one or the other upstream technology in a sequence of 'snapshots'. In line with Gans (2011), static analysis can already be a sufficient proxy for dynamics considerations in some cases. For example, the presence of dual inducements — downstream adoption improves the quality of the upstream and vice versa — can be modeled as shifts towards the left of the $\zeta(I)$ curve, while the presence of learning effects (Arrow, 1962; Thompson, 2010), meaning that the gains in efficiency of one technology production (in general or respect to the competing alternative) are captured by a movement on the left of the $\omega(I)$ curve (with $w_N(I)$ decreasing faster than $w_E(I)$). The presence of dual inducements or faster learning effects in the established technology may also give rise to non–linearities (and therefore potentially to multiple equilibria) in the both demand and supply relative curves, a possibility here ruled out by our assumption on the shape of $\zeta(I)$ and $\omega(I)$.

Consider again for a moment the classic BT GPT model; there is no alternative to an already established GPT. The possibility that a pseudo–diffusion (GPT adoption by the ASs) process takes place within the game is captured by assuming an invariant ranking of ASs with respect to $V(w, z)$ (the ASs' value function of innovation gross rents) and letting z and w to vary in order to determine the unique 'marginal' or threshold AS that finds profitable to adopt the GPT (Bresnahan and Trajtenberg, 1992). Formally, 'for $n(w, z)$ indicating the largest number of AS that finds profitable to use the GPT as input given w and z, then $n_w(w, z) < 0$, $n_z(w, z) > 0$' (the subscript indicating the partial derivative of n with respect to w and z), meaning that, 'the set of using sectors expands as the quality of the GPT improves and its price goes down' (Bresnahan and Trajtenberg, 1992, p. 13). The adoption process captured by the changes in $n(w, z)$ is already a broad proxy for a dynamics of purposes acquisition, if one assumes that ASs are heterogeneous and that therefore an increase in the number of downstream adopters widens the set of functions and uses the GPT provides. This is correct, however, only because it is *given* in the model the presence of a single already established GPT. The change in the number of ASs adopting an upstream input does not depend on the upstream competition among alternative technologies struggling for success and pervasiveness. In a stylized sense, our model extends this process going in the direction of a general case with several potential GPTs j and with $n_j(w_1, w_2, \ldots, w_j, z_1, z_2, \ldots, z_j)$, that is, the number of ASs 'choosing' a potential GPT j is function of the quality and the cost of all the relevant alternatives.

A graphical representation of the outcomes of the model is provided in Figures 1 and 2. The two different cases provided are discussed next.

3.2 Discussion of the Two–upstream Technologies Case

As anticipated at the beginning of the paragraph, two main constellations in the two–upstream technologies case can be distinguished. We label them as the *competition (and potential takeover)* case and the *niche case*.[9] In the competition case (see Figure 1), the intersection of $\zeta(I)$ and $\omega(I)$ determines the downstream economy's specialization, which at the very beginning may feature the established upstream technology to maintain its 'control' over a wide share of downstream applications. Varying the comparative (relative) advantages in upstream usefulness and cost, the new upstream industry starts to acquire purposes (that is, the borderline downstream industry moves to the left), leading in the limit to a full takeover. In this sub–case, the new upstream technology may well be labeled as a GPT, but only after a process that put it in the position to serve the largest share of the downstream market. The new upstream technology enters the market as a specific purpose technology, gains pervasiveness and acquires purposes until it dominates the downstream market and becomes a GPT.

In the second scenario (see Figure 2), that we label niche case, $\zeta(I)$ and $\omega(I)$ do not intersect, so that despite the increasing attractiveness and comparative advantage of the new upstream along the distribution of downstream applications the technological argument does not compensate for the economic one, with $\omega(I)$ lying completely above $\zeta(I)$, so that $I_e = I_n$. In this case a novel upstream technology and potential candidate to become a pervasive GPT fails to emerge as such (van Zon et al., 2003) and remains a niche component used by a very

[9]They respectively mirror the 'Ricardo case' and the 'innovation case' in Cantner and Hanusch (1993).

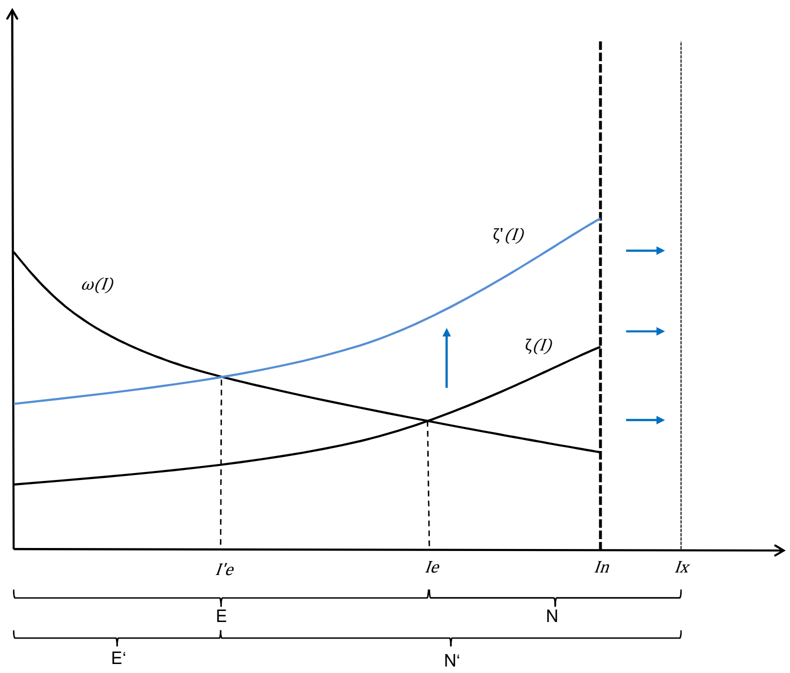

Figure 1: Competition case

Note: the continuum of downstream industries is represented on the horizontal axis. The upward shift in the $\zeta(I)$ curve indicates an increase in comparative advantage for the new upstream technology. Continuum sub–intervals labeled E, E', N and N' indicate the result of the competition for the downstream market, respectively for technology E and N before and after the change in relative usefulness. The rightmost interval $[I_n, I_x]$ indicates the set of novel downstream industries that come together with the new upstream technology — there the $\zeta(I)$ curve is not defined. The rightmost arrows show the emergence of new downstream industries — the extension of the continuum — from I_n to I_x .

limited set of applications, at the limit only those new downstream applications emerged due to the introduction of the new upstream technology in the economy. A niche case can always turn into a competition/takeover case, when a shift to the left of $\zeta(I)$ or a shift to the left of $\omega(I)$ re–establishes an intersection between the two curves and sets $I_e < I_n$, meaning that the borderline downstream application is an internal point of the interval.

The model can also account for the consequences generated by the emergence of new downstream applications (for example novel downstream products and infant economic activities) that, as mentioned earlier, may follow the introduction of N.[10] This is formalized by extending on the right side the interval $[0; I_e; I_n]$ to $[0; I_e; I_n; I_x]$. Here $[0; I_e[$ indicates the interval of applications attached to the established upstream technology and $]I_e; I_n; I_x]$ indicates the extended interval. This includes the existing applications adopting the upstream technology N, from the borderline I_e to I_n and those just entered in the market, labeled with x and identified in the additional interval $]I_n; I_x]$. In the niche case I_e and I_n will coincide. We assume that newborn downstream applications can produce for the final market only if connected to the new upstream

[10] The appearance of new downstream sectors can be also understood in the terms of Bresnahan and Yin (2010), as the emergence of latent sectors whose demand was beforehand unserved under the dominance of the established upstream technology.

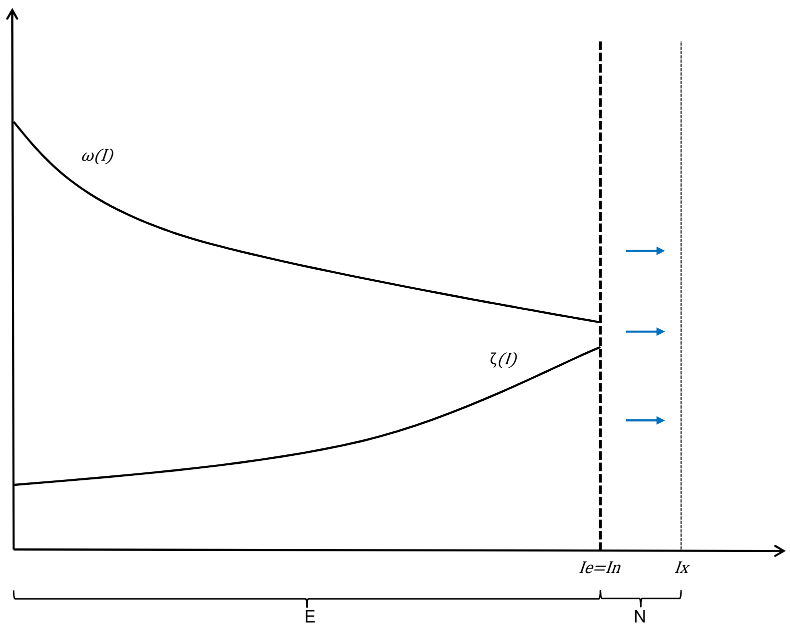

Figure 2: Niche case

Note: the relative usefulness of the new upstream technology does not compensate for the relative cost along all the downstream continuum of industries. Only the novel downstream industries that emerge together with technology N adopt it. N never succeeds in acquiring purposes as long as $\zeta(I)$ and $\omega(I)$ are not defined and do not intersect in the $[I_n, I_x]$ interval.

technology, meaning that they do not evaluate comparative advantage (formally, they have an infinitely high comparative advantage in $\zeta(I)$ and an infinitely low $\omega(I)$). New downstream applications add in an ordered succession to the ranked distribution of the downstream market. The presence of newborn downstream applications provides upstream technology N with a 'buffer' stock of users. In a dynamic setting featuring positive feedbacks from the number of adopters to the increasing comparative advantage in adoption (meaning that absolute changes in z_j and w_j, indicated respectively with $\dot{z}_j$ and $\dot{w}_j$, are function of the sizes of the applications intervals served), such a stock may trigger a purposes acquisition dynamics leading N to become a GPT. In this sense, the new upstream technology enters the upstream market as a specific purpose technology and its applications are only those downstream links existing at its 'birth'. If the user base in these downstream industries is large enough, the relative usefulness of N is affected positively, leading to an upward shift of the $\zeta(I)$ curve or to a downward shift of $\omega(I)$, depending on how network effects are modeled. This, ceteris paribus, increases the size of the downstream interval served by N. In practical terms, this means that N diffuses through the heterogeneous downstream industries, increasing its applicability and, therefore, acquiring purposes.

3.3 Three Competing Upstream Industries

The static model outlined above can be extended to the case of three (or more) upstream technology. Following Acemoglu and Autor (2011), we introduce in the set of upstream technologies a newer one, labeled M, so that the set of upstream technologies becomes $j = \{E, N, M\}$. Given that downstream applications already face the decision to stay or switch between E and N depending on the value and shape of the relative usefulness and relative cost curves, to find the new upstream–downstream market assignment with three upstream alternatives it is sufficient to derive two new curves, describing the comparative performance and cost between upstream technologies N and M. Assuming that the ranking of downstream applications remains unchanged, we rename $\zeta(I)$ and $\omega(I)$ as $\zeta_{EN}(I)$ and $\omega_{EN}(I)$ and introduce $\zeta_{NM}(I)$ and $\omega_{NM}(I)$ as the two new comparative relations. The same assumptions on continuity, monotonicity and reversibility hold. Figure 3 presents the scenario just discussed.

Shifts of in $\zeta_{EN}(I)$, $\omega_{EN}(I)$, $\zeta_{NM}(I)$, and $\omega_{NM}(I)$ may lead to a broader set of technological specializations in the economy. Once again, the established upstream technology may maintain its prevalent role in the economy, the new upstream may take over downstream market shares becoming prevalent (that is, acquiring the status of GPT) or the newer upstream may substitute for the new one, making the latter a failed potential GPT and the former a pervasive technology. Finally, the downstream market may well be split among the three competing upstream, avoiding the tendency for any GPT to appear. The three upstream technologies case can be further extended to a many–to–many relations assignment model, with a continuum of downstream applications matching with a continuum of upstream technologies (see Costinot and Vogel (2015) for such a generalization in the case of Ricardian trade models). However, the three upstream industries case is already general enough to highlight the main outcome of this paper: the standard GPT model is just a special case of a model of competition for the downstream market by upstream technologies that can display a richer set of outcomes and structural configurations.

In fact, such generalization has the virtue to show how technological competition for the downstream market may be resolved in a broad constellation of outcomes, with only some of them leading to the replacement of a GPT with a new one and to a successful process of purposes acquisition and increase in generality, applicability and pervasiveness for one of the upstream technologies. Furthermore, the three upstream technologies case provides another insight on the process of technological competition in vertically related markets: the higher the number of upstream technologies, the bigger the number of variables affecting the final outcome. Relative usefulness and relative costs can all be subject to change, and, therefore, the determinants of purpose acquisition may be non–trivial to identify. This, on the other hand, means that also the number of 'levers' to affect the results of upstream technological competition increases — opening room for a wide set of possibilities for policy intervention.

3.4 Policy Interventions

The static version of the model also allows for basic policy 'thought experiments'. From BT we know that, in a GPT framework, policy intervention in the form of well–designed contracts and public procurement is a condition to solve the coordination problem and to select better (higher) equilibria by exploiting the dual inducement mechanism and internalizing vertical and horizontal

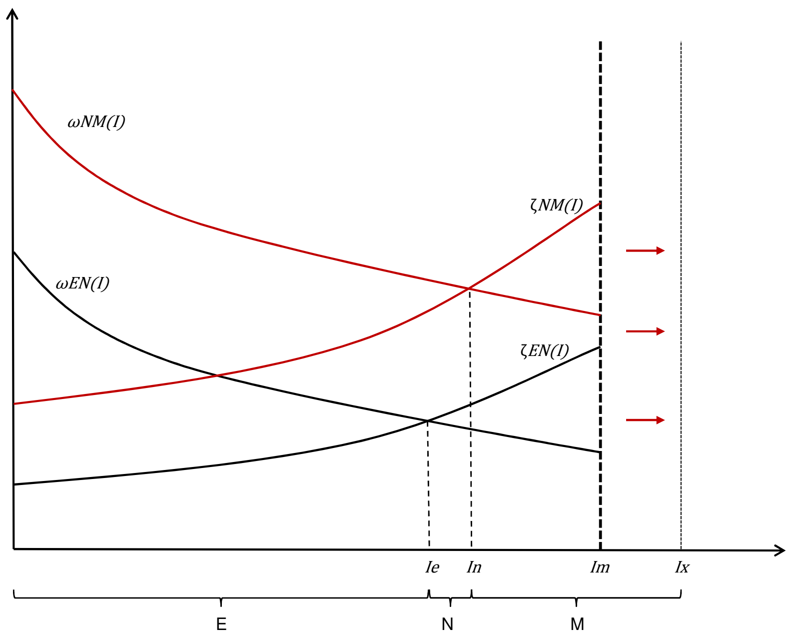

Figure 3: Three–upstream technologies case

Note: the arrival of a newer upstream technology M increases the competition for the downstream market based on comparative advantages and costs. In this case, the newer technology 'steals' downstream market shares to N, and the whole market is shared on rather equal basis by the three alternative upstream technologies.

externalities. In fact, 'learning is just part of the story: independent scientific advances as well as massive investments in purposive R&D have contributed as much to the staggering pace of technical advance (...)' (Bresnahan and Trajtenberg, 1992, p. 8). Such 'massive investments in purposive R&D', realized either supporting private actors or by directly intervening in the economy can be represented in the model. Policy interventions affect either the usefulness or the cost of the upstream technologies, and can be therefore by expressed as discrete changes in z's and w's. Accordingly, $\Delta z_j(I)$ and $\Delta w_j(I)$ are the magnitudes of policy interventions, where $j = \{E, N\}$ indicates that policy can affect one, the other, or all the upstream technologies. Policy can intervene either on the economic or technological side, or even in policy–mix fashion.

For example, a policy easing the establishment of contacts and linkages among firms belonging to different industries (e.g. a cluster policy or the support to multidisciplinary science parks) affects the usefulness dimensions. Better information on the features of the upstream technologies, resulting from policies designed to favor exploration and experimentation can change the downstream distribution of thresholds for adoption. On the economic side, subsidy and tariff schemes influence the relative cost of the established technology compared to the new one. Interventions of this kind are evident in the case of upstream competition among alternative energy supply technologies, where governments support the entrant upstream technologies — namely renewable technologies — intervening on the relative prices discriminating by the source of energy.

A purposive 'push' in one of the upstream technologies shifts the borderline application (applications, in the three upstream technologies case), helping one or the other upstream component to defend its share of downstream user from the competing technologies or to ease the process of purposes acquisition. In short, public intervention can act on different upstream levers, leading the system to one out of many possible specialization patterns. Public policy can also decide to allocate its efforts to sustain different upstream technologies at the same moment with the objective to explore different trajectories in parallel (Cohen and Klepper, 1992).

Policy interventions, therefore, affect not just the intensity of innovative activities, but their direction as well. An interesting point to be mentioned in this context is that the possibility of parallel explorations of different trajectories (upstream technologies) allows the economic system as a whole to screen a wider set of states of the world. However, the allocation of resources to alternative and competitive ends reduces the 'demand effect' that has been identified as key to kick–in dual inducement dynamics; this, in turn, raises the chances that a potential GPT gets locked–in to an inferior equilibrium in terms of performance and size of the user base.

The policy discussion just provided has important real–world implications. In fact, the recent revival of interest about industrial policy (Pianta, 2015) and the role of state in fostering the rate and direction of innovative activities (Nelson, 1962; Mazzucato, 2016) calls for a more sophisticated rationale for the support of research and innovative activities — a support to be provided in a complex environment and through well–designed non–trivial mechanisms. Our insights on how the road to technological pervasiveness and economies' structural transformation may be not so linear and smooth can be of help here: policy–makers have many levers for action at their disposal, but must be aware that the success of any 'strategy of economic development' (Hirschman, 1958) relies on the fine–tuning of the structure of industrial linkages and their dynamic adjustment driven by technological change.

The policy–related thought experiments allowed by the comparative statics of the model are certainly a simplification with respect to the contextual and history–dependent factors influencing the outcome of competition between alternatives. In fact, the convergence towards technological monopolies (the lock–in problem) is a well–known feature of history–dependent processes of choice and diffusion (Arthur, 1989; David, 1985) that can be tackled from several perspectives — path dependency being only one process among others like, for example, path renewal and path creation (Cantner and Vannuccini, 2016). However, recent contributions (Bassanini and Dosi, 2006) offer a 'milder' view on technological monopolies and suggest that room is open of intervention — including policy intervention — allowing an escape from lock–in. In sum, the process of purpose acquisition occurring when technologies compete for pervasiveness in a linked–payoffs setting is constrained by history and the attraction exerted by established dominant options, and induced by purposeful interventions and changes in the relative usefulness and cost relationships. However, as history–dependent processes are by definition unfolding in time, an assessment of their relevance for our argument has to build on a dynamic version of the model. Considered that, we provide this extension in the next paragraph.

3.5 A Simple Dynamic Setting

The static version of the model illustrates the main claim of the paper: when more than one candidate GPT compete as an upstream technology for a downstream market of applications, a potential GPT can either succeed or fail to gain pervasiveness. A GPT is not anymore assumed to exist a priori in the economy — the case is instead that of a specific–purpose upstream technology that acquires purposes and becomes a GPT. A dynamic extension of the model can, however, shed some light on how different outcomes in the competition for the downstream market are obtained, meaning how different equilibria in the structure of specialization of the downstream economy can be reached. Dynamic models of technology competition and diffusion such as the one of Loch and Huberman (1999) describe how adoption of alternatives evolves over time, usually modeling it as function of performance, in turn affected by network effects. The case described in our model is, however, different, as the population of adopters (the downstream applications) is heterogeneous. This means that performance does not depend only on technology characteristics (for example, expected returns or profits) and market characteristics (the magnitude of network externalities) but also on application–specific preferences (thresholds) that are captured by the shape of the $\zeta(I)$ curve.

Let's consider again the two–upstream technologies case. A dynamic version of the model has to determine the law of motion of three variables: $\zeta(I)$, $\omega(I)$ and I_e. Following Cimoli (1988), it is useful to derive first a scalar measure for the responsiveness of the downstream specialization to changes in the fundamental technological and economic conditions. To ease the reading, the functions $\zeta(I)$ and $\omega(I)$ are indicated as ζ and ω. We define

$$\epsilon_{I_e,\omega} = \frac{\partial I_e}{I_e}\frac{\omega}{\partial \omega}$$

as the comparative costs elasticity of the borderline downstream application. $\epsilon_{I_e,\omega}$ indicates, for a given $\zeta(I)$ function, the percentage change in borderline application given a percentage change in the relative cost of the two upstream technologies. As the new upstream technology gets more expensive (cheaper) relatively to the established one, the threshold downstream sector moves rightwards (leftwards) at a higher rate the higher is $\epsilon_{I_e,\omega}$. A similar expression can be derived for the comparative usefulness elasticity of the borderline downstream application, $\epsilon_{I_e,\zeta}$, where

$$\epsilon_{I_e,\zeta} = \frac{\partial I_e}{I_e}\frac{\zeta}{\partial \zeta}$$

indicates the percentage change in the borderline application given a percentage change in the relative usefulness of the new upstream technology with respect to the established one. The higher $\epsilon_{I_e,\zeta}$, the bigger the share of downstream market the new upstream gains (lose) if its quality improves (worsen) relatively to the established one.

The dynamics of I_e can be modeled as follows:

$$\frac{\partial I_e}{\partial t} \equiv \dot{I}_e = I_e E_{I_e,\omega,\zeta}\left[\dot{\zeta}(I) - \dot{\omega}(I)\right] \tag{1}$$

where $E_{I_e,\omega,\zeta} = \frac{\epsilon_{I_e,\omega}\cdot\epsilon_{I_e,\zeta}}{\epsilon_{I_e,\omega}+\epsilon_{I_e,\zeta}}$ is the elasticity of I_e with respect to any changes of the ω and ζ functions. A dot indicates the absolute change of a variable and t is the time index. The dynamics of the borderline downstream application is a function of the current state I_e, of the elasticity E and of the net absolute changes of the relative usefulness and cost curves. These can be expressed as

$$\frac{\partial \zeta(I)}{\partial t} \equiv \dot{\zeta}(I) = \hat{z}_N - \hat{z}_E \tag{2}$$

$$\frac{\partial \omega(I)}{\partial t} \equiv \dot{\omega}(I) = \hat{w}_N - \hat{w}_E \tag{3}$$

where a hat over a variable indicates a growth rate. Each comparative curve evolution results from the net change between the numerator and the denominator. Inserting equations 2 and 3 into 1 we have

$$\frac{\partial I_e}{\partial t} \equiv \dot{I}_e = I_e E_{I_e,\omega,\zeta} \left[(\hat{z}_N - \hat{z}_E) + (\hat{w}_E - \hat{w}_N) \right] \tag{4}$$

Functional forms are kept implicit until now. In order to identify an equilibrium I_e, we need to specify them. It is reasonable to assume that either the relative usefulness or the relative cost is affected by network effects (Arthur, 1989; Farrell and Klemperer, 2007), that is, by the number of downstream application attached either to N or E. Another way to measure the network effect is by the size of the intervals $]0, I_e]$ and $]I_e, I_n]$. Setting $I_n = 1$ (meaning that we fit the continuum of downstream applications to the unit support),[11] the number of downstream users of E is I_e, while the number of downstream users of N is $(1 - I_e)$.

On the performance side, introducing network effects equals to say that as the gap in usefulness widens, the more downstream applications switch to use upstream technology N. On the cost side, the network effects play a role on the steepness of learning curves: the more downstream applications switch to N, the faster the new upstream technology can reduce its price. As the focus of the paper is to model acquired purposes, we assume for consistency that network effects play a role only on the performance side: as diffusion of the new upstream technology takes place, the relative usefulness perceived increases. This is a proxy for the process of discovery of new purposes that over time makes a specific purpose technology to gain pervasiveness downstream and to become a GPT. Of course, in real–world contexts network effects do play a role on both the technological and the economic side.

As a caveat, it is important to stress here that the network externalities as modeled here are not an exact proxy for the dual inducement mechanism that in BT takes place between the single GPT existing in the market and its applications. In fact, while the dual inducement is confined to incentives to innovative activities, here we take a broader perspective that incorporates technological and economic determinants. Moreover, downstream industries do not optimize over any choice variable, but just react to upstream relative performance and cost. In our model, however, an increase in relative usefulness triggers an increase in downstream adoption, and vice versa. A mutual feedback similar to the dual inducement mechanism is therefore indirectly captured.

We assume for the moment that upstream technology purchasing costs for E and N are the same for each I (since all downstream applications purchase one unit of upstream component

[11] Or $I_x = 1$, in case new downstream industries emerge together with N.

at the same price from the same supplier), so that $w_{j,I} = w_j$ for $j = \{E, N\}$ is constant over the downstream continuum. The dynamics of w_j follows a simplified learning curve over time of the type

$$\dot{w}_j = -\gamma_j w_j \tag{5}$$

with $\gamma_j = -\hat{w}_j$ as the (negative) upstream technology constant (and technology specific) percentage rate of cost reduction. As concerns performance, we model improvements in usefulness — and thus acquisition of purposes — as a function of downstream adoption. The process of performance improvement is usually represented as following an S–shaped pattern (Loch and Huberman, 1999); here we opt for a simpler linear version:

$$\dot{z}_N = \theta_N z_N(I)(1 - I_e) \tag{6}$$

$$\dot{z}_E = \theta_E z_E(I)(I_e). \tag{7}$$

We assume also that the z function takes the shape $z_j(I) = e^{\alpha_j I}$ for $j = \{E, N\}$, to represent the monotonically increasing property of upstream technology usefulness along the downstream continuum. α is a technology specific scaling parameter, while θ captures an exogenous rate of technological improvement that is also dependent on the upstream technology chosen. From this, equations 6 and 7 become

$$\dot{z}_N = \theta_N e^{\alpha_N I}(1 - I_e) \tag{8}$$

$$\dot{z}_E = \theta_E e^{\alpha_E I}(I_e) \tag{9}$$

and the respective growth rates

$$\hat{z}_N = \theta_N(1 - I_e) \tag{10}$$

$$\hat{z}_E = \theta_E(I_e) \tag{11}$$

The percentage change in the usefulness of E and N depends therefore only on the exogenous parameter and — endogenously — on the respective downstream market shares.

Inserting 5, 10 and 11 in 4 we obtain

$$\frac{\partial I_e}{\partial t} \equiv \dot{I}_e = I_e E_{I_e,\omega,\zeta}\left[(\theta_N(1 - I_e) - \theta_E(I_e)) + (\gamma_N - \gamma_E)\right] \tag{12}$$

The structural equilibrium is identified when $\dot{I}_e = 0$, where the changes in relative usefulness and relative cost perfectly compensate each other. One trivial equilibrium is obtained in the corner solution in which N fully dominates the market. This occurs when $I_e = 0$. This means that, using the categories introduced in the static setting, only in the niche case,[12] when relative

[12]And only assuming that the interval $]I_n, I_x] = 0$ or that the downstream industries that emerge together with upstream technology N do not generate any network effect.

usefulness and cost do not intersect, the new upstream fails to gain pervasiveness and to become a GPT. As soon as N is adopted by a minimum share of downstream application, the system moves to the stable equilibrium in which $I_e = 0$, as shown in Figure 4. For N to fail to gain pervasiveness equation either one or both the elasticity terms are zero (meaning that one or both the curves are rigid), or 12 has to show multiple equilibria. However, this is possible only when non–linearity in the shape of the curves is introduced. We do that by relaxing the assumption that costs change uniformly along the downstream continuum. One justification for this is related to the possibility for the established upstream technology to 'fight back', meaning to actively respond to the challenge to dominance started by the new upstream technology.[13] An illustration of this 'incumbent reaction', that somehow captures what is usually called the 'sailing–ship effect' (De Liso and Filatrella, 2008), is represented through the following law of motion for the cost curves:

$$\dot{w}_N = (-\gamma_N - Ie^{-\beta I})w_N \tag{13}$$

$$\dot{w}_E = -\gamma_E w_E \tag{14}$$

where the term $Ie^{-\beta I}$ indicates that besides the exogenous component γ_N the percentage decrease in upstream technology cost of N is also function of the specific downstream application, and $\beta > 1$ is a parameter. The higher in the ranking a downstream sector is, the higher its potential cost reduction, but also the stronger the reaction of the established technology. Eventually, the potential effect and the reaction effect interact, generating a bell–shaped function. Dividing by w_j we obtain the percentage changes and thus the equation for $\dot{\omega}(I)$, from 3 yields $\dot{\omega}(I) = \gamma_E - \gamma_N - Ie^{-\beta I}$.

Plugging the expression for $\dot{\omega}(I)$ just derived into 12 we find the new law of motion for I_e:

$$\frac{\partial I_e}{\partial t} \equiv \dot{I}_e = I_e E_{I_e,\omega,\zeta}\left[(\theta_N(1 - I_e) - \theta_E(I_e)) + (\gamma_N + Ie^{-\beta I} - \gamma_E)\right] \tag{15}$$

In this case, the more N gains purposes, so I_e shifts to the right, the more ω increases its convexity. Depending on the elasticity of ω, the response of the established technology can lead to two structural equilibria (as shown in Figure 5), the leftmost being locally stable and the rightmost being unstable.

In sum, by turning to a dynamic setting, we are able to outline the processes influencing the pervasiveness in the making of a potential GPT. First, the competitive context matters. This is captured by the relative usefulness and cost curves and their elasticities; in other words, but the gap in performance and cost between alternatives and how this gap 'weights' with respect to the specialization of the downstream economy. Second, the presence of network externalities drives the dynamics of purposes acquisition. Third, the resistance of incumbent established upstream technologies creates the conditions for drifting the process from certain technological monopolization towards co–existence of technologies.

[13] An alternative way to is to assume that network effects have decreasing returns, so that increasing adoption rates lead to further adoption, however at a slower pace.

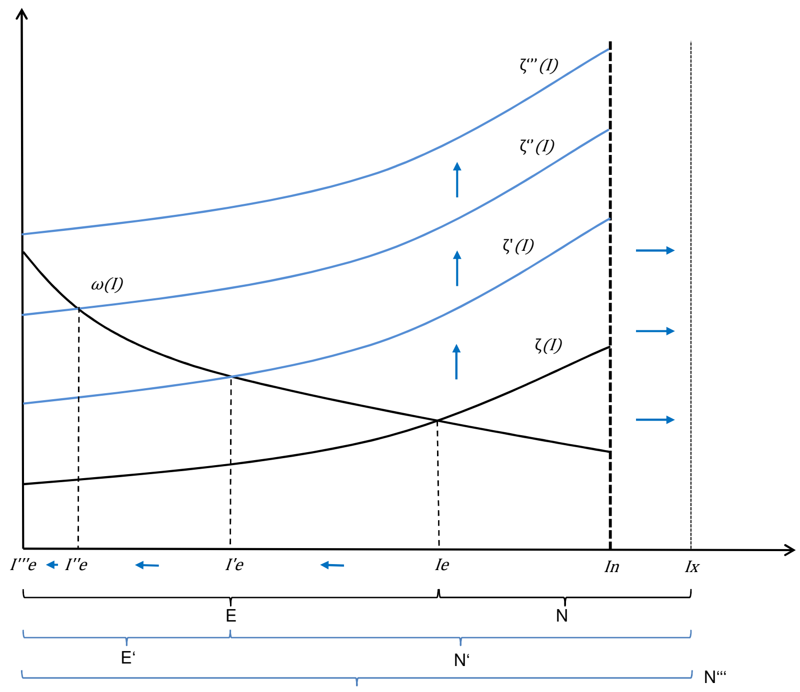

Figure 4: Dynamics of the Ricardian model — acquired pervasiveness of technology N

Note: the chart shows the dynamics of the model when $\dot{I}_e$ is affected by network effects operating on the $\zeta(I)$ function. The equilibrium is identified when $I_e = 0$ — meaning that the whole downstream market is served by the new upstream technology.

4 Discussion and Conclusion

In this paper, we studied the factors and mechanism shaping technological pervasiveness within industrial linkages. In order to do that, we chose a novel conceptual path: that of generalizing the theory of GPTs to a theory of upstream technological competition for a downstream market of heterogeneous potential applications. To describe our phenomenon of interest, we combined contributions belonging to different strands of literature: economic linkages, GPTs, network effects, technology evolution, and structural change. We defined a ‘purposes acquisition’ process as the dynamics leading a technology, developed to deploy specific functions or to solve specific problems, to identify further purposes and uses than the ones the technology was originally planned or designed for. In short, we created a bridge between neoclassical and evolutionary thinking by developing a specific literature (that on GPTs) as a special case of a broader trajectory delving into the process of economic transformation around core ‘infrastructural’ upstream technologies.

To illustrate that, we applied a simplified version of the Ricardian model of international specialization (Dornbusch et al., 1977) to a context of industries connected in a hierarchical (vertical) relation. In order to highlight the role different factors play in the competition for the downstream market, we kept a distinction between technological and economic explanatory variables. The model, notwithstanding its basic setting and the fact that it does not explic-

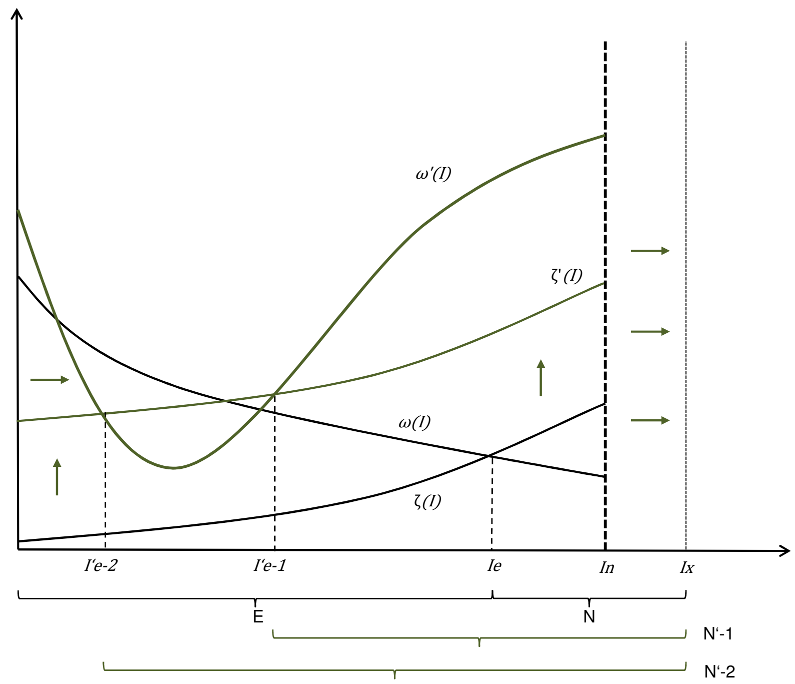

Figure 5: Dynamics of the Ricardian model — multiple equilibria

Note: the chart shows the dynamics when the established technology 'strikes back' acting on $\omega(I)$, but in a heterogeneous way, function of the downstream continuum. Two equilibria are identified.

itly formalize the endogenous determination of payoffs, is useful to shift the focus of analysis towards relative (gap), rather than absolute dimensions. Learning mechanisms and feedbacks, as well as policy interventions, can be taken into account in a stylized way as comparative statics in the basic setting of the model. Also, it is showed that in the case featuring three upstream technologies the many possible specialization patterns that can occur in an economy with upstream–downstream linkages may lead to technological pervasiveness, to technological co–existence, and to non–pervasiveness (localized change), with potential GPTs that remain confined in downstream market niches.

From a critical viewpoint, it is possible to argue that while the paper claims that no GPT is foreseeable in advance, the model implicitly assigns the status of latent GPTs to the upstream technologies, therefore falling again into the 'a priori assumption' fallacy of GPT theories. On the one hand, such critique rightly points at a limitation of the paper; on the other hand, the main purpose of this study is to show how potential GPTs can fail to become a GPT given that to acquire purposes is not a trivial process but the result of technological competition in upstream markets. The model describes such process by offering a view based on comparative advantage and avoiding assuming which GPT dominates the market in equilibrium; this is a novel contribution that complements the existing literature.

Another critique has to do with the possibility to define a relative usefulness curve. Given the deep uncertainty characterizing new technologies, one can reasonably posit that some downstream industries have not just an imprecise valuation of the possible uses of upstream technologies, but that they do not have valuation at all, because the uses of the new upstream technology are not even considered among the possible states of the world. This remark, being certainly well taken, does not change the fact that downstream industries can always be ranked according to the relative benefit they expect from the new upstream technology. In case of deep uncertainty, the value of w_N will be 0 and the function $\zeta(I)$ in correspondence to those industries will lay on the horizontal axis. As our model produces evolutionary outcomes relying on a neoclassical framework, the possibility to derive a usefulness curve over the downstream continuum is granted by assumption. Our main argument is robust to different functional specifications, in the sense that a discontinuous or piece–wise non–continuous function, even though making impractical to identify equilibria, will not reverse our claims. In fact, a continuous $\zeta(I)$ function represents the less stringent context for our dynamics of interest to occur. If potential GPTs can fail to acquire purposes in a deterministic context, stochastic settings only increases the chance of this outcome.

From an evolutionary point of view, the model represents the competition for downstream market shares (where shares are the fraction of applications served by an upstream technology out of the total downstream market existing application). In this sense, it shares some features with the replicator dynamics model of Schumpeterian competition for the market (Metcalfe, 1994) and with models of reinforcement such as those building on the Polya urn setting (Marengo and Zeppini, 2016).

For what concerns the extensions of the model, a thorough derivation of endogenous dynamics should go in the direction to explain specialization patterns as a 'self–discovery' process in presence of uncertainty and learning (Hausmann and Rodrik, 2003). Another possible extension relates technological competition in vertically related markets to Industry Life Cycles theories (Klepper, 1996). Maybe even more relevant for a potential extension of the model, our study can be considered as the lower bound of simplification in modeling the shift of industrial linkages and the composition of an economy. A many–upstream to many–downstream assignment model — representing a fully-fledged dynamic input–output structure — is without doubts another direction worth exploring; this would contribute to an advancement of our understanding of micro– and meso–inducements driven by core technologies — a dynamics captured by now only by models on Long Waves such as Silverberg and Lehnert (1993). Finally, the empirical side of this research could be developed starting from decomposition exercises (Cantner and Krüger, 2008) to be extended to vertically related industries.

In sum, the main contributions of the paper are i) the framing of GPT theory into a general analysis of vertically related industries and pervasiveness formation through linkages; ii) the modeling of a downstream market choice when alternative upstream technologies are available and the dynamics of GPT establishment, from a 'specific' (niche) upstream industry to a pervasive one capturing broad structural change; iii) the resulting possibility for potential GPTs to fail to diffuse into the economy.

To conclude, the process leading to acquired purposes is not supposed to automatically lead to the establishment of a pervasive technology. Rather, the establishment of GPTs is a process that shares similarities with a complex phenomenon, with multiple possible (even if not equally possible) outcomes. Besides the technical features of technologies, it is the task and the responsibility of economic agents (including policy–makers) to determine which alternative specialization path is to be taken.

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- We model the ‘purpose acquisition process’ resulting in different degrees of technological pervasiveness
- We use our framework to provide a microeconomic explanation of the establishment of general purpose technologies
- We read contributions on general purpose technologies and structural change as special cases of linked markets
- We explore static and dynamics formulation of the model and discuss the determinant of pervasiveness also from a policy perspective