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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 henceforth)? Following the theoretical arguments of Cantner and Vannuccini (2012) as well as building on some critical issues of the received theory of GPTs (see Bresnahan 2010 and 2012 for the latest contributions) we provide a simple model of industrial dynamics accounting for the endogenous emergence of GPT-based industries. The model takes into account several conditions under which an upstream technology may succeed to emerge widely gaining pervasiveness or remains confined to small subsets of downstream applications in the economy. The paper contributes to a microeconomics of vertically related and dynamic industries by analyzing the pattern of technological specialization of an economy using a "ricardian" model. The policy dimension of the analysis is highlighted, as well as the potential empirical studies building on the proposed modeling framework.

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1. Introduction

Economic connectivity is fashion again. While input-output theorists and development scholars have always been interested in the inner structure of connections and bottlenecks (Hirschman, 1958) shaping economic systems in order to fine-tune public intervention and to identify the best routes for industrialization processes to escape a handful of "traps", standard economic modeling mostly focused its attention either on aggregated dynamics or on industry level structural features.

The analysis of the linkages between industries is recently experiencing a silent resurgence. We outline three main reasons, not mutually exclusive: (i) New and Schumpeterian growth theory reached an upper bound (or the decreasing returns part of the curve) of explanatory power, inducing scholars to investigate beyond the surface of aggregation and framing macro issues such as fluctuations as phenomena emerging from localized and micro 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 productive way to understand and represent production relations, industrial transformations (Carvahlo and Voigtländer, 2014; McNerney et al., 2013; Contreras and Fagiolo, 2014), specialization and international trade (Hidalgo and Hausmann, 2007; Hausmann and Hidalgo, 2011) and the dispersion of manufacturing in global value chains (Timmer et al., 2014); (iii) the economic crisis and a timely rediscover of the role of the public sector in the economy boosted a novel discussion on the aims and tools of industrial policy (Mazzucato, 2013; Hausmann and Rodrik, 2006; Foray, 2014; Stiglitz et al., 2013).

The three trends described above produced increasing returns in use for useful theoretical building blocks that were confined until recently in the niches of appreciative theorizing, evolutionary, innovation and development economics, granting them additional shares in the market for ideas. Concepts such as coordination problems and multiple equilibria (Hoff, 2000; Stiglitz, 1987; Stiglitz and Greenwald, 2014), learning, ergodic and out-of-equilibrium processes (Arthur, 2013), positive feedbacks, linkages (Hirschman, 1958) blossom again and enter the toolbox of economists. The nature of these concepts, rooted in strategic interaction and path-dependence, helps to highlight the need for well-known economic stylized facts and dynamics to be grounded and conditioned on the state of connectivity.

More specifically, stating that economic outcomes depend on the structure of connectivity – that is on the strength and distribution of linkages between the units of analysis – has consequences for the study of industrial dynamics – especially for what concerns some unresolved puzzles. For example – as claimed before – the endogenous technological and economic mechanisms at work in a market leading to well-known stylized facts and regularities regarding selection (Cantner, Krüger and Sollner, 2012), turbulence (Cantner and Krüger, 2004) and industry (product) life cycles patterns (Klepper and Graddy, 1990; Klepper, 1996) may be just a part of a larger story. Connectivity may affect the speed of selection and survival probabilities, the rate and pace of technological progress, the duration of cycles or their taking place at all. In other words, external effects may play a much broader role in innovation and economic activities than it is usually accounted for.

In this paper we study how connectivity affects some structural features of an economy, namely the technological specialization of industries (their upgrading, in development economics jargon) and the acquired pervasiveness of a certain technology. The idea that ties matter in influencing firms' behaviors is not new: in innovation economics the debate on open innovation, cooperative invention, R&D collaborations and patent networks (Cantner and Graf, 2006) is well developed. 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, 2002).

At one end of the "catalogue" of potential connectivity structures, the more stylized and simple case to be studied is that involving an upstream-downstream relation between a supplier and a customer industry. While 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), what is interesting in our view is 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 of, on the one hand, two-sided markets models and platforms (standards) formation and, on the other hand, of organizational ecologies' densities interdependencies (De Figueiredo and Silverman, 2012). We focus on a case which stands in the middle between a unique upstream connection and a more complex network structure: that of a vertical (so hierarchical) relation between a handful of upstream sectors and a large set of downstream applications.

In a sense, we classify under the rubric of industries' linked payoffs the theory of General Purpose Technologies, henceforth labeled as GPT (Bresnahan and Trajtenberg, 1992; 1995; Bresnahan, 2010; Cantner and Vannuccini, 2012). While GPT theory has been developed in industrial organization (Bresnahan and Trajtenberg, 1995), growth theory (Helpman and Trajtenberg, 1998) and also evolutionary approaches (Carlaw and Lipsey, 2006; 2011) its "general purpose" features have barely been extended to a full-fledged theory of economic connectivity and linked payoffs in the context of vertical industries relations. We fill this gap by extending the coordination problem and the externalities arising from the GPT structural features to the case in which the GPT is not decided a priori, and the prevailing and pervasive upstream technology emerges from a feedback mechanism that may feature different degrees of connectivity with one or another upstream industry. The motivation for such a contribution lies in the definitional underpinnings of the GPT concept (Cantner and Vannuccini, 2012; Fields, 2008), which "has come under growing attack" (Ristuccia and Solomou, 2010).

In standard GPT models vertical connectivity is key – for economic performances and most importantly for innovation performances, given the existence of the so-called "dual inducement mechanism" between generic technologies (core components) and applications – but the problem in such context is just to determine and solve the coordination issue between downstream industries and a pre-determined upstream sector. Coordination is therefore *wanted*; a linked payoffs structure may lead to deviations from such wanted coordination and carry inferior outcomes with respect to the social optimum, due to horizontal and vertical externalities (Bresnahan and Trajtenberg, 1995). Such result is related to the well-known double marginalization problem (Tirole, 1988), studying the suboptimal outcomes of monopolistic market structures in upstream industries. In our exercise, coordination is *unwanted*, in the sense that the upstream sector is not aware of its GPT "status"; it learns it through its (successful or not) dynamics toward prevalence, persistence and pervasiveness (Cantner and Vannuccini, 2012).

Modeling the specialization structure of a stylized economy with vertical relations is closely connected with four strands of literature: first, there are similarities with models dealing with infant industries and early stages of industrialization (Hausmann and Rodrik, 2003; Hoff, 1997), so that we may think of ours as a case of "infant technology" development. Second, modeling the problem of "acquired purposes" closely resembles the issues that studies on specialization and competing technologies (Arthur, 1989) deal with. Third, modeling the process of purposes acquisition through feedbacks and connectivity in the economy can be framed as a standard problem in industry dynamics, which is that of entry/exit patterns. In our case the "agent" who enters is not a firm, but an entire industry that enters in the (potential) GPT sector. Fourth, the paper enriches the theory of retardation (Metcalfe, 2003): when payoffs are linked, meaning when technological progress is function of investments or expenditure choices taken upstream, the dynamics of output growth rates (retardation or acceleration) may result from a non-trivial causal mechanism.

The paper simplifies the issues at stake, modeling acquired purposes as a case of dynamic specialization in an economy structured in a hierarchical way, limited to an upstream and a downstream level. We proceed as follows: Section two lists the theoretical building blocks to be used later on in the modeling exercise. Section three describes a simple Ricardian (toy) model and derives some comparative statics under different model settings. Section four discuss possible extensions and concludes.

2. Theoretical Building blocks

A first theoretical building block for our model comes from Bresnahan and Trajtenberg (1992; in what follows we refer to the journal version of the study, unless the contents of interest are available only in the 1992 extended working paper). They explore the simplest case of vertical relationship between industries: a "hierarchical pattern" of technological interdependence between one GPT sector and many downstream application sectors (AS). They define an AS "*as one 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"* (Bresnhahan and Trajtenberg, 1992, p. 11).

In short, the Bresnahan and Trajtenberg model is a coordination game in innovative activities with linked payoffs that produce on the one hand a potential positive feedback process (a so-called dual inducement mechanism) and, on the other hand, suboptimal equilibria due to a vertical externality (linked payoffs between GPT and AS – a bilateral moral hazard problem) and an horizontal one (linked payoffs between AS given their indirect connection through the GPT). The main variables affecting sectors' optimal decision making (via the expected gross returns on innovative activities for the AS and the expected profits for the GPT) are z (a scalar for the GPT technical "quality"), w (the price for the GPT input) and c (the constant marginal cost of production for the GPT sector), that is, both economic and technological explanatory variables are considered.

A pseudo-diffusion/adoption process – usually overlooked in the Bresnahan and Trajtenberg model, probably because it is formally developed only in its working paper version – is captured by assuming an invariant ranking of AS's with respect to $V(w, z)$ (the AS's value function of innovation gross rents) and letting z and w to vary in order to determine the unique "marginal" AS that finds profitable to adopt the GPT. 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), 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). Such an adoption mechanism already unveils a sort of purposes acquisition process, however *ceteris paribus* the presence of an already established GPT. In order to establish a direct connection with the previous literature, our model represents the industries' vertical relations in the same fashion and uses the same set of explanatory variables.

Besides the modeling strategy, our paper's claims are justified by a second theoretical building block regarding the representation of the process of technological takeover. In Adner and Zemsky (2005) which – to our knowledge – is the only attempt to model the process of pervasive technology "in the making", we find a formal discussion of the conditions for a disruption to occur. The authors carefully explore the economic conditions for a novel technology either to invade the mainstream market (and the timing of such invasion) or to remain confined in a niche in the case of two competing technologies and heterogeneously distributed firms' willingness to pay. Even if the argument there is not made explicit, the model can be framed as a one of technological specialization in upstream competing technologies and serves to our purpose to show the multiple equilibria in a vertically related market with linked payoffs and more than one GPT. Adner and Levinthal (2002) make a conceptual step beyond the model and compare the pervasiveness in the making of a technology with the evolutionary phenomenon of speciation. Speciation in the economy is the application of existing technologies to a new domain of application, just as a candidate GPT gains shares in the downstream application domain. The same process is labeled as technological upgrading in development theory (Stiglitz et al., 2013) and re-domaining in complexity economics (Arthur, 2009) and can be thought as a case of technological structural change, involving the transformation of the technological base of industries rather than employment allocation through broad sectors.

In what follows the theoretical building blocks just discussed are used to construct a toy model of GPT emergence and acquired purposes.

3. A Ricardian Model of Technological Specialization

We propose a simple model that represents the dynamics of purposes acquisition when more than one upstream technology is available in the market. The outcome of the resulting competition for downstream activities (consumers of the upstream product, a "generic" technological component) may vary according to the structural economic and technological variables at work. We distinguish three broad outcomes: (i) a new upstream technology gains pervasiveness in the market and in the limit takes over and "serves" the whole economy; (ii) an established upstream technology maintains its pervasiveness in the economy and a novel one remains confined in a niche; (iii) a third, newer upstream technology displaces the new one, making the former a sort of "failed GPT". The units of analysis of the model are generic individual industries, meaning that firm behavior is not explicitly taken into account (as in Durlauf, 1993). For the purposes of our paper 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 could only magnify a phenomena already emerging under more simplifying restrictions.

The model is a modification of the Fisher, Dornbusch and Samuelson (1977) matching model of international specialization in line with Cantner and Hanusch (1993) and Acemoglu and Autor (2011). In our version the match occurs between upstream technologies/industries (instead of countries in Cantner and Hanusch and skills/labor in Acemoglu and Autor) and downstream industries (instead of products in Cantner and Hanusch and tasks in Acemoglu and Autor). For the sake of generality, hereinafter instead of "downstream industries" we use the broader term "downstream applications", in order to take into account a more disaggregated and richer set of activities.

We first develop a two-upstream industries case (featuring an established and a novel upstream technology) that we later extend to a more interesting three-upstream industries scenario.

3.1. The Case of Two Competing Upstream Industries

We assume that each upstream sector produces a single technology (so that the use of the terms upstream industry and upstream technology in the paper is indifferent). The upstream technology is in turn used as a unique component in the downstream applications' production function. Upstream industries are labeled E (for the established technology), N (for the new technology) and M (in the three upstream industries case, for the lastly appeared newer technology). Given that downstream applications' production technology depends only on the upstream product, they can be differentiated by their valuation 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.

In Cantner and Hanusch (1993) products are characterized by a labor requirement (the inverse of labor productivity), with a decrease in labor requirement capturing an increase in production efficiency. If consumer demand is constant, there is neither population growth nor quantity expansion and firms earn zero profits – a rather rare case that however may fit with a mature economy in steady state. In our model we assume that – for example due to strong complementarities – the upstream components quantity requirement is constant (and normalize it to one) and what change are just the rents of using one or the other upstream technology. The ranking over the continuum of downstream applications, which is assumed to be invariant over time, distributes them therefore according to the relative benefit of using the new upstream technology. With relative benefit we mean the returns for a downstream application to "attach" to the new upstream industry compared with the choice of staying with the established one. This is therefore a measure summarizing in a scalar a number of features that are well known in the literature, such as technological intensity or performance gap (Cantner and Hanusch, 1993, p. 220), relative technological opportunities (Dasgupta and Stiglitz, 1980), price/performance sensitivity (Pavitt 1984; Dosi and Nelson 2010; Almudì et al., 2013) or relative willingness to pay for the upstream technologies. All these are potential proxies for the *easiness* of technology switch, and represent the technological side of model in terms of the relative usefulness of a specific up-stream technology.

Since all the above measures can be interpreted as functions of the perceived "usefulness" of the GPT, we call $z_j(I)$ such application-dependent usefulness, where $j = \{E, N\}$, E is the established and N the novel upstream technology. The specific 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 $\xi(I) = z_N(I)/z_E(I)$, the relative technological usefulness (attractiveness) of upstream industries. It is important to highlight here that while in Bresnahan and Trajtenberg model z is a unique value (the GPT "quality") known to all the AS, in our case z is a downstream application valuation of the upstream technology quality. The model is deterministic, hence we do not interpret w 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 propensities and the model can be included in the class of probit or threshold models of adoption (Geroski, 2001).

Given that it is defined over the span of downstream applications, $\xi(I)$ is a function – the relative (upstream) technology usefulness (performance) curve. Following Cantner and Hanusch (1993) we make the following assumptions on the shape of $\xi(I)$: (i) it is continuous and differentiable in $[0; I_n]$; (II) it is monotonically increasing in I due to the downstream applications' ordering, with $\xi' > 0$; (iii) it is reversible ($\xi^{-1}(I)$ does exists). In short, $\xi(I)$ represents the comparative increasing rewards obtained purchasing the new upstream components rather than the established one. At this point, it has to be added that industry size does not play a role in the model; in particular each downstream application, defined over an infinite continuum, has an infinitesimal size with respect to the whole economy. Sub-intervals of technologically proximate applications may be identified and aggregated in order to identify broad industries and to provide a more realistic representation of the unequal weight of economic sectors in the economy; such a refinement is left aside in the baseline version of the model, even if 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 matching, the technology relative usefulness (performance) curve has to be coupled with a relative cost curve. While in Dornbusch, Fisher and Samuelson (1977) and in Cantner and Hanusch (1993) the corresponding curve (which in their model is characterized as a demand relation to be coupled with the international goods supply) is defined as the integration of consumption shares over the continuum of goods given the Cobb-Douglas preferences of consumers, here we simplify the model assuming a mapping between price and cost of the upstream technology. Again from Bresnahan and Trajtenberg (1995) we define $w_j(I)$ as the cost of the upstream technology, (where once again $j = \{E, N\}$, E is the established and N the novel upstream technology). We do not deal with price-cost margins (and so profits) in the upstream market, because the change in downstream market shares is completely driven by downstream applications' adoption decisions. The ratio $\omega(I) = w_N(I)/w_E(I)$ represents the relative cost (downstream expenditure) curve; regarding the shape of $\omega(I)$ the same assumptions we made on $\xi(I)$ hold, with the difference that – *ceteris paribus* the applications' ranking – the novel upstream technology will be relative more (less) costly for downstream applications with comparative disadvantage (advantage) in switching, meaning that $\omega(I)$ is monotonically decreasing in I. Such a formulation is more flexible to be used for comparative statics purposes, but $\omega(I)$ can also be modeled as constant, meaning that no comparative advantage (disadvantage) exists and that the relative cost is stable over the whole distribution of applications propensity to demand one of the available upstream technologies.

In general, the model determines an industry I_e that separates the market between applications using upstream component E and applications using upstream component 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

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

which transforms in a usefulness/cost ratio $z_j(I)/w_j(I)$. By the properties of the ξ- and the ω-functions there is a downstream application I_e for which the following holds:

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

In I_e the model yields the unique threshold or borderline downstream application that is indifferent in the choice of upstream technology. In addition to the identification 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 could be applied to the length of the $]0, I_e]$ and $]I_e, I_n]$ intervals to define and evaluate the GPT nature of each upstream technology and to track the dynamics of the purposes acquisition process.

The endogeneity of $\xi(I)$ and $\omega(I)$ curves' determination is purposefully avoided in the model, in order to decompose the effect of pure technological and pure economic determinants of the specialization towards one or the other upstream industry. Feedback mechanisms both on the demand and supply side can be easily included by fractioning the dynamic adjustment process of specialization in one or the other upstream technology in a sequence of "screenshots", studying the movement of the curves in a comparative statics way. For example, the presence of dual inducements – downstream adoption improves the quality of the upstream and vice versa – can be modeled as shift towards the left of the $\xi(I)$ curve while the presence of learning-curve features (Arrow, 1962; Thompson, 2010), meaning that the gains in efficiency of one technology production are captured by a movement on the left of the $\omega(I)$ curve (with $w_N(I)$ decreasing more 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 $\xi(I)$ and $\omega(I)$.

A graphical representation of the model is provided in Figures 1a to 1c, showing some cases of shift in $\xi(I)$, $\omega(l)$ as well as the possibility of new downstream applications' entry in the market that we are going to analyze next.

3.2. Further Discussion on the Two-upstreams Case

As anticipated in the beginning of the paragraph, two solutions are the main outcomes of the two-upstream case. We can label them as the *competition (and potential takeover) case* and the *niche case*. They respectively mirror the "Ricardo case" and the "innovation case" in Cantner and Hanusch (1993). In the first scenario, the shape of $\xi(I)$ and $\omega(I)$ determines the 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 (and potentially to a locked-in situation). In this sub-case, the new upstream technology may well be labeled as a GPT, but only after a dynamic feedback process lead it in the position to serve the largest share of the downstream market – which is just a way to describe its gained pervasiveness.

In the second scenario, that we label "niche" case, $\xi(I)$ and $\omega(I)$ do not intersect, so that despite the increasing attractiveness and comparative advantage of the new upstream over the downstream applications distribution the technological argument does not compensate for the economic one, with $\omega(I)$ lying completely above $\xi(I)$, 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 for a limited set (at the limit one or none) of applications. A niche case can always turn into a competition/takeover case, when a shift on the left of $\xi(I)$ 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 take account for the dynamics put in place by the emergence of new downstream applications (for example novel downstream products and infant economic activities). 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 including the applications adopting the upstream technology *N*, from the borderline I_e to 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 only produce for the end market if connected to the new upstream technology, meaning that they add in an ordered way to the applications ranking (formally, they have an infinitely high comparative advantage in $\xi(I)$ and an infinitely low $\omega(I)$. The presence of newborn downstream applications provides the new upstream technology with a buffer stock of users. In presence of positive feedbacks from the number of adopters to the increasing comparative advantage in adoption (meaning that $\dot{z}_j$ and $\dot{w}_j$ are function of the sizes of the applications intervals served) such a stock may trigger a purposes acquisition dynamics.

3.3. Three Competing Upstream Industries

The deterministic model outlined above can be extended to the case of three (and more) upstream technology. Following Acemoglu and Autor (2011), we introduce in the set of upstream technologies a newer one (labeled *M*). Given that downstream applications already face the decision to stay or switch according to the value and shape taken by the comparative returns and comparative costs curves between E and *N*, to find the new market matching between the vertically related industries it is sufficient to derive two new curves, describing the relative performances (gap) between upstreams *N* and *M*. Assuming that the ranking of downstream applications remains unchanged, we rename $\xi(I)$ and $\omega(I)$ as $\xi_{EN}(I)$ and $\omega_{EN}(I)$and introduce $\xi_{NM}(I)$ and $\omega_{NM}(I)$ as the two new comparative relations. The same assumptions on continuity, monotonicity and reversibility hold.

Movements of $\xi_{EN}(I)$, $\omega_{EN}(I)$, $\xi_{NM}(I)$ 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 takeover 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 upstreams case can be further extended to a many-to-many relations model, with – in the limit – a continuum of downstream applications matching with a continuum of upstream technologies. However, the three upstream industries case is already general enough to highlight how the standard GPT model is just a specific case of a model of competing technologies in a hierarchical setting that produces a richer set of outcomes and structural configurations.

3.4. Policy Interventions

Our model also allows for policy experiments. Since Bresnahan and Trajtenberg (1995) we know that in a GPT framework policy intervention, in form of well-designed contracts and public procurement is key to solve the coordination problem and to push the mutual innovation incentives game to higher equilibria by internalizing the vertical and horizontal externalities. In general, "*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", either supporting private actors or directly intervening in the economy can be included in the Ricardian model. Policy interventions affect either the usefulness or the cost of the upstream technologies. A purposive "push" in one of the upstream shifts the borderline application (applications, in the three upstreams 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 may act on different upstream "levers", leading the system to one out of many possible specialization patterns. Public policy may also decide to allocate its efforts to sustain different upstream technologies at the same moment, therefore influencing the conditions for competition.

4. Conclusions and Further Research

In this paper we contributed to the re-emerging research endeavor on economic connectivity by focusing on the specific case of linked payoffs in vertically related industries. Such a case generalizes the theory of general purpose technologies by offering a broader view on upstream technological competition and on the possibility for some potential GPTs to fail becoming prevalent and pervasive in the economy.

We applied a simplified version of the Ricardian model of specialization to a context of industries connected in a hierarchical (vertical) relation, building on the choice of variables taken by previous GPT microeconomic models and keeping a distinction between technological and economic factors in explaining observed patterns of technological specialization within an economy where the propensities to switch to a novel supplier is heterogeneously distributed. The model, despite its basic setting and the fact that does not explicitly formalize endogenous determination of payoffs, shifts the focus from absolute to relative (gap) measures driving adoption and change. Learning mechanisms and feedbacks, as well as policy interventions, can therefore be taken into account. In particular, developing a three upstream technologies version of the model allowed us to show the many possible specialization patterns in an economy with upstream-downstream linkages, some of them leading to technological pervasiveness, others to technological co-existence, and finally other to "failed" GPTs that remain confined in market niches.

From an evolutionary economics point of view, the model can be thought as a competition (race) for downstream market shares (where shares are the fraction of applications served by an upstream technology out of the total market available), that is, as a case of replicator dynamics in which the fitness is function of quality and the cost of the upstream technological components.

As for possible extensions, stochasticity (Durlauf, 1993) and endogenous dynamics can be added, explaining specialization as "self-discovery" in presence of uncertainty and learning (Hausmann and Rodrik, 2003) and extending Industry Life Cycles (ILC) theories (Klepper, 1996). On the latter point, both theoretical (De Figueiredo and Silverman, 2012) and empirical (Bonaccorsi and Giuri, 2001) studies have started thinking in terms of vertical connectivity and of networked transmission channels in order to explain the structural evolution of industries (entry, exit, concentration, division of labor and innovation patterns) – so their dynamics over time. An extended model built on Klepper (1996) may well serve the scope to formalize a process of “entry into the upstream”. Finally, research could benefit from empirical studies of technological and economic outcomes in vertically related industries which may rely on some decomposition exercise (Cantner and Krüger, 2008) or evolutionary accounting (Dosi and Grazzi, 2006).

The main contributions of the paper are (i) to frame GPT theory into a more general view of vertically-related industries with interdependent structures and innovation incentives; (ii) to model a downstream market specialization and choices between alternative upstream technologies and the dynamic of GPT emergence, from a “specific” (niche) upstream industry to a pervasive one; (iii) to account for the possibility of failing GPTs. To conclude, the process of “acquiring purposes” is not supposed to lead automatically to the establishment of a pervasive GPT; rather, it is more close to an emergent 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 and policy-makers to determine which alternative specialization path is to be taken.

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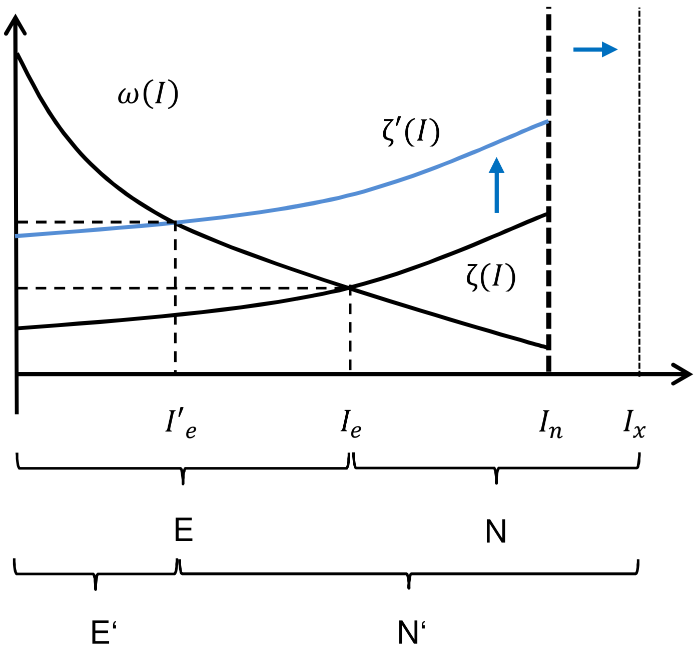

Fig. 1a: Increase in comparative advantage for the new upstream technology (competition case) with new downstream applications emergence.

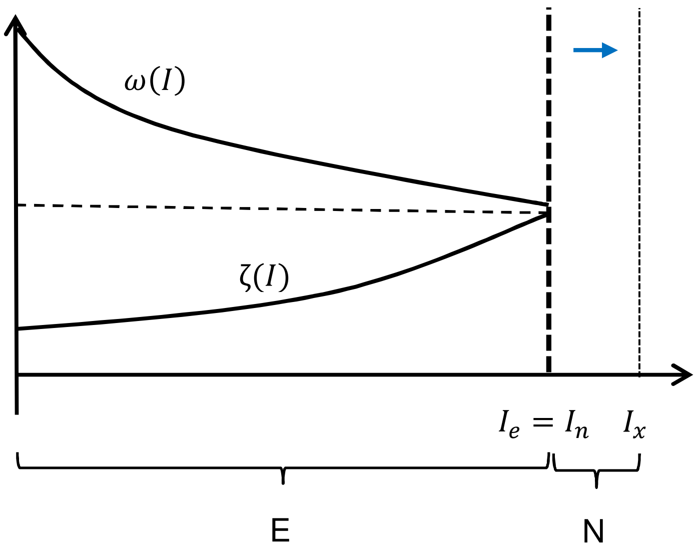

Fig. 1b: Specialization in the niche case with new downstream applications emergence.

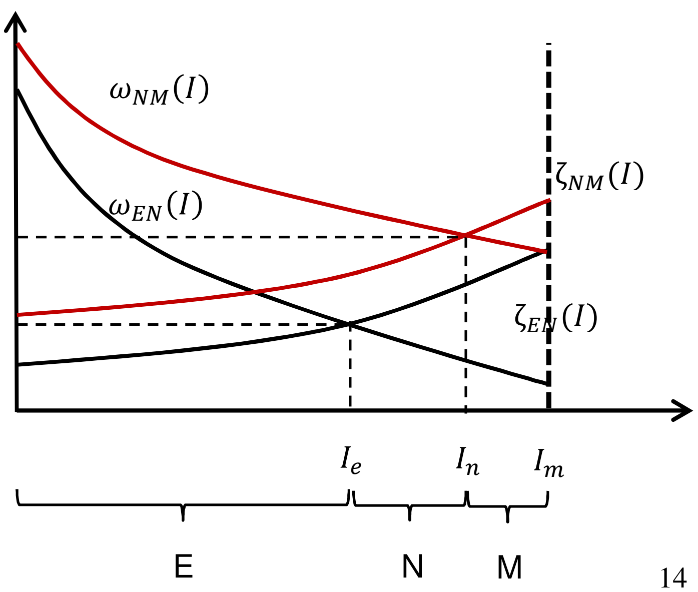

Fig. 1c: Three upstream technologies case, with none of them being fully pervasive in the economy.