SPECIALIZING IN GENERAL PURPOSE TECHNOLOGIES AS A FIRM LONG-TERM STRATEGY

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ABSTRACT

An important legacy of Nathan Rosenberg’s work is the notion of general purpose technologies (GPTs). This paper studies whether and when firms specialize in developing GPTs and trading them in intermediate markets, a strategy we call “specialization in generality.” In particular, we address whether this is a strategy adopted by young firms or instead a long-term strategy adopted by established firms—against the “common wisdom” that such firms specialize in downstream product markets.

1. Introduction

One of Nathan Rosenberg's most important contributions is the role played by general purpose technologies (GPTs)—technologies such as the steam engine and electricity, characterized by their broad applicability in many markets—as engines of economic growth (e.g. Rosenberg, 1982). This intuition spurred an established and still growing body of research. Within this research stream, some scholars explored the conditions under which the development of a GPT determines technical advance in downstream sectors in a decentralized economy (e.g. Bresnahan and Trajtenberg, 1995); other scholars focused on the economy-wide impact in terms of innovation and productivity levels that GPTs generate as they diffuse in the economy (Helpman and Trajtenberg, 1998); yet others analyzed the interdependence between GPTs and the division of innovative labour (Bresnahan and Gambardella, 1998).

Most research on GPTs, however, has investigated the impact and the implication of such technologies at the economy level. Only recently have scholars begun to look at general technologies from a firm-level perspective, focusing more closely on the appropriability concerns of an individual firm that has developed a general technology and that aims to capture its value.

Understanding more about the firm-level issues related to the development and exploitation of general technologies is clearly important from a societal perspective—if anything because, due to the lack of private incentives, there might be a suboptimal number of firms specializing in the production of GPTs (Bresnahan and Trajtenberg, 1995). However, it is also important, and possibly even more so, from a managerial perspective, because the existence and the exploitation of GPTs might enhance the variety of strategies that firms pursue (Gambardella and McGahan, 2010).

In particular, firms might take advantage of GPTs by vertically specializing in producing and selling them to downstream players (Conti *et al.*, 2017; Bresnahan and Gambardella, 1998; Rosenberg, 1982), a strategy we label “specialization in general purpose technology” or “specialization in generality.” However, we still know little about this strategy. In particular, to what extent can it be a long-term strategy pursued by companies as they age?

This paper aims to respond to these questions by exploring whether and under what conditions specializing in generality is a transitional strategy—exclusively employed by firms while still collecting the resources they need for growth (e.g. Kogut, 1991; Teece, 1986)—or whether it is sustainable in the long term, and therefore adopted by firms as they age. We also identify two conditions—one external and one internal to the firm—conducive to embracing specialization in generality as a long-term strategy: the former is the extent to which the downstream market faced by firms takes a deep versus a broad configuration (Bresnahan and Gambardella, 1998); the latter is the extent to which firms have committed resources to R&D.

We empirically test our predictions in the laser industry in the period 1993–2001. This is an ideal empirical setting for testing our theoretical framework, for several reasons. First, the crucial upstream resource in this industry is the laser technology itself, and firms might choose to produce (and sell) more general purpose or more dedicated laser technologies, that is, technologies having more or fewer applications (each one linked to a specific downstream market). Second, the laser industry is vertically disintegrated: it is populated by laser producers (producing “lasers” as standalone intermediate technologies) and laser systems manufacturers (embedding lasers into “laser systems,” which are “ready to use” downstream products). This implies that, in this context, intermediate markets for laser technologies exist and work smoothly.

Our results are consistent with the hypotheses we develop and show that specialization in generality can be a long-term strategy, especially when firms have made substantial investment in R&D, and potential technology buyers are homogenously distributed across the different downstream markets where the GPT can potentially be applied.

2. Theory and Hypotheses

Nathan Rosenberg’s research contributes greatly to our understanding of the connections between the technical characteristics of a technology and its economic implications, and in particular of the degree to which a technology can spur growth by inducing vertical specialization and the division of the innovative labor.

In particular, according to Rosenberg, some technologies have an impact only in some sectors of the economy, while others—such as the steam engine and electricity—have widespread impact, beyond the industry for which they were originally created (Rosenberg, 1982). This is due to their *general-purpose-ness*, or their capacity to perform a generic function that is central to the functioning of a large number of products and production systems (Rosenberg and Trajtenberg, 2001). As general technologies diffuse, they tend to generate complementary investments in the application sectors, which lead to increased demand for general technologies and ultimately generate sustained economic growth (Helpman and Trajtenberg, 1998; Rosenberg and Trajtenberg, 2001).

The connection between GPTs and demand is particularly interesting: demand for a GPT comes from all sectors in which the general technology might be applied (Rosenberg, 1982). Thus, general technologies are more likely to impel the division of innovative labour and vertical disintegration in the economy. Indeed, the "extent of the market" tends to be larger for general technologies than for dedicated ones. Therefore, GPTs are more likely to economically sustain vertical specialization, or the creation of a class of upstream companies that specialize in producing GPTs and that trade, in intermediate markets, such technologies to downstream firms (Bresnahan and Gambardella, 1998; Smith, 1776; Stigler, 1951). Rosenberg (1982: 71) himself emphasized that general technologies lead to "wholly new patterns of specialization," with "the emergence of specialized firms and industries that produce no final product at all—only capital goods."

Rosenberg (1982: 71) also suggested that as the economy becomes increasingly characterized by the presence of specialized GPT suppliers and high rates of GPT purchases from downstream buyers in other industries, not taking these buyer–supplier "relationships fully into account is a fundamental limitation of most of the recent literature on technological innovation." Trying to address such limitation, in the last 30 years, research in this area has explored the implications of the existence of a class of specialized GPT suppliers at the economy and industry levels. Most such research has taken a social welfare perspective. For instance, Bresnahan and Trajtenberg (1995) considered the role of GPTs as "engines of growth," pointing out that advances in GPT lead to new opportunities for applications and that, at the same time, development of GPT-using applications increases returns to new advances in GPT. This positive feedback between the upstream GPT industry and the downstream application sectors is challenged by coordination problems, however: when the GPT and the applications are supplied by different firms, these different parties do not internalize all the benefits from their investments for the technical progress of the GPT or its applications. As a result, each party might end up investing "too little, too late" such that the economy might display a (socially) suboptimal level of investment in GPT.

However, most industry-level studies on GPT, including Bresnahan and Trajtenberg (1995), assumed the existence of a class of upstream GPT suppliers—and possibly investigated the extent to which the existence of such a class is socially optimal (e.g. Bresnahan and Gambardella, 1998). Our work, by taking a private firm perspective—and in particular the perspective of an upstream firm considering whether to invest in a general technology for trading or not—studies instead the internal and external conditions that make a class of upstream suppliers more likely to emerge and persist over time. In this sense, our work tries to provide the micro-foundations to the GPT industry-level studies.

To this purpose, we address two main questions: Which contingencies lead upstream firms to specialize in the production and trading of general technologies in intermediate markets? And, in particular, under which conditions is this specialization in generality a "temporary" strategy (mainly pursued by firms lacking the complementary assets and the expertise to enter downstream) versus a "long-term" strategy chosen by firms as they age?

Important insights to address these questions are provided by research focusing on the strategies that firms can use to commercialize their technologies (e.g. Teece, 1986). Two main modes of commercialization—cooperative and competitive—have been identified in this domain. A *cooperative* commercialization mode corresponds to the situation in which an upstream firm that has developed a technology commercializes it by trading or cooperating with other downstream firms, who will then integrate it into their products and sell these in the product markets. Cooperation between the upstream technology developer and the downstream buyer can be regulated in different ways, for example via arm's-length transactions, licensing agreements or alliances (e.g. Aggarwal and Hsu, 2009; Kogut, 1991; Teece, 1986). In a *competitive* commercialization mode, instead, the upstream firm directly integrates downstream and commercializes its technology into products (e.g. Arora *et al.*, 2001).

Research in this area has generally assumed that cooperative commercialization modes or strategies are the natural precursor to competitive commercialization strategies, such that firms tend to use cooperative strategies early on to compensate for their lack of the relevant physical or reputational resources to directly enter downstream (e.g. Eisenhardt and Schoonhoven 1996; Teece, 1986). The intuition here is that the development or acquisition of these downstream assets is subject to time-compression diseconomies, such that firms must necessarily begin their commercialization efforts by cooperating with other firms that already possess those assets. Once a firm has gathered the relevant downstream resources and expertise, however, it can switch to competitive commercialization modes.

Nevertheless, very recent research in this area suggests that this course of action—cooperative commercialization as the precursor to competitive commercialization—might not apply to some firms (e.g. Gans and Stern, 2003; Marx and Hsu, 2015), calling for new research in this domain. For instance, firms might persist in a cooperative commercialization mode when the downstream market is characterized by strong economies of scale (and therefore resembles a natural monopoly with no room for entrance) or strong competition (and downstream entry is therefore not attractive for upstream firms), or when IPR protection is strong (and therefore upstream firms might continue trading their technologies, as they do not face the risk of expropriation by potential buyers; e.g. Gans and Stern, 2003; Marx and Hsu, 2015).

Even more important for our research question, most research on commercialization strategies has mainly explored firms' commercialization choice in isolation, overlooking its interdependence with the choice about the nature of the firm's technological investments. This is a notable gap, since there is a close interdependence between the nature of a technology that a firm has invested in—and in particular whether this technology is general or dedicated—and the technology commercialization mode (e.g. Bresnahan and Trajtenberg, 1995; Macher and Mowery, 2004; Rosenberg, 1982).

Indeed, when the choice of technology commercialization mode (cooperative vs. competitive) and the choice of whether to invest in a GPT or not are considered simultaneously, four possible technology commercialization strategies emerge (Table 1): *simple trading*, where a firm does not integrate downstream and instead commercializes in intermediate markets a dedicated technology via arm's-length or cooperative agreements; *specialization in generality*, where a firm does not integrate downstream and instead commercializes a general technology via arm's-length or cooperative agreements; *simple downstream entry*, where a firm selectively enters the few downstream sectors where its dedicated technology can be applied; and *synergistic downstream entry*, where a firm enters the multiple downstream sectors where its general technology can be applied.

******* INSERT TABLE 1 ABOUT HERE *******

Note that—within prior research that has neglected the interdependence between the nature of the technology and the type of commercialization chosen—the first two strategies (“simple trading” and “specialization in generality”) would be seen as equivalent, in that they fall into the “cooperative strategy” category. Similarly, the latter two strategies (“simple downstream entry” and “synergistic downstream entry”) would both be generally classified as belonging to the “competitive strategy” category. This supports the idea that simultaneously considering both choices of technology commercialization mode and of whether to invest versus not to invest in a GPT is important: following the traditional categorization, any strategic difference related to the nature of the commercialized technologies would be completely neglected. Recognizing this difference helps refine the tenet that older firms, given the necessary marketing expertise, choose to enter downstream, whereas younger firms choose instead to trade (e.g. Teece, 1986). We argue that this conclusion is only partly true, as the relationship between firm age and commercialization mode also crucially depends on the general versus dedicated nature of the technology the firm has invested in.

Specifically, it is true that the commercialization of either a dedicated or a general technology through downstream entry requires firms to gain access to those downstream complementary assets in order to incorporate the technology into a product that can be sold to the final consumer (e.g. Teece, 1986). Getting proprietary access to these assets requires time. Hence, younger firms are more likely to choose arm’s-lengths transactions (or licensing agreements or alliances), whereas older firms, which control the necessary downstream assets (including marketing expertise), are, in general, more likely to exploit technologies by entry—the basic tenet of Teece (1986).

However, compared with the use of a "cooperative" strategy for the commercialization of a dedicated technology, the commercial exploitation of a *general* technology through a cooperative strategy is more complex and requires developing peculiar expertise, which is likely to happen gradually and over time. In fact, trading a GPT to downstream users operating in different markets is conditional on a crucial intermediate step, in that the general technology needs to be "adapted" to those different markets (e.g. Bresnahan and Gambardella, 1998). Adapting the design of a general technology to different markets requires that firms acquire relevant complementary assets such as market expertise in the different target markets as well as design expertise to modify the underlying technology. The accumulation of these assets is subject to time-compression diseconomies. Hence, the cooperative commercialization of a general technology via arm's-length agreements (i.e. a specialization in generality strategy) is likely to require more time than the simple trading of a dedicated technology (e.g. Teece, 1986). This implies that a specialization in generality strategy is more likely to be employed by firms as they age and develop the required expertise to pursue such a strategy—which therefore, similar to downstream entry, is most likely a "long-term" option. Therefore, we propose the following:

Hypothesis 1: Similar to downstream entry, a specialization in generality strategy is more likely to be employed by firms as they age.

A question naturally emerges: As firms age, which ones choose a specialization in generality strategy (as opposed to entering downstream)? That is, which conditions make specialization in generality a viable strategy? We suggest that such relevant conditions might be either internal to the firms or external and related to the economic environment where they operate.

In particular, from the external standpoint, the long-term viability of a specialization in generality strategy will depend on the characteristics of downstream demand for technologies (e.g. Rosenberg, 1982). The distribution of demand for technologies in downstream markets can take multiple different configurations (Bresnahan and Gambardella, 1998) and range between "broad"—the potential technology buyers are spread equally across the various markets where the technology could be applied—and "deep"—the potential technology buyers are concentrated in just one or a few markets. For example, suppose 100 downstream firms (i.e., the potential technology buyers) are spread over 10 markets. We would say that demand is broad if there are 10 downstream firms in each of the 10 markets. We would say that demand is deep when, instead, 91 downstream potential technology buyers operate in one market and the other 9 markets include only just downstream firm each.

As firms age, their cumulative acquisition of technical and market expertise to adapt a general technology to different markets makes specialization in generality possible. Yet, the appeal for the focal firm of specialization in generality as a strategy is likely to be higher when demand for technologies is broad, because a general technology is particularly appropriate for exploiting the diverse needs of multiple downstream markets of similar size. When demand for technologies is deep, instead, specialization in generality is not particularly attractive for a focal firm: because most potential technology buyers are concentrated in one or a few large markets, targeting markets in addition to the main one(s) where most of the buyers are concentrated does not increase demand substantially, and it requires additional technology adaptation costs. Overall, the broader (vs. deeper) the demand, the more firms are likely to pursue a specialization in generality strategy. Therefore, we hypothesize as follows:

Hypothesis 2: The likelihood of specializing in generality increases with age especially when demand is broad versus deep.

From the firm's internal standpoint, the exploitation of a more general technology requires investment in technical skills for adapting the technology to the different markets in which the technology can be used (Bresnahan and Gambardella, 1998; Bresnahan and Trajtenberg, 1995). As firms age, they tend to develop market knowledge of the needs of users in different markets and of how the technology could potentially serve those markets. However, market knowledge needs to be complemented with investment in technological ability to modify the general technology and apply it to the different markets. In other words, to pursue a specialization in generality strategy, firms must combine market expertise with substantial investment in R&D. Hence, we propose as follows:

Hypothesis 3: The likelihood of specializing in generality increases with age, especially when firms have invested more resources in R&D.

3. Data and Empirics

3.1 Empirical setting

We tested our prediction building a novel longitudinal dataset on the US laser industry in the period 1993–2001, using an industry directory (the Photonics directory, by Laurin Publishing) to define industry boundaries. The term "laser"—"light amplification by stimulated emission of radiation"—refers to devices that emit light through a process of optical amplification based on the stimulated emission of electromagnetic radiation (Hecht, 2011).

The laser manufacturing industry has two vertical layers. Firms in the upstream layer produce lasers, a technology with essential components: a lasing material (the gain medium), a pump source, and a laser cavity. To be used, lasers tend to be ultimately integrated into laser systems, which are sold to the final users. Upstream firms can either integrate downstream into laser systems or vertically specialize upstream, in the production of lasers, and sell them to downstream firms producing laser systems.

Depending on their medium, lasers differ in power and in the wavelength of light they emit. This affects the extent of applicability (i.e. the "generality" or "general-purpose-ness") of each individual type of laser and, consequently, the extent to which it can be used in different laser systems targeted to biomedical/medical (e.g. medical imaging, dermatology), information processing (e.g. scanning, optical disk reading), telecommunications (e.g. data transmission, pulse generation), military (e.g. target designation), and industrial (e.g. cutting, welding, marking) applications.

To build our sample, we selected all firms that in 1993 were active in the upstream laser industry but not in the downstream laser system industry. We collected data for these firms until 2001 or until the year they entered the laser system industry, whichever was earlier. Conversation with industry experts and cross-checks across sources revealed that this sample is generally representative of the industry during that period. It also includes firms that entered or exited the industry during the period, limiting any survival bias.

We extracted information on firm characteristics (e.g. independence status, size, age, location) for each year from the industry directory. We used the same directory to collect information on the laser and laser system types that each firm was producing in each year as well as information on firm entry and trading. We chose our time window for empirical reasons: during the period 1993–2001 the number of possible laser applications increased considerably due to the dramatic diffusion of the Internet.

We matched data on firms' characteristics with firms' patent data from the National Bureau of Economic Research (NBER) patents database using firm names and locations and matched them to patent assignees' names. The NBER data set provides patent data consolidated at the parent–portfolio level for public firms. For private firms, we used the D&B Who Owns Whom database to build a list of their worldwide subsidiaries for each year of the study. We matched this list with the NBER data set to obtain the list of patents filed by each of the firm's subsidiaries and to consolidate the list of patents at the parent–firm level. This procedure yields a sample of 82 firms corresponding to 306 firm-year observations.

The laser industry is an ideal setting for testing our theory, for several reasons. First, the industry has a clear vertical structure and smooth and efficient intermediate markets where laser technologies are exchanged between upstream suppliers (i.e. companies producing lasers) and downstream buyers (firms buying those lasers for embedding them into final downstream products).

Second, firms vary in the generality of their upstream technological knowledge such that some firms have more general upstream technological knowledge (and thus produce lasers for use in a large number of laser systems for different markets) and some have less general upstream technological knowledge (and thus produce lasers targeted to specific downstream applications and related downstream markets).

Third, in the period studied, the applications of lasers expanded considerably in new downstream markets, such that firms in the laser industry faced precisely the choice of whether to enter these new markets by direct entry or by trading in the corresponding intermediate markets. Interesting for our analysis, the directory we use for data collection is meant to be an outlet for firms to advertise their lasers and/or laser systems. Hence, by construction, if a firm is reported in the directory, it is exploiting new markets either by trading as an upstream supplier of intermediate products (lasers) or by operating downstream (as a seller of laser system)—consistent with our theoretical framework.

3.2 Methodology

We tested our hypotheses by using a linear probability model and estimated the probability that a firm employs a specialization in generality strategy as a function of its age, and the interaction between age and the core independent variables. Following previous studies (e.g. Azoulay *et al.*, 2010), we use a linear probability model (rather than a non-linear logit or probit model), for three main reasons. First, a linear probability model allows us to easily control for firm time-invariant unobserved characteristics without losing any observations. Accounting for any firm-constant characteristics is crucial to obtaining reliable estimates. For instance, high-quality firms not only might survive more (such that firm time-invariant quality might be positively correlated with age) but also might choose a specialization in generality strategy—which, as we said, is a demanding strategy. This would obviously bias our estimates. Second, we are interested not only in the direct effect of age on the choice to pursue a specialization in generality strategy but also on the interaction effect between age and the structure of demand, on one side, and firm R&D investment, on the other side. Using a linear probability model makes the economic and statistical interpretation of the interaction effect quite straightforward. Finally, we are theoretically interested in assessing the effect of age on the probability of any firm changing its strategy over time, which occurs in about 13% of our observations. Indeed, our main research goal is to understand the effect of time passing on such within-firm strategy variation—and in particular on the likelihood that a focal upstream firm adopts a specialization in generality strategy.

3.3 Variables

Dependent variable. Our dependent variable, *Specialization in generality,* is a dummy variable that takes the value 1 if the firm vertically specializes in the production of general technologies. Specifically, it takes the value 1 if two conditions occur simultaneously: (1) the firm trades the technology in intermediate markets and does not integrate downstream in year *t*, and (2) the firm invests in general technology; that is, it increases the generality of its technological portfolio, in year *t*. Specifically, to measure investment in general technology, we look at each firm's laser portfolio. We take advantage of the fact that laser technology has several possible market applications depending on the laser medium.[i] Based on the medium, lasers can be classified into the following categories: Alexandrite; ArF; Argon–Ion; CO_2; CO_2 TEA; Metal Vapor; Diode; Dye; Er:Glass; Er:YAG; Excimer; HeNe; Krypton–Ion; Nd:YAG; Ruby; Thulium; HeCd; KrF; Lead Salt; Nd: Glass; Ti:Sapphire; Color–Center; HF/DF; and Holmium YAG. Each laser category can be used in a broader versus narrower range of applications. For instance, a KrF laser can be applied to industrial drilling but not to applications in dermatology. An Er:Glass laser, however, is appropriate for use in dermatology but not in laser drilling. A third alternative, the Alexandrite laser, can be used for applications in both dermatology and industrial drilling. Therefore, the Alexandrite laser is a more general technology than the KrF or the Er:Glass lasers. To measure the generality of firm technology, we first measure the individual laser's degree of generality by calculating the ratio of the number of uses/markets to which the specific laser type can be applied to the total number of applications/markets across all laser types. We then compute the degree of the firm's technology generality in each year by considering the average degree of generality of the lasers in the firm's portfolio. Finally, we measure whether firms invested in general technologies by looking at whether a firm has increased its average laser generality from year *t*–1 to year *t*.

Independent variables. Our core independent variable is *Firm age,* measured as the number of years elapsed from the firm's foundation to year *t*–1. We observe its association with the dependent variable to test our first hypothesis. We interact this variable with two other variables to test our second and third hypotheses. We construct the variable *Breadth of demand* as 1 minus the Herfindhal index of concentration of downstream buyers across markets, for each firm-year. In more detail, for each firm in the sample that supplies lasers, and for each year in which that firm is active, we consider the markets in which the focal firm's lasers are potentially applicable and how broadly the downstream firms are operating in these markets (which therefore constitute potential buyers for the focal firms' lasers) distributed across them. Finally, we construct the variable *R&D intensity* as the ratio of the firm's number of engineers to the firm's number of employees.

Control variables. In all specifications, we include as an additional control variable the *Number of lasers*, which controls for the number of different types of lasers produced by the firm and which might correlate with both the commercialization mode chosen by the companies, on one side, and the age of firms (e.g. older and more experienced firms might produce more lasers). We also control for the *Number of patents* applied for and granted to the firm in the five years prior to the focal year, as the technological competence of a company might naturally correlate not only with the general or dedicated nature of firm technologies but also with firm age. Also, *Firm size* (number of employees) appears to be a natural control to include in the regression, given its obvious correlation with age. Finally, we introduce year fixed effects,[ii] to control for time-variant factors affecting all firms in our samples—for example, economic downturns—and firm fixed effects to control for firm unobserved and time-invariant heterogeneity.

4. Results

Tables 2 and 3 display the descriptive statistics and pairwise correlations between variables. Overall, in the period considered, firms' likelihood to choose a specialization in generality is about 18%, which suggests that this strategy is relevant. Note also that the probability of investing in GPTs almost perfectly overlaps with the probability of adopting a specialization in generality strategy. That is, in our sample composed of firms without any downstream assets, all firms that invest in GPTs decide to remain upstream and to trade technologies in intermediate markets—this naturally implies that we do not have any firms investing in GPTs to enter downstream, which is what we called a "synergistic entry" strategy.

******* INSERT TABLES 2 & 3 ABOUT HERE *******

Table 4 reports the results of several linear probability models, including firm fixed effects. We first consider the effect of age on the mere probability of staying upstream (vs. entering downstream)—which is what the previous literature mainly considered. Results in column (1) show that firm age is negatively associated with the choice of a cooperative commercialization mode, that is, remaining upstream and commercializing technologies by trading them or cooperating with other downstream firms (beta=-0.017, p–value<0.01). Note that the variable *Cooperative commercialization mode* does not account for the type of technology the firm has invested in (i.e. whether general or dedicated). This result is in line with the results of prior research on technology commercialization strategies that suggested that—as they age—firms tend to enter downstream.

However, our theory specifically concerns the effect of age on the *joint* probability of trading and investing in more general technologies, which defines the specialization in generality strategy. When we consider the choice to "specialize in generality" (column 2), we find that *firm age* is positively associated with the probability of staying upstream and trading GPTs, that is, the probability of employing a specialization in generality strategy (beta=0.039, p–value<0.05) providing support for our first hypothesis. The effect of age is also sizable, as the passing of one more year increases the likelihood of choosing a specialization in generality strategy by almost four percentage points.

Overall, the previous results imply that looking at the effect of age on the simple choice to enter versus trade might be misleading. Indeed, as suggested by previous research, firms do on average choose to enter downstream as they age, adopting a "competitive" technology commercialization mode (e.g. Teece, 1986). Yet, some firms choose instead to trade general technologies. In this sense, specializing in generality appears to be a viable long-term strategy that some firms pursue.

To better characterize our findings, we also show the impact of age on the probability of employing a simple trading strategy (column 3) and simple downstream entry strategy (column 4). Results are consistent with our theoretical reasoning and show that age has a positive association with both specialization in generality and downstream entry—as both strategies require the development of assets subject to time-compression diseconomies—whereas this association is reversed for the case of a simple trading strategy. Looking at columns 2 through 4 jointly, we can conclude that as firms age they tend to abandon a simple trading strategy (beta=-0.053, p–value<0.01) and that, of those firms that switch to a different strategy, most switch to a specialization in generality strategy (beta=0.038, p–value<0.05) rather than to a downstream entry strategy (beta=0.017, p–value<0.01).

******* INSERT TABLE 4 ABOUT HERE *******

The analysis reported in Table 5 deepens our analysis further, showing the conditions under which older and more experienced firms are more likely to employ a specialization in generality strategy. Results show a positive association between specialization in generality and the interaction between *Firm age* and *Breadth of demand* (beta=0.063, p<0.05) as well as between specialization in generality and the interaction between *Firm age* and *R&D intensity* (beta=0.063, p<0.01), supporting our second and third hypotheses. Therefore, as firms age, the appeal of a specialization in generality strategy is higher when downstream buyers are homogeneously distributed across all possible downstream markets—because experienced firms choose to exploit such demand breadth, by investing in GPTs and trading them in intermediate markets—and for firms investing in R&D—because the technological knowledge acquired through R&D investments complements the market knowledge acquired by experienced firms, and both are needed for pursuing a specialization in generality strategy.

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One possible concern about the previous results is that our variable firm R&D intensity (equal to the ratio of firm engineers to the overall number of firm employees) might be endogenous to the strategy that a firm adopts. To alleviate this problem, as a robustness check we used a time-invariant—and possibly exogenous—measure of R&D intensity, by computing such variables in the first year that a company enters our database. The new time-invariant measure of R&D intensity is naturally exogenous with respect to any firm's strategy change—which is the dependent variable we consider when including firm fixed effects and using within-firm variation. The results we get by using the new measure are again consistent with our theory (Table 6).

We also checked whether our results are robust to the use of a logarithmic transformation of age, size, and number of patents. Note that the non-linearity of the logarithmic function makes the log of age non-collinear with the year and firm fixed effects. Results are confirmed even when adopting such a specification (Table 7).

******* INSERT TABLES 6 & 7 ABOUT HERE *******

Finally, for the sake of comparison, we also show the effect of the aforementioned interactions on the other possible strategies that firms might undertake. Interestingly, results clearly show that these interactions are not conducive to the other two types of strategies that firms in our sample have pursued (Table 8).

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5. Conclusions

Nathan Rosenberg had sharp ideas about innovation. One was that market structures, and particularly the vertical relationships between suppliers and buyers, have important implications for the efficiency with which innovations are generated. In this respect, an important insight that he provided to economists, strategy scholars, and policy makers is that in some markets the production of GPTs can have profound implications for the vertical division of innovative labor—and thus for overall economic efficiency. His representation of the American machine tool industry in the 19th century is a vivid illustration of how GPTs arise and function (Rosenberg, 1982). This has spurred important research. In particular, Bresnahan and Trajtenberg (1995) highlight that GPTs create economic growth because of the externalities they produce. In fact, as they note, these externalities imply that firms have suboptimal incentives to produce GPTs.

In this paper, we also take a firm-level perspective, which we believe is an important complement to the work of Rosenberg, and of Bresnahan and Trajtenberg. To be sure, we do not and cannot answer whether firms have suboptimal incentives to invest in GPTs because of the externalities associated with these technologies. However, we do address some micro-foundations on whether young or, rather, experienced firms invest in GPTs, and whether they do so to trade such GPTs in intermediate markets rather than to enter downstream.

Tackling such questions has important implications for assessing the relevance of GPTs, which would obviously be magnified in a situation where GPT is a long-term specialization strategy, such that firms find it profitable to sell GPTs in intermediate markets as part of their normal business activities—rather than considering it as a transitory phase before finding the right product application in which they specialize.

Indeed, if companies investing in GPTs to trade them in intermediate markets were largely young firms that have not yet understood in which markets or technologies to specialize, investments in GPTs would likely be a residual form of investment in our economies. This is because many of these firms could fail, and if they succeeded, once they became older, they would specialize in some downstream markets and no longer produce technologies that can offer advantages of specialization and increasing returns in terms of serving, with the same fixed investment, many application markets. Similarly, if GPTs were only the province of investments by large and diversified firms that internalize the underlying externalities—as suggested by Penrose (1959) and Nelson (1959)—their potential would still be limited, in that these firms may apply them not to all potential domains in which GPTs can be applied but only to the domains in which the firm commercializes its final products.

The question is therefore: Do firms specialize in trading GPTs as a long-term strategy? That is, do we observe that firms, as they age, see long-term opportunities in creating a business model in which they invest in a general technology that they trade to several downstream application firms?

Using data on the laser industry, we find that this is the case. As firms age they are more—rather than less—likely to adopt a strategy of specialization in generality as opposed to specializing in one or a few downstream product markets or trading dedicated technologies. Of course, as firms age they are also more likely to adopt the standard strategy of specializing in some product markets. However, we find that this is not the only strategy they pursue. Some instead specialize in generality. We also find that specialization in generality is more likely when downstream markets are homogenous—in the sense that fairly homogenous shares of buyers elicit the opportunity to sell technologies that are applicable to different markets—and when firms are R&D-intensive. This latter point is also intriguing. Specializing in generality is the strategy of companies that are committed to R&D, technology, and innovation; therefore, it is likely to be a strategy pursued by most innovative companies.

Interestingly, today, several firms simultaneously invest in upstream resource generality and trade in intermediate markets the services and products deriving from their upstream resources. For instance, the most valuable resource that IDEO—a leading design company known for pioneering a new business model—has invested in is the overall procedural knowledge for designing new ideas. This knowledge was developed to be extremely general, such that it could lead to developing products in multiple downstream market domains, including electronics, robotics, and apparel. However, IDEO has not entered these downstream markets. Rather, by taking advantage of corporate downsizing in the 1990s and the creation of "markets for designing," IDEO traded in intermediate markets the services coming from its procedural and general knowledge, offering design services to several companies operating in several downstream markets (e.g. Apple, AT&T, Samsung, Phillips, Amtrak, Steelcase, Baxter International, and NEC Corporation; Conti *et al.*, 2017).

That companies like IDEO still prosper is consistent with our prediction that this can be a sustainable, long-term strategy of firms. And it is even more intriguing that Nathan Rosenberg realized this many years ago, when he could rely only on his sharp economic logic and a deep understanding of the functioning of markets, technologies, and the division of labor across firms and industries.

TABLES

Table 1. Firm strategies

		Commercialization mode	
		Cooperative (i.e. via arm's length, licensing or alliances)	**Competitive (i.e. direct entry)**
Nature of technology investment	**No investment in general technology**	*Simple trading*	*Simple Downstream Entry*
	Investment in general technology	*Specialization in Generality*	*Synergistic Downstream Entry*

Table 2. Summary statistics

	Count	**Mean**	**S.D.**	**Min**	**Max**
Specialization in generality	306	.180	.385	0	1
Cooperative commercialization mode	306	.954	.209	0	1
Investment in generality	306	.183	.387	0	1
Firm age	306	22.242	21.007	2	106
Breadth of demand	306	.689	.133	0	.749
R&D intensity	306	.321	.218	.001	1
Number of lasers	306	1.601	1.073	1	5
Firm size	306	297.871	1618.441	1	21760
Number of patents	306	58.593	332.066	0	3257

Table 3. Pairwise correlations between variables

	1	2	3	4	5	6	7	8	9
1. Specialization in generality	1								
2 Cooperative commercialization mode	0.102	1							
3. Investment in generality	0.989***	0.063	1						
4. Firm age	-0.038	0.057	-0.028	1					
5. Breadth of demand	0.136*	0.032	0.138*	0.119*	1				
6.R&D intensity	0.010	0.015	0.005	-0.496***	-0.220***	1			
7.Number of lasers	-0.048	-0.140*	-0.037	0.010	0.111	-0.166**	1		
8.Number of employees	0.153**	0.018	0.159**	0.266***	0.059	-0.213***	0.175**	1	
9. Number of patents	0.097	0.037	0.095	0.346***	0.063	-0.148**	-0.072	0.401***	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4. Relationship between firm age and the probability of choosing different strategies: Linear probability model

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Cooperative commercialization mode	Investment in generality	Specialization in Generality	Simple Trading	Simple Downstream Entry
Firm age (t-1)	-0.017***	0.039**	0.039**	-0.057***	0.017***
	(0.006)	(0.015)	(0.015)	(0.016)	(0.006)
Breadth of demand	0.895***	0.608**	0.608**	0.287	-0.895***
	(0.109)	(0.258)	(0.258)	(0.350)	(0.109)
R&D intensity (t-1)	0.098	-0.043	-0.043	0.140	-0.098
	(0.091)	(0.191)	(0.191)	(0.170)	(0.091)
Number of lasers (t-1)	-0.011	0.002	0.002	-0.013	0.011
	(0.010)	(0.069)	(0.069)	(0.067)	(0.010)
Firm size (t-1)	0.000	0.000***	0.000***	-0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of patents (t-5 to t-1)	0.000	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm fixed effects	Included	Included	Included	Included	Included
Year fixed effects	Included	Included	Included	Included	Included
Constant	0.706***	-1.068**	-1.071**	1.778***	0.290*
	(0.162)	(0.412)	(0.412)	(0.481)	(0.162)
Observations	306	306	306	306	306
R-squared	0.116	0.291	0.291	0.278	0.116
Number of firms	88	88	88	88	88
Log-likelihood	198.1	2.390	2.390	-29.20	198.1

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 5. Relationship between firm age and the probability of choosing a specialization in generality strategy: Linear probability model

VARIABLES	(1) Specialization in Generality	(2) Specialization in Generality	(3) Specialization in Generality
Firm age (t-1)	-0.004	0.018	-0.039
	(0.015)	(0.015)	(0.023)
Breadth of demand	-0.456	0.593**	-0.812*
	(0.393)	(0.261)	(0.470)
Firm age X Breadth of demand	0.063**		0.084**
	(0.030)		(0.034)
R&D intensity (t-1)	-0.034	-0.830**	-0.852**
	(0.192)	(0.308)	(0.305)
Firm age X R&D intensity		0.063***	0.066***
		(0.022)	(0.022)
Number of lasers (t-1)	-0.005	0.011	0.001
	(0.072)	(0.066)	(0.068)
Firm size (t-1)	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Number of patents (t-5 to t-1)	0.000	0.000	0.000
	(0.001)	(0.000)	(0.000)
Firm fixed effects	Included	Included	Included
Year fixed effects	Included	Included	Included
Constant	-0.357	-0.673	0.288
	(0.299)	(0.400)	(0.376)
Observations	306	306	306
R-squared	0.294	0.321	0.327
Number of firms	88	88	88
Log-likelihood	3.077	9.017	10.26

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 6. Relationship between firm age and the probability of choosing a specialization in generality strategy (time-invariant measure of R&D intensity)

VARIABLES	(1) Specialization in Generality	(2) Specialization in Generality	(3) Specialization in Generality
Firm age (t-1)	-0.004	0.004	-0.043
	(0.015)	(0.022)	(0.028)
Breadth of demand	-0.459	0.512**	-0.578
	(0.387)	(0.214)	(0.399)
Firm age X Breadth of demand	0.064**		0.065**
	(0.030)		(0.029)
Firm age X R&D intensity		0.110*	0.121*
		(0.061)	(0.066)
Number of lasers (t-1)	-0.006	0.022	0.013
	(0.069)	(0.065)	(0.069)
Firm size (t-1)	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Number of patents (t-5 to t-1)	0.000	0.001	0.001
	(0.000)	(0.001)	(0.001)
Firm fixed effects	Included	Included	Included
Year fixed effects	Included	Included	Included
Constant	-0.368	-0.822**	-0.120
	(0.314)	(0.353)	(0.300)
Observations	306	306	306
R-squared	0.294	0.305	0.309
Number of firms	88	88	88
Log-likelihood	3.060	5.400	6.343

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 7. Relationship between firm age and the probability of choosing a specialization in generality strategy (specification with logarithm of age, size, and number of patents)

VARIABLES	(1) Specialization in Generality	(2) Specialization in Generality	(3) Specialization in Generality	(4) Specialization in Generality
Firm age (t-1)	0.410***	-0.072	-0.211	-0.548*
	(0.143)	(0.280)	(0.171)	(0.287)
Breadth of demand	0.459***	-0.420	0.653*	-0.702
	(0.128)	(1.090)	(0.361)	(0.593)
Firm age X Breadth of demand		0.374		0.486*
		(0.411)		(0.246)
R&D intensity	0.321*	0.253**	-1.319***	-1.351***
	(0.181)	(0.096)	(0.202)	(0.187)
Firm age X R&D intensity			0.738***	0.750***
			(0.121)	(0.114)
Number of lasers (t-1)	-0.001	0.012	0.020	0.017
	(0.054)	(0.060)	(0.058)	(0.058)
Firm size (t-1)	0.151**	0.134**	0.176***	0.172***
	(0.054)	(0.061)	(0.058)	(0.060)
Number of patents (t-5 to t-1)	-0.121	-0.146	-0.140	-0.140
	(0.075)	(0.085)	(0.094)	(0.093)
Firm fixed effects	Included	Included	Included	Included
Year fixed effects	Included	Included	Included	Included
Constant	-0.695	0.449	0.832**	1.751***
	(0.558)	(0.499)	(0.327)	(0.429)
Observations	306	306	306	306
R-squared	0.157	0.317	0.346	0.348
Number of firms	88	88	88	88
Log-likelihood	-24.07	8.086	14.75	15.23

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 8. Relationship between firm age and the probability of choosing other strategies: Linear probability model

VARIABLES	(1) **Simple downstream entry**	(2) **Simple downstream entry**	(3) **Simple downstream entry**	(4) **Simple trading**	(5) **Simple trading**	(6) **Simple trading**
Firm age (t-1)	-0.014	0.017**	-0.016	0.018	-0.035*	0.055**
	(0.012)	(0.007)	(0.012)	(0.017)	(0.017)	(0.024)
Breadth of demand	-1.673***	-0.895***	-1.686***	2.129***	0.302	2.498***
	(0.452)	(0.109)	(0.447)	(0.607)	(0.353)	(0.610)
Firm age X Breadth of demand	0.046*		0.047*	-0.110***		-0.131***
	(0.023)		(0.023)	(0.032)		(0.035)
R&D intensity (t-1)	-0.091	-0.109	-0.122	0.125	0.939***	0.974***
	(0.089)	(0.154)	(0.157)	(0.172)	(0.285)	(0.279)
Firm age X R&D intensity		0.001	0.002		-0.064***	-0.069***
		(0.007)	(0.007)		(0.021)	(0.021)
Number of lasers (t-1)	0.005	0.011	0.006	0.000	-0.022	-0.006
	(0.010)	(0.011)	(0.010)	(0.072)	(0.065)	(0.067)
Firm size (t-1)	-0.000	-0.000	-0.000	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of patents (t-5 to t-1)	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Firm fixed effects	Included	Included	Included	Included	Included	Included
Year fixed effects	Included	Included	Included	Included	Included	Included
Constant	0.813***	0.296*	0.837***	0.540	1.373***	-0.128
	(0.278)	(0.166)	(0.276)	(0.454)	(0.470)	(0.491)
Observations	306	306	306	306	306	306
R-squared	0.123	0.116	0.124	0.286	0.304	0.315
Number of firms	88	88	88	88	88	88
Log-likelihood	199.4	198.1	199.5	-27.52	-23.67	-21.22

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

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[i] We computed generality using all 96 specific applications of a laser across the six main markets, to fully capture the real generality of a laser. For instance, a laser that can be used in the industrial market, as it can drill and cut, is more general than a laser that can only cut: in other words, a firm's possibility of entering the industrial submarket (or of trading the laser in the corresponding intermediate market) is higher when provided with the former as opposed to the latter laser. However, our results are robust to adopting an alternative measure of generality obtained considering whether a laser has at least one application per submarket, without counting the exact number of applications. Furthermore, as the application table was just available after 1997, for the period 1993–1997 we considered as valid the laser applications in 1998.

[ii] Given that firm age and year fixed effects are perfectly collinear when introducing firm fixed effects, in the analysis we drop the dummy variables referring to the first and the last observation year. Hence, the standalone coefficient of firm age might be interpreted as the effect of time passing, in the period between the first and the last observation year, on the dependent variable. However, when considering either the interaction effect between firm age and demand breadth or between firm age and R&D intensity, we find no collinearity issues between firm age, firm fixed effects, and year fixed effects.