Life Cycle of Technology Domains and Comparative Technological Advantage*

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Abstract

In research intensive industries, firms' ability to growth, stay ahead or catch-up with competitors, crucially depends on their ability to master the evolution of technology. This problem is made more complex by the fact that industries use a variety of different technologies, whose life cycles may not be synchronized. Therefore, to understand industry evolution, and firms long-term performance, we first need to recognize the heterogeneity of technology domains underlying a given industry. Then, we need to study the relationship between the life cycle of a technology domain and the comparative advantage of new innovators and incumbents. We contribute a new method to define technology domains and identify their life cycle stage. The method is based on a dynamic analysis of patent citation networks. We apply it to study the evolution of the Semiconductor Industry over the period 1975-2006 and measure the strength of comparative advantage of incumbents and new innovators.

Technology Domains, Life Cycle, Comparative Advantage, Catching-up, Patent Citations
JEL codes: L16, O12, O31, O32, O33

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1 Introduction

In this paper, we analyse the relationship between the life cycle of technology domains and the revealed technological capabilities of incumbents and new innovators. We study the global Semiconductor Industry as an example of a research intensive industry in which new players from latecomer countries repeatedly managed to narrow the skills gap or even overtake previous industry leaders. The sustained fast economic growth and the enormous structural transformation experienced by countries like the Asian Tigers (Hong Kong, Taiwan, South Korea and Singapore) and China have been explained by a variety of points of view. A widely accepted explanation points to the role played by technology and knowledge upgrading as engines of economic growth and sources of sustained international competitiveness (Kim and Nelson 2000). The development of indigenous skills and the access to foreign technology are the key factors behind the process of catching-up (Fagerberg and Godinho 2005; Hobday 2000; Perez 1988; Verspagen 1991; Abramovitz 1994). Technology is in continuous evolution and the direction and speed of technical change, by creating and replacing capabilities at different paces, determine the availability of entry and catch-up opportunities (Lee, 2013; Lee and Lim, 2001 and Dosi, 1982) and changes in industry structure (Breschi et al. 2000; Malerba and Orsenigo 1997; Schmookler 1962). Therefore, the life cycle of technology domains and firms' ability to constantly have strong capabilities in emerging technologies are determining factors that shape industry evolution and determine the fate of growth, sustained leadership or catching-up efforts.

The goal of this paper is to improve our understanding of the relationship between technology domain life cycle and the comparative advantage of new innovators. Following Dosi's definition of technological trajectories, we conceptualize technology evolution as the process of solving engineering problems (Dosi 1982). This involves searching for solutions, possibly by trying different approaches. We argue that the emergence of an accepted approach to problem solving and the stability of the set of problems is the technology domain level analogy to the rise of a dominant design at the product-level. We define technology domains as areas of research that define a set of common engineering challenges that are tackled applying similar mindsets and toolboxes. Some of these engineering challenges may be common to several technologies that may be embodied in multiple products. This highlight how technology, product, and industry life cycles are deeply intertwined.

Despite the variety of theoretical contributions to the literature of technology life cycle and dominant-design, few attempts have been made to empirically and objectively trace the evolution of technology. The few notable contribution to the study of life cycles at the technology level are the work by Jaffe and Trajtenberg 2002 and Lee 2013. Jaffe and Trajtenberg 2002 analysed the average time lag between cited and citing patents. They found that, on average, the number of citations to a given patented invention rapidly increases up to 3-4 years after the patent has been granted. It then relentlessly decreases. Lee 2013 argues that the citation lag trend is a good proxy of the technology life cycle as it reveals for how long the piece of technical information represented by a given patent keeps being a useful source of knowledge for improvement of technology. We argue that to link the technology and the industry level it is necessary to analyse the life cycle of the system of technologies within an industry, rather than focusing on single sub-classes. Furthermore, looking only at the citation lag provides a measure of the speed of change but do not provide a picture of the scope and direction of change. In this paper we contribute a method to identify technology domains within a common industry and analyse their life cycle. We can trace the stage of the evolution of a technology domain by looking at changes in the attractiveness of the engineering problems pertaining the given domain and the stability of the approaches followed to tackle them. Our method is based on a dynamic analysis of complex patent citation networks. We focus on the semiconductor industry as a case study as it provides a particularly suitable ground for testing such relationship. Industry leadership has changed over time, because of different waves of successful latecomer entrance. The industry is characterized by a persistently evolving knowledge base, increasing global competition and short business cycles (Brown and Linden 2011). Furthermore, given the focus of this paper, it is particularly interesting to notice that the technology life cycle of semiconductors is considerably shorter than other industries, as shown by Lee 2013. This has been proposed by Lee as a key explanation of the success of catching-up efforts due to the speed of knowledge replacement. Therefore, it is crucial to understand in which semiconductor technology domains new entrants specialize, determine the stage of their life cycle and assess whether latecomers comparative advantage progressively upgrade to emerging domains. In particular, we answer the following research questions: (i) In which life-cycle stages new innovators have a comparative technological advantage over incumbents? (ii) Are there significant differences in the revealed technological advantage of new innovators from different countries?

We identify domains and trace their evolution by analysing patent citation networks. Patent are understood as proofs that an innovative solution to a selected engineering problem has been found. Citations identify the best previously available solutions that are similar to the patented invention. Therefore, they can be interpreted as highlighting the most similar existing approaches followed to tackle the particular engineering challenge. We use data from the second version of the NBER patent citation database (Hall et al. 2001), which covers the window of time between 1976 and 2006. To reduce noise in the data coming from the highly skewed distribution of patents' technical and economic value (Gambardella et al. 2008; Hall et al. 2005; Reitzig 2003), we first identify the set of patents that are most influential from the point of view of the historical trajectories of technology development within the Semiconductor industry. This is done by extracting the 'Network of Main Paths', which can be seen as the backbone of the citation network. This approach has been originally developed by Hummon and Dereian 1989 and subsequently refined and applied in recent work by (Verspagen 2007; Fontana et al. 2009; Martinelli 2008, 2009; Bekkers and Martinelli 2010). Within this set of patents, we identify several interrelated technology domains using a community detection method proposed by Newman 2004. Then we develop a methodology to describe the life cycle stages of these domains according to the attractiveness of their engineering problems and the stability of the approaches followed to seek the solution. The basic intuition is that the centrality of the problems pertaining a given domain decreases over time, while the stability of the approaches to problem-solving increases.

The paper is structured as follows. First, we present a short overview on the technology and industrial dynamics of the global semiconductor industry (Section 1.2), to make the reader familiar with the background of this study. Then we introduce the theoretical framework that we followed to define technology life cycle (Section 1.3) and the necessary methodological steps to identify technology domains and infer the stage of their life cycles (Section 1.4). Finally, we present the results that answer the two research questions (Section 1.5).

2 Review of the Literature on Industry, Product, and Technology - Life Cycles

Industry, product, and technology - life cycles are fundamentally related. They can be seen as being the result of a nested fuzzy system in which industries are collections of products that embody and are produced by several different technologies. However, the same technology can be used to make or can be part of several products, which themselves can have a central role in more than one industry. Therefore, confusing the three levels of analysis can generate conflicting predictions on the specialization patterns of new entrants. Industry life cycle theory (Klepper 1997, 1996; Afuah and Utterback 1997; Jovanovic and MacDonald 1993; Suarez and

Utterback 1995; Utterback and Abernathy 1975) predicts higher entrance to occur in the earlier stages of the life cycle. This is when there are plenty of technological opportunities and a dominant design has yet to emerge. Consequently, the entry barriers are weaker due to the lack of cumulative technical and market knowledge advantage. Innovation management literature has also extensively analysed specialization of new entrants with respect to industry and product life cycles. However, the latter is even more specific than industry life cycle theory in predicting the type of technologies that are instrumental for successful entrance. Christensen disruptive technologies are the favourite competitive battlefield of new innovators (Christensen 1997; Christensen 1993). There are two main conceptual puzzles in these branches of literature. First, these theories focus exclusively on entrance from advance countries. Second, the theoretical framework does not clearly distinguish at which level between industries, products and technologies the mechanisms behind the life cycle operates. The literature provides two alternative theoretical approaches that focus on global competition: international product life cycle theory and catching-up. The international economics literature on product life cycle (PLC), sparked by the seminal contribution of Vernon, predicts that latecomers are more likely to specialize in obsolete technologies that are progressively abounded by leader countries and whose production moves to developing countries to exploit their comparative advantage based on cheap labour (Vernon, 1966). Recent findings in this strand of literature follows Vernon's framework (Bergek et al. 2013; Karniouchina et al. 2013). Vernon's theory has raised some criticisms, which focused mostly on the fact that today's production is characterized by fragmented value chains, and modular technologies and can therefore happen in more places simultaneously. Catching-up and technology regimes literature emphasizes how innovative entrance depends on changes happening at the technology level, as the introduction of new technologies or radical change in existing ones create higher technological opportunities which, ceteris paribus, tend to favour the entry of new innovators (Lee 2013; Lee and Lim 2001; Breschi et al. 2000).

A unifying framework that provides a systemic perspective relating industries, products and technologies is provided by Murmann and Frenken 2006. Industries can be seen as collection of vertically and horizontally related products which themselves are made of several components whose design and manufacturing require distinct technologies. Industry life cycle therefore depends on the life cycle of the underlying set of products. There is a wide agreement in the literature that a key factor that shapes product life cycle is the emergence of a dominant design after a phase of fluidity that involves searching several possible design paths (Afuah and Utterback 1997; Suarez and Utterback 1995; Anderson and Tushman 1990; Utterback 1994).

Yet products do not necessarily offer the best resolution to study search across the design space and the emergence of orthodoxy in the design approach. Products are systems of components and sub-components whose development follows own technological trajectories. Therefore, the life cycle of technology domains clearly affects product and industry life cycles. A micro-founded analysis of entrance and catching-up must necessarily focus on studying change at the technology level, as it is at this layer that learning happens. The theoretical framework that guides our analysis is presented in the following section.

3 Theoretical Framework

3.1 Definition of technology domains and their relation with products and industry

The answers to the questions "how does technology change?" and "how are products and industries affected?" have been seek in a variety of ways. As we have discussed in literature review section, the prevailing belief is that the emergence of a dominant product design is the selection mechanism that stops the search process and, consequently, reduces the number of players in the competition arena. This allows focusing innovative efforts to process innovation, which, by making the product cheaper, sparks its adoption. Eventually the fossilization of product design constrains the generation of novelty and lead to the emergence of decreasing returns to adoption. This eventually increases the probability that the dominant design is re-thought or abandoned in search of a new product to introduce to the market.

This is an accurate representation of the life cycle of a single product and there is evidence that the pattern of market entry and exit in the industry is consistent with the predictions of product life cycle theory (Klepper 1996, 1997). Yet its application to industries with a large heterogeneity of products, some of which are highly customized and based on highly modular technologies, is limited by conceptual difficulties. Semiconductor devices are made by several independent components. Some of them contribute to different products. As such, their underlying engineering problems and the way solutions are seek affect the life cycle of several products. Second, in high-tech industries long-run market survival depends on technical capabilities Lee and Lim 2001. Therefore, innovative entry (and exit), defined as the ability to tap in the right technological trajectory, is more informative of a firm's long-run success than market entry. The latter could purely be due to a transitory cost-advantage, in particular for catching-up firms. In an industry characterized by a multi-technology space, a firm's ability to persistently come-up with inventions that shape the direction of future technological development, depends on its skillfulness in mastering the life cycle of several technology domains. We therefore claim that, for industries like Semiconductors, life cycles should be studied at the technology level.

We define a technology domain as an area of engineering research bounded by a set of common design problems and by similar approaches to problem solving. We adapt Murmann and Frenken 2006 nested hierarchy approach to theoretically link the technology domain level to the product level. This theoretical exercise does not have to be seen as an attempt to formally build a correspondence table between products and technologies. More humbly, the goal of this section is to briefly illustrate the systemic nature of technology and the relationship between industry, product and technology domains' life cycle. The purpose of this is to stress how the most insightful unit of analysis to understand the evolution of comparative advantage in the Semiconductor Industry is the technology level. Our theoretical framework is illustrated in Figure 1.

Source: Author's adaptation of Figure 3 from Murmann and Frenken (2006)

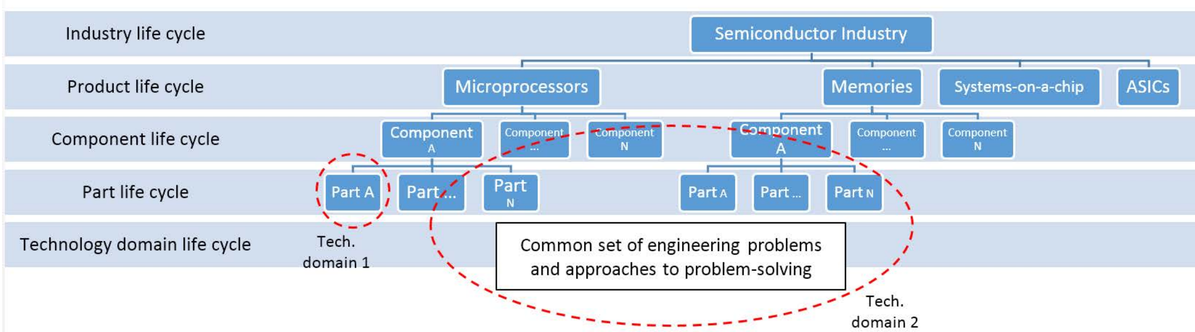

Figure 1: Nested hierarchy of life cycles

An industry is made by a collection of products. There is general agreement in the recent economic Murmann and Frenken 2006, engineering (De Weck et al. 2011) and complex system (Arthur 2009) literature in describing products as systems of nested hierarchies made by layers of components and parts. The degree of modularity of the system determines whether components can be designed and produced in isolation from each other's. Technology domains can span the system both vertically and horizontally or they can be confined to a given component or product. This ultimately depends on the generality of the underlying engineering problems. For instance, miniaturization or reduction of energy-consumption, are very general and ubiquitous problems. The former carries a variety of related sub-problems like velocity saturation or degradation due to overheat, as the technology scaling reaches channel lengths less than a micron. These problems are not isolated and related to a single product or component. In contrast, they affect the whole system. Change at the domain level propagates in the system along multiple paths, generating positive feedbacks or creating cascades of design problems, as shown by (Giffin et al. 2009). Therefore, the search for solutions to key design challenges ultimately affects the life cycle of components and products. Consequently, incumbents' and new entrants' innovation prospects depend on their technical capabilities and their knowledge upgrading paths measured at the domain level.

3.2 Theoretical definition of the life cycle of a technology domain

We argue that the evolution of a technology domain can be described by two variables: the *importance* of the underlying technical problem and the persistence of the *variety* of approaches to problem solving. An archetypal description of the evolution of a technology domain is presented in Figure 2. Let us suppose that the origin of a given technology domain is a *breakthrough* innovation. These innovations bring a completely new set of engineering problems that are very loosely related with previous solutions. The problem-solving approach is therefore disconnected with past experience. This implies that a variety of search strategies is applied to seek the solution. Breakthroughs are obviously rare and are usually identified as such only ex-post. Our approach identifies potential breakthroughs ex-ante as clusters of related problems with no or loose connections with the past that attract a lot of innovative effort by some of the players. In other words, finding solutions to these problems is considered as an important task. If the underlying problems are recognized as important and a path to a solution starts to be envisaged, then the variety of search strategies starts to decrease. Problem solving begins to be path-dependent and the persistence of a common approach increases. The underlying problems are still considered as important but they attract slightly less innovative efforts than before. The domain moves toward its *early development* phase. When a given approach is largely recognized as the most fruitful way of improving the technology by most of the people involved in research in the particular domain, the technology domain enters in its *maturity* phase. This consolidates what is recognized as the stock of useful knowledge. Furthermore, the search of alternative approaches greatly reduces and the engineering problems underlying the domain become to be perceived as less important. This can be due to at least three reasons. First valid solutions have already been found (i.e. technological progress have moved further). Second, technological development at the product level has taken a different trajectory and other engineering prob-

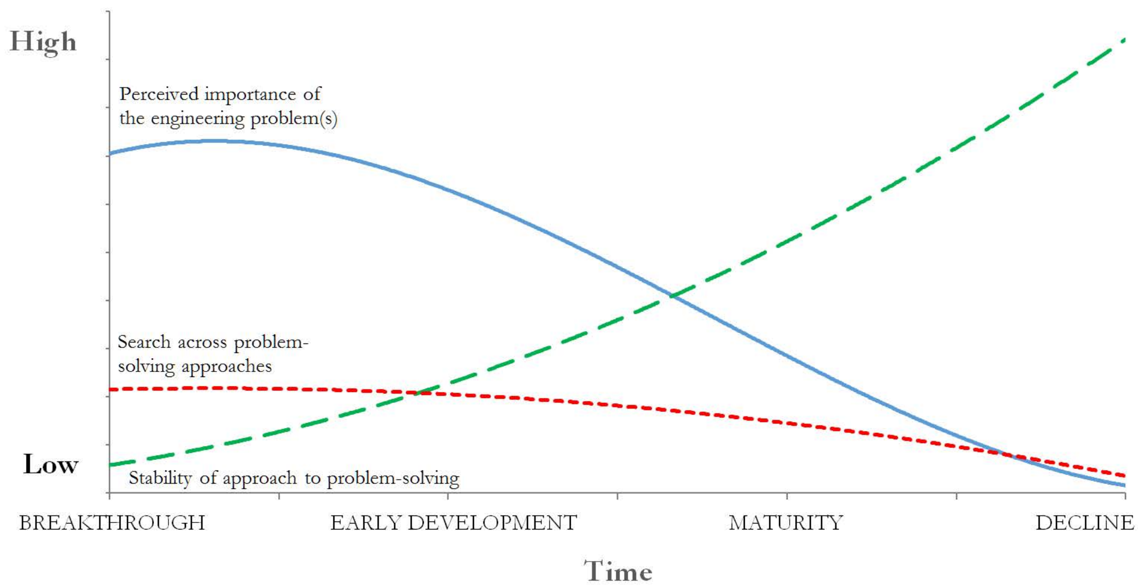

Figure 2: Archetypal life-cycle of a given technology domain starting with a breakthrough

lems are now perceived as bottlenecks of progress. Third, the engineering problems start to be perceived as unsolvable (i.e. progress in the domain has reached a dead end). In any of the three cases, if a general agreement on the reduced importance of the problem emerges, the domain moves to a *declining* stage. Innovative efforts drop dramatically and the remaining gleams of inventive activity, if still existing at all, follows clearly predefined problem-solving approaches. This destiny is not ineluctable. Some players might think that searching for better solutions is still worthy, perhaps because of a different vision of the future development of the technological trajectory or because of the attempt to improve older generations of a given product or technology. This is likely to be the case for players engaged in technological catching-up endeavours. When this happens, there is a renewed interest in the set of technical problems and a revamp in the search of alternative approaches. The domain enters into a *renewing* phase. This type of life cycle is portrayed in Figure S.1 in the Supplemental Information S.1. If the renewal phase is successful and the new approaches are promising, a new life cycle might start again. Otherwise the domain might face permanent decline.

When we described the archetypal life cycle of a given technology domain we assumed it started with a breakthrough. Besides a successful renewal of an old domain, another exception to the breakthrough kick off exists. A life cycle might be initiated by the emergence of *disruptive* technology domains. Christensen 1997 defined disruptive technologies as those that initially perform worse than the current best practices and address a different market but eventually outperform current technologies even in their own market. We use the word disruptive to describe domains whose engineering problems initially do not attract much innovative effort. Their importance may be overlooked, because an existing solution may not be currently believed possible. For this reason, a broad variety of approaches to problem-solving is searched in disruptive domains by those who do believe that a solution may indeed exist. If promising approaches arise, the importance of the problem and the value of the new engineering approaches to solve it will eventually be recognized by many players. These domains would then start attracting more inventive effort. Eventually, this would spark the life cycle. An illustration of a life cycle starting with a disruptive stage is reported in the Supplemental Information S.1 in Figure S.2.

The exploration of different approaches to a problem, has a clear theoretical relationship with the concept of technological trajectories. A technological trajectory is defined by Dosi (1982) as the direction of problem-solving activities within a technological paradigm. Yet, although conceptually related, there is an important difference between the two concepts with respect to the level of analysis and the way they relate to overall technological progress. Trajectories are typically defined at the product level. They are the results of design choices on which features of the product to improve, especially when these features are affected by trade-offs (e.g. computational power vs. energy consumption). Technological trajectory affect and are affected by the life cycle of technology domains. On the one hand, choices along the trajectory obviously imply that some engineering problems will be perceived as more important than others and consequently attract more innovative efforts. Depending on the novelty of the problem, the urge to find appropriate solutions will either spark a variety of search strategies or follow predefined and more conservative approaches. On the other hand, the solution of problems that affect several components and/or products, pushes innovative efforts toward some products features rather than others or might even allow braking the trade-off.

There is also a clear relationship between the life cycle of technology domains and the catching-up strategies followed by latecomers. Lee and Lim 2001 defined three types of catching-up: path-following, stage-skipping and path-creating. When the latecomer firm just follows the same path taken by the forerunner (with a narrowing delay), the catching-up process is said to be *path-following*. In contrast, when the latecomer firm learn so rapidly that is able to skip one or more generations of the technology, catching-up follows a *stage-skipping* pattern. The authors also define *path-creating* catch-up. This is defined as the situation in which the process of learning and assimilation of older generations of a given technology by a latecomer firm, results into significant technical improvements that take a different direction compared to the current path followed by leaders. The authors argue that stage-skipping and path-creation are better described as leapfrogging rather than catching-up as they involve doing something different from what previously done by the leaders. There is a strong analogy between the life cycle stage of a given technology domain and the type of catching-up followed by latecomers. Successful path-following catching-up would correspond to initially specializing in exhausted areas and then systematically move backward along the life cycle, by specializing in mature, early-growth and emerging areas at each subsequent time. If any of the steps would be skipped along the catching-up process than we could describe it as a stage-skipping type, or leapfrogging. Taking Lee and Lim's definition literally, path-creating would correspond to an early specialization in breakthrough or disruptive areas, as it reveals that the latecomer is exploring its own path. However, we claim that specialization in renewing areas also falls into the path-creating category of catching-up, given the exploratory nature of the learning endeavour.

4 Data

To empirically identify technology domains within the Semiconductor Industry, assess their life-cycle and investigate the comparative advantage pattern of new innovators and incumbents, we make use of patent data. We use the second version of the NBER patent citation database (Hall et al. 2001) containing information on patents granted by the United States Patent and Trademark Office (USPTO) the period between 1975 and 2006. Since the US is a major market for semiconductors and still the global center of semiconductor devices design. Therefore, we can safely assume that whenever important semiconductor-related inventions are created, the inventor or the company where the invention was made, will eventually apply for a US patent, even if the invention was made elsewhere. Hence, we believe the pool of US granted semiconductor patents is representative of the sample of global semiconductor inventions.

To identify all patented inventions representative of the Semiconductor Industry, we rely on the US Patent Classification System (USPC). Semiconductor technologies belong to the macro-category "electronics" of the USPC system. They are classified into five different subclasses. They are the followings: 257: Active solid-state devices (e.g. transistors, solid-state diodes) 438: Semiconductor device manufacturing: process 326: Electronic digital logic circuitry

505: Superconductor technology: apparatus, material, process 716: Design of semiconductor devices

To identify patent ownership, we use harmonized patent assignee names included in the 2006 version of the NBER-USPTO database. We further manually cleaned typos and inconsistencies in the way the company name is reported. Note that no effort was made to merge subsidiaries or divisions belonging to the same parent company. This is done on purpose, as these different entities can follow very different inventive strategies and have different technical capabilities. However, we assign patents to countries based on the country reported in the residential address of the first inventor.

4.1 Extraction of the *Network of Main Paths* out of the whole patent citation network

The distribution of patent technical and economic value is known to be highly skewed (Silverberg and Verspagen 2007; Trajtenberg 1990). Only a minority of patented inventions have real influence on the course of technical change and have a significant economic value. Therefore, we argue that, for the purpose of identifying the technology domains underlying a given industry and analyze their life cycle, it is important to remove technically unimportant patents from the sample. Selecting only the most technologically influential patents allows to reduce the noise in the data caused by marginal patents and their citations. We therefore employ a methodology called Network of Main Paths (NMPs), to extract the backbone of a patent citation networks. The NMPs identifies the most central routes through which information flows in large citation networks (Martinelli 2009; Fontana et al. 2009; Verspagen 2007). When applied to patent citation networks this methodology allows analysing the evolution of the main sequences of technological improvements in a given industry or technological area. The first building block of this approach relates to the meaning of patent citations. As described in the USPTO Manual of Patent Examination Procedure (MPEP)(USPTO 2015)[1], citations highlight which are the existing functionally-related inventions that provided a prior solution to a particular engineering challenge. If patent A cites patent B then the former improves upon the latter. In other words, patent B represents the state-of-the-art concerning the particular technology described in patent A at the moment in which patent application A was filed. Therefore, citations can be interpreted as a measure of technological relatedness and provide insights on the direction of technological

[1]The USPTO MPEP is available online at this website: http://www.uspto.gov/web/offices/pac/mpep/

change[2]. Obviously, a patent can cite and be cited by many other patents. Hence, if we want to follow the main trajectories of technology evolution among a set of patents, we first need to decide which direction to take at every junction. This is what the algorithm to define the NMPs does. First, we calculate the weight of every citation using the search path node pair (SPNP) algorithm, developed by Batagelj 2003 based on the original measure introduced by Hummon and Dereian 1989. The SPNP returns the number of times that each citation link lies on all possible paths connecting any node to anyone else. This is easily calculated by multiplying the number of patents that reach (through direct and indirect citations) the cited patent by the number of patents that are reached (directly or indirectly) by the citing patent. Therefore, a high SPNP weight indicates that the given citation and the two patents involved are located in a highly connected and connecting area of the network. This means that the given citation has a strong technological influence, as many paths of technological improvement pass through it. The NMPs is then identified by following the paths emanating from start nodes (nodes that are cited but not cited), taking at each junction the direction of the citation which carries the highest weight, till an end point (a node who cites but is not cited) is reached. This process can be repeated several time by accumulating windows of time, (e.g. from time t till t+1, then from t till t+2, and so on). By computing the NMPs for each period we can observe how the entrance of young patents at each point in time affects the presence of old ones in the network of main paths (i.e. the persistence of old technological trajectories). When newly granted patents connect to previously well-connected patents, technical improvements follow the same paths of citations of the previous period(s). In this case, the technological trajectories are said to be stable and cumulative. We interpret this case as an instance of stability of problem-solving approaches. To the contrary, if the new patents connect to paths that were previously underexploited the patent composition of the NMPs changes and the technological trajectories are affected by a discontinuity. We interpret the latter as a case of search of alternative problem-solving approaches. Therefore, at each point in time, there are three types of patents that are part of the NMPs: patents granted after the end date of the previous time partition of the network (*recent patents*), older patents that appeared in previous time snapshots of the NMPs (*old persistent patents*), and older patents that show-up for the first time in the NMPs (*old disruptive patents*). This

[2]From this perspective, the well-known fact that many, if not most, of the citation are added by the patent examiner rather than the applicant plays in our favor. Indeed, patent applications are examined by expert in the field of the technology described by the patent. Therefore, citations added by examiners can be seen as an even more objective measure of technological relatedness among patents. Obviously examiner-added citations are instead much more of a problem if one wants to use them as a measure of knowledge spillover between patent assignees. This does not apply to this work.

information is very important to understand our method to determine the life cycle stage of a technology domain. We explain the method in the next section.

We apply the NMPs methodology to the whole citation network of semiconductor technology-related patents granted by the USPTO between 1976 and 2006. First, we extract all US patents belonging to the following five US technology sub-classes: 438–process, 257-product, 326-materials, 505-programmability, 716-design. Then we create the citation network and extract the largest connected component. The latter is used to feed the NMPs algorithm that extract the most important paths of citations based on the SPNC weights and identify the patents laying on them. The largest component of the resulted reduced network is composed by the set of patents that we claim being the most influential from the perspective of technical progress. This is true for all time periods in our dynamic temporal analysis of the NMPs, except for the last 6 years in our time window (2001-2006). At the beginning of the 2000s, newly granted patents connected more to the second largest component of the NMPs than to the first. This means that a change in the ranking of engineering problems' importance occurred in this period. Priority of innovative effort shifted from those related to domains pertaining to the largest component to those found in the second one. The analysis of patents titles and abstracts revealed that technology domains found in in the second component focused on engineering problems related to LCD displays, in particular for e-readers and flat televisions. This suggests that the second largest component of the NMPs is composed of domains more related to entertainment and portable devices than to desktop computers and laptops. What we observe in this period could therefore be a case of overlap between the life cycle of products and technology domains. Given the importance of engineering problems related to the second component of the NMPs in the last period under observation, we include it in the analysis performed in the rest of the paper. The final Semiconductor patent dataset, which we use in this work, is then made of 114097 patents granted by the USPTO over the period 1976-2006. For more information, Table S.1 in the Supplemental Information S.2 reports the network size at each layer of data reduction. Figures showing the main component of the NMPs for each of the six periods are also reported in the Supplemental Information S.3 (Figures from 3 to 8). The technology domains are highlighted in different colours (these areas have been identified through the community detection procedure explained in Subsection 5.1).

Selecting only the most technologically influential patents, besides cleaning the data, also allows distinguishing innovators from inventors. By the former, we mean players that are able to generate novelty that is later recognized as useful from the point of view of technical progress.

The latter are players whose inventive output does not attract sufficient attention to determine the course of technology evolution. In this sense, we use the term innovation in a Schumpeterian way, implying that inventions became innovations only when they are recognized as useful and, therefore, start diffusing. We further distinguish between *incumbent* and *new innovators*. Note that the use of the terms "new innovators" or "incumbent innovators" rather than new entrants or simply incumbents is purposely made. Industrial organization theory would distinguish between firms that have started *producing* for the first time (new entrants) or have been doing it for a while (incumbents). Since we look at the technological dimension rather than the manufacturing one, we characterize firms by their ability to *generate technological inventions* that lately attracted a significant stream of engineering improvements. A figure which breaks down patent assignees in our final dataset by incumbent and new innovators over time is reported in the Supplemental Information S.4 (Figure S.9).

5 Methodology

5.1 Empirical detection of technology domains

We have defined technology domains as areas of research characterized by commonality of problems and approaches. We have also discussed how citations between patented inventions highlight functional and technical similarity between the citing and the cited patents. It follows that network community detection methods can be applied to identify technology domains. It has become a common practice to analyse large networks' community structure in order to split them into partitions. Partitional and agglomerative hierarchical clustering methods have been defined to identify such structure. We use a method proposed by Newman 2004 based on the concept of modularity. Modularity is defined as the fraction of links (citations in our case) in the network that falls within a community. The algorithm maximizes modularity. This allows identifying communities as areas of the networks whose nodes are more related to each other's than they are to nodes outside the community. Technical details about the Newman's community detection algorithm can be found in the Supplemental Information S.5, where we also validate the quality of the algorithm's results. We chose to use the Newman algorithm because, contrary to other popular community detection algorithm like, for instance, the Newman and Girvan 2004, the former provides a benchmark to evaluate the quality of the partition and does not require to arbitrarily choose the number of communities to be identified. Indeed the modularity maximization procedure and the comparison with equivalent random networks returns the best

	76-80	76-85	76-90	76-95	76-00	76-06 (1st Comp.)	76-06 (2nd Comp.)
Number of patents	694	1540	2678	2043	4557	3544	2762
Modularity	0.8567	0.8789	0.9013	0.9066	0.9161	0.9021	0.8967
Number of domains	14	15	14	14	15	15	14
Size of the main domain	128	328	368	272	637	701	489
% of patents in main domain	18,44%	21,30%	13,74%	13,31%	13,98%	19,78%	17,70%
Size of smallest domain	15	29	52	65	62	73	53
% of patents in smallest domain	2,16%	1,88%	1,94%	3,18%	1,36%	2,06%	1,92%
Average cluster size	49,57	102,66	191,29	145,93	303,80	236,27	197,29
St.dev.	34,16	80,38	80,41	69,76	143,03	149,51	118,04
Coefficient of variation (St.dev/Av)	0,69	0,78	0,42	0,48	0,47	0,63	0,60

Table 1: Basic statistics for the technology domains identified by Newman's algorithm.

partition of the network analysed, without assuming a pre-existing community structure.

Some basic statistics about semiconductor technology domains identified by Newman's algorithm are reported in Table 1. The high values of modularity (always higher than 0.85) reveal a strong underlying community structure within the largest component (and the second one in the last period) of the NMPs. This provides empirical support for the existence of several, relatively separated, areas of research within the Semiconductor Industry. The algorithm identifies a number of domains varying between 14 and 15 over the periods observed. The size of the largest area changes quite a lot. So does the standard deviation and the coefficient of variation. The large size differences among technology domains hint to the importance of analysing their life cycle.

In the next subsection, we explain how we identify the life cycle stages of technology domains that we have just identified.

5.2 Characterizing technology domains by their life cycle stage

Our method to identify the life cycle of technology domains is based on the existence of three types of patents that are found in the NMPs at each point in time: young, persistent old and new old. Young patents are those granted in the last period of observation. Persistent old patents are those that have already been part of the largest component of the NMPs at least once in the periods before the one observed. In our analysis, we focus on six periods: 1976-1980, 1976-1985, 1976-1990, 1976-1995, 1976-2000 and 1976-2006. Let us take, for instance, the last period 1976-2006. For this period, the three patent categories can be described as follows. Young patents are those granted after the end of the previous period (i.e. from 2000 till 2006) which connects to the main component of the NMPs. Persistent old patents are those who showed up in the main component of the NMPs at least once in one of the previous five periods. New old patents are those granted before 2001 which had never been part of the main component of the NMPs before. The distinction between persistent old patents and new old patents allow us to distinguish domains where there is no search of alternative approaches, from those who are exploring a new path. Furthermore it also help us to differentiate between areas which are young but nevertheless building on previously explored technological paths and young areas which are not related to any technological solution that have been developed in the past. Figure 3 shows the relationship between the type of old patents and the age of the technological areas. Each circle stands for one of the technology domains identified over the six periods. Its position on the horizontal axis reflects the age of the area. The vertical axis coordinate is given by the percentage of old new and old persistent patents found in the domain (each domain counts for two circles in Figure 3). Dashed lines are lines of best fit obtained by linear regression using a second degree polynomial as mathematical model. The figure shows that young domains are more likely to build on previously unexploited technological solutions (new old patents) than known ones (persistent old patents). Therefore, search across possible problem-solving approaches is higher. To the contrary, the more a domain grows old, the more likely it will follow a stable and previously defined approach to problem solving. The two curves closely resemble the patterns sketched in Figure 3. This confirms our theoretical predictions based on the cumulative nature of technological change. Figure 3 also clearly shows that patent composition within a technological area changes drastically with age. Our classification method follows the intuition that it is possible to categorize domains' life cycle stages based on the relative number of young, persistent old and new old patents, they are composed of. This allows defining all the stages of the life cycle of technological areas, from emerging to declining.

Based on the theoretical framework discussed in Section 4.3 and the empirical findings shown in Figure 3, we propose the following theoretical correspondence between each life cycle stage and the patent composition that reflects it.

Breakthrough

Breakthroughs break the usual pattern of knowledge cumulativeness that normally characterizes technical change. Their relationship with previous solutions is very little if existent. We argue that domains in their breakthrough stage are characterized by a large number of young

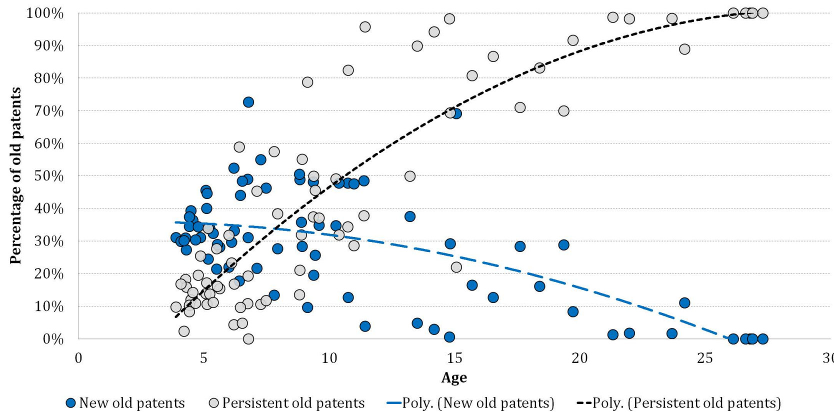

Figure 3: The relationship between persistent old patents, new old patents and the age of semiconductor technology domains

patents and a few new old and persistent old patents if at all.

Disruptive emerging areas

We argue that disruptive technological areas are characterized by the presence of several young patents that builds largely on previously disconnected patents and very little on persistent old ones. This reflect the high search across possible approaches to problem solving which characterize emerging areas but also the peculiar focus on previously unexploited existing solutions which make the domain disruptive in nature. The other marking trait of disruptive domains is that the underlying set of problems initially does not receive much attention. The latter two characteristics distinguish disruptive domains from breakthroughs.

Early development

If successful, disruptive or breakthrough domains are developed further and move to a stage of early growth. During this stage, the attractiveness of the area of research is high and the technological trajectory starts to consolidate. Therefore, the number of young patents is high, the presence of persistent old patents increases and the one of new old patents decreases.

Maturity

Maturity is similar to the early development stage with the only difference that the domain now attracts much less innovative efforts (i.e. fewer young patents connect to it) and technological change becomes increasingly cumulative. This means that the number of persistent old patents keeps growing, to the detriment of the exploration of alternative approaches.

Renewing

After the maturity stage the evolution of a given technology domain is at a crossroad. The development of the given technology could be either stopped or get new vigour. In the former case, the domain begins exhausting. In the latter, it enters into a renewing stage. In this case, alternative paths are explored to avoid obsolescence. This might begin a new life cycle or just extend the life of a technology domain for a short while without avoiding its imminent decline. The renewing stage is characterized by a few young patents that build extensively on new old ones and on some persistent old patents.

Exhausting

Exhausting (or declining) areas are characterized by very few, if any, young patents, a large number of persistent old patents and almost no new old ones.

At this point, we have a theoretical definition of the life-cycle stages of technology domains and the preliminary characterization of them according to the relative number of young, old persistent and old new patents that is found in each domain. To make our methodology operational we need a practical way to formally distinguishing one stage from the other. Consider a triangular shaped space in which the horizontal axis measures the relative number of old persistent patents in a given domain and the vertical axis reports the relative number of young patents. The structure of the space is such that domains can only locate in the lower triangle that is defined by the axis and the diagonal connecting the maximum values of the two axis (i.e. 100). This is because the relative number of patents per each category is constrained between 0 and 100. Therefore, by construction the orthogonal distance of each domain from the diagonal measure the relative number of old new patents. We call such space the life-cycle space of technology domains as the entire life of a given domain can be described by movements along this space. The space is reproduced in Figure **??**. However, before to discuss the figure, let us first explain step-by-step the process behind its creation. We first need to draw borders on such space that will help us identifying the areas corresponding to each life-cycle stage. To accomplish this task we need to formally quantify the relative number of young, persistent old and new old patents that a domain must have for its life cycle to be in a given stage. Quantify how much is a lot is a task that is best done by comparison. Therefore, we first take all domains identified by Newman's algorithm over the periods 1976-1985[3], 1976-1990, 1976-1995, 1976-2000 and 1976-2006, we look at the percentage of young, persistent old patents and new old ones in each area and then we plot the distribution of these percentages. This is shown in Figure 4, where

[3]We cannot use the first period, 1976-1980 because, being the initial period, by construction all the areas are entirely composed by young patents.

each of the domains is split into three observations indicating the percentage of young, new old and persistent old patents it is composed of. On the horizontal axis, we have the values for the percentages of each category of patents that are part of one of the technology domains, whereas on the vertical axis we have the cumulative percentage of the distribution, meaning the percentage of observations with a value smaller than the value on the horizontal axis. We drew two horizontal dashed lines to clearly separate the top 20 percent from the mid-60 percent and the bottom 20 percent of the distribution. This allows us to identify the border values for the first quintile and the last quintile. For instance, if we look at the distribution of the relative number of young patents among all technology domains we see that 20 per cent of the domains have less than 1.14 per cent of young patents, 60 per cent have between 1.14 per cent and 49.35 per cent of them and 20 per cent have more than 49.35 per cent of young patents. For instance, this means that a given domain can be said to have many young patents if more than 49.35 per cent of its patents are young. In this case, the remaining 50.65 per cent is distributed between new old patents and persistent old ones. The same exercise can be applied to new old patents and persistent old ones. In the former case 20 per cent of the domains have less than 11.11 per cent of new old patents, 60 per cent have between 11.11 per cent and 45.57 per cent of them and 20 per cent have more than 45.57 per cent of young patents. Finally, if we look at the distribution of the relative number of persistent old patents we see that 20 per cent of the domains have less than 11.97 per cent of them, 60 per cent have between 11.97 per cent and 86.67 per cent and 20 per cent have more than 86.67 per cent. It is important to notice that there are no domains purely composed by young or new old patents. Nevertheless, a few are entirely made of persistent old patents. From a NMPs methodological point of view we can argue that a domain purely made by young patents or by new old ones would be disconnected from the main component of the NMPs by construction and therefore not observed. To the contrary, albeit rarely, domains entirely composed by persistent old patents can be found in the main component of the NMPs. They indicate technological ancestors upon which newer solutions build.

Now that we have more precise quantities of young, new old patents and persistent old ones, we can use them to elaborate a more precise definition of the life cycle stages of technological domains. Table 2 reports the thresholds that define the amount of each type of patents to be found in a given domain for it to be classified in one of the life cycle stage reported in the left column. We call this thresholds quantile borders. For instance, for a domain to be classified as a breakthrough it needs to have at least 49.35 per cent of young patents, less than 45.57 per cent of new old ones and less than 11.97 per cent of persistent old patents. However, the

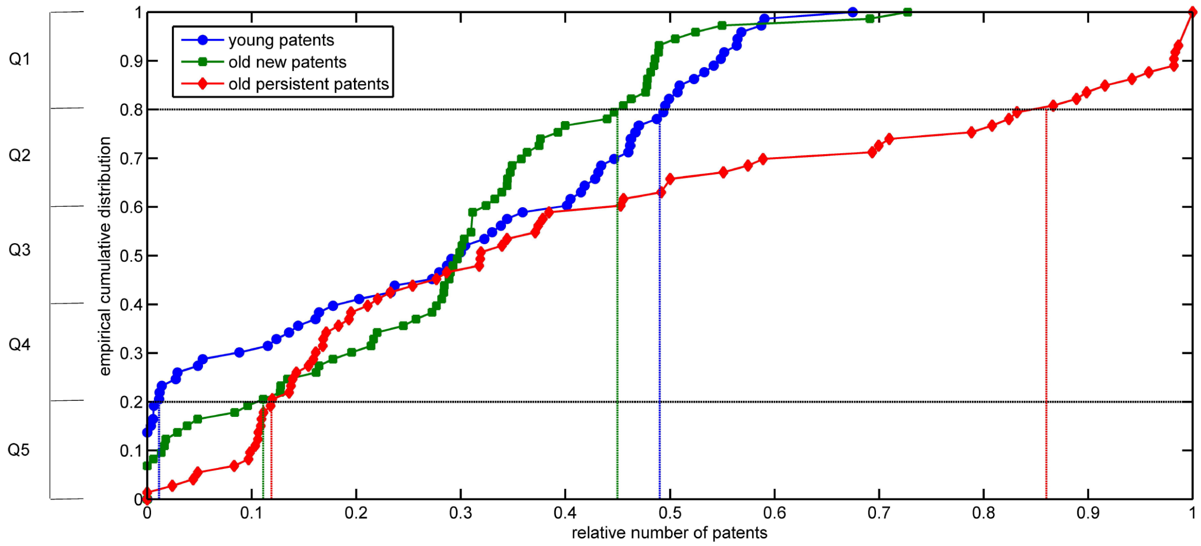

Figure 4: Empirical cumulative distribution of the percentage of young, new old, and persistent old patents for all the technology domains in the periods 1976-1985, 1976-1990, 1976-1995, 1976-2000 and 1976-2006.

Quantile classification

Many	Q1 (i.e. top 20%)
Mid	Q2, Q3, Q4 (i.e. mid 60%)
Few	Q5 (i.e. bottom 20%)

Quantile borders for the technological area life cycle stages

	Young patents	New old patents	Persistent old patents
Breakthrough emerging areas	Many = Q1 (>49.35%)	Few-mid = Q2-Q5 (<45.57%)	Few = Q5 (<11.97%)
Disruptive emerging areas	Few-mid = Q2-Q4 (<49.35%)	Many = Q1 (>45.57%)	Few = Q5 (<11.97%%)
Early growth areas	Many = Q1 (>49.35%)	Few-mid = Q2-Q5 (<45.57%)	Mid Q2-Q4 = (11.97%≤ ...<86.67%)
Mature areas	Few-mid = Q2-Q4 (<49.35%)	Few-mid = Q2-Q5 (<45.57%)	Mid Q2-Q4 = (11.97%≤ ...<86.67%)
Renewing areas	Few-mid = Q2-Q4 (<49.35%)	Many = Q1 (>45.57%)	Mid Q2-Q4 = (11.97%≤ ...<86.67%)
Exhausting areas	Few = Q5 (<1.14%)	Few = Q5 (<11.11%)	Many = Q1 (>86.67%)

Table 2: Patent distribution quantile borders by patent type and life cycle stage.

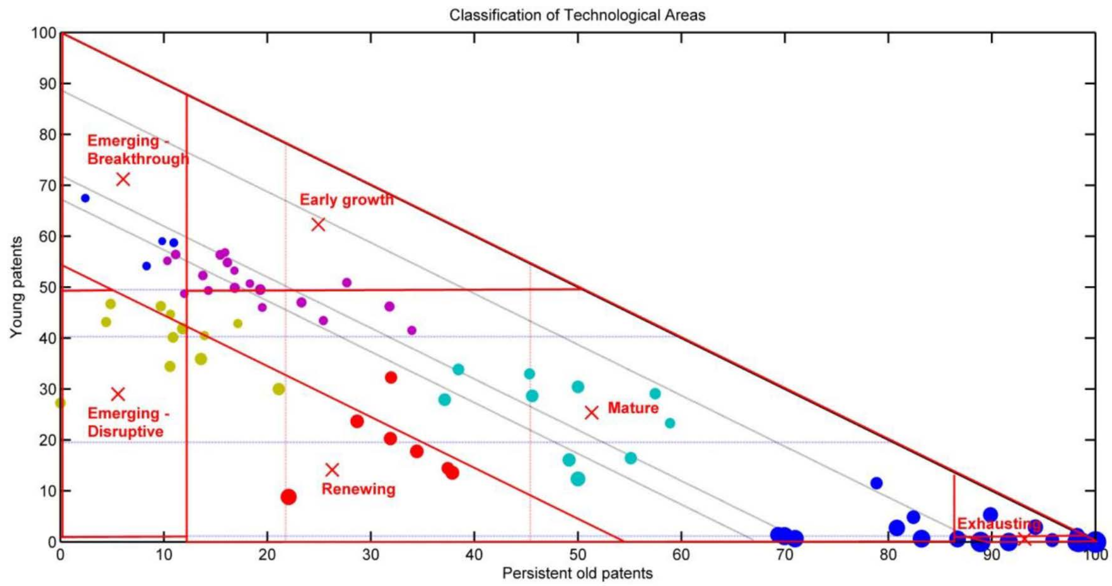

Figure 5: The technology domains' life cycle space

quantile borders alone are not sufficient to determine life cycle stages. The main reason is that, being thresholds, quantile borders suffer from the drawback that areas that lay very close to the border might actually be more similar to the areas located on the other side of the border than to the other areas located on the same side. This problem is similar to the one of defining homogeneous groups of people living in areas whose borders have been set on paper, without considering the common characteristics of people living close to the border. In other words, we would like to have borders that respect the geography of the life-cycle space. Therefore, the initial quantile borders are used to calculate centroids, which serve as basins of attraction. To sum up, first we calculate the quantile borders for the distribution of the percentage of young, new old and persistent old patents for all the domains in the periods 1976-1985, 1976-1990, 1976-1995, 1976-2000 and 1976-2006 (Table 2). Then we use them to preliminary identify regions of the life-cycle space that are coherent with the theoretical description of the life cycle stages of technology domains and the empirical distributions of young, persistent old and new old patents. Afterwards we calculate the centroid for each of the preliminary defined areas of the life-cycle space. Finally, we compute the distance to each of the centroids for each technology domain identified through Newman's algorithm. The life cycle stage of each technology domain is then identified by assigning each domain to the closest centroid. This procedure is shown in Figure 5.

Each node stands for one of the technology domains identified in Section 4.2. The size of the node is proportional to the size of the given domain measured by the number of patents. The location of a domain on the life-cycle space is informative of its patent-composition and therefore of its life-cycle stage. In Figure 5 red lines highlight quantile borders reported in Table 2 and centroids are marked with a red 'x'. Domains that share the same colour fall within the basin of attraction of the same centroid. This means that they are closer to that centroid than to any other one and therefore are in the life-cycle stage indicated by the centroid. Note that by connecting centroids of subsequent life cycle stages and tracking the evolution of the relative number of young, old persistent and old new patents, curves similar to those reported in Figure 2 emerge. This highlights the strong connection between the theoretical description of the life-cycle of technology domains and the methodology used to trace it.

Now we have a classification of the life cycle stage of each technology domain. To test its logical consistency we trace movements from each life cycle stage to the other ones. Of course, for our classification to be coherent, we should observe movements consistent with time. This means that, for instance, patents that are classified into a technology domain in its early development stage in period T should be mainly part of a domain classified as mature in the next period. Some might still be found in an early-development stage. This would indicate that the life cycle of that domain is relatively slow. Some others might jump over stages and be found in renewing or exhausting domains. This would indicate that the life cycle of that domain moved faster in the period observed. The crucial aspect is that they should not be found in large numbers in an earlier stage, otherwise the time consistency of our methodology would be broken. A small number of patents could actually move back to an earlier stage but this can only happen when some patents from one domain serve as foundation for a younger one in the next period. This possibility is intrinsic to the evolution of communities as defined by Newman's algorithm and the network of main path approach. However, this cannot happen in large numbers because otherwise the new domain would not be younger than the original one and would then be classified in the same life cycle stage than the latter, or in one of the followings.

Table 3 shows how many patents from domains which, in period T, were in one of the life cycle stages listed on the rows moved, in the next period, to any of the domains whose life cycle stage in T+1 is indicated in the columns. The table clearly proves that our methodology is logically consistent as most of the patents follow the expected movement to "older" life cycle stages (to the right of the diagonal) and very few moves to "younger" domains whose life cycle

	Breakthrough	Disruptive	Early growth	Mature	Renewing	Exhausting
Breakthrough	0.00%	**24.36%**	**50.00%**	6.41%	16.67%	2.56%
Disruptive	1.99%	4.42%	**25.88%**	24.56%	**29.65%**	13.50%
Early growth	0.39%	1.49%	14.48%	**29.89%**	15.88%	**37.87%**
Mature	2.00%	1.80%	4.60%	**12.00%**	6.00%	**73.60%**
Renewing	0.00%	0.77%	0.77%	3.84%	**9.72%**	**84.91%**
Exhausting	0.00%	0.00%	0.13%	0.00%	0.00%	**99.87%**

Table 3: Movements from one life cycle stage to the others over consequtive periods.

stage is antecedent the one of origin (to the left of the diagonal). Having proved the consistency of our methodology, we can now introduce the answers to the paper's research questions.

5.3 Measuring comparative advantage along the life cycle

In the introduction of our paper, we raised two research questions about the role played by incumbent and new innovators along the life-cycle of technology domains. In order to analyse aggregate comparative technological advantage we propose an original index that returns a macro-aggregation of micro-comparative technological advantage of individual firms. Our specialization index, which we call SPEC, builds on the well-known revealed technological advantage index (RTA). The RTA is a specialization index defined by Soete 1987, which builds on the Ricardian concept of comparative advantage and, more precisely, on the revealed comparative advantage index as defined by Balassa 1965. The intuition behind the RTA is that even if a given entity (countries, firms, geographical regions) might have less patents than other entities in absolute terms, there might still be areas of technology in which it enjoys a comparative advantage. This means that such entity could be able to produce comparatively more patents in a given technological area than in the overall industry. Indeed, the index reveals the domains in which a given entity performs comparatively better. This reflects the entity's comparative advantage in terms of research productivity in those domains. Neoclassical economic theory would suggest that agents (firms or countries) should specialize in those domains where they enjoy comparative advantage. Obviously, this is a static suggestion that does not take into account the possibility of knowledge upgrading. Our use of the SPEC index is intended to investigate in which life-cycle stages agents' capabilities significantly differ, in particular between new and incumbent innovators. However, it must not be understood as a suggestion that agents should necessarily specialize in those domains permanently. To the contrary, in Section

4.5.2, we seek evidence of knowledge upgrading by looking at how the revealed comparative advantage changed over time. The original version of the RTA index is calculated as follows.

$$RTA_{ik} = \frac{\frac{x_{ik}}{\sum_i x_{ik}}}{\frac{\sum_k x_{ik}}{\sum_{i,k} x_{ik}}} \tag{1}$$

Where x_{ik} is entity's (country or firm) i number of patents in domain k. The RTA index is equal to zero when entity i holds no patents in the given domain k. When the index is equal to 1 entity i's patent share in area k is equal to its share in all areas. Values of the index greater than 1 indicate comparative advantage in the given domain. The original version of the index is not symmetric, meaning that it is bounded to zero for comparative disadvantage in the domain but unbounded for comparative advantage. This causes problems when one wants to compare the shape of its distribution for different entities or when the RTA is used in econometric models. In this work we intend to do the former. Hence, we opt for the symmetric version of the RTA (SRTA), which is calculated as follows.

$$SRTA_{ik} = \frac{RTA_{ik} - 1}{RTA_{ik} + 1} \tag{2}$$

In its symmetric version the index ranges from -1 (full negative specialization) to $\lim_{RTA \to \infty} SRTA_{ik} = 1$ (full positive specialization), with values greater than 0 indicating comparative advantage in the domain. We use the symmetric RTA as a basis to construct an index that gives a micro-founded picture of specialization patterns at the aggregate level. We first need to estimate the probability density function (pdf) of the SRTA for each country. The pdf returns the probability to observe a given SRTA value if we choose a firm at random out of the sample of firms belonging to a given country. We use a kernel smoothing function to estimate the probability distribution that best fits the empirical (cumulative) distribution of the SRTA for the given entity. The kernel density function estimates the probability to observe a given SRTA for the whole range of the SRTA index (from -1 to 1). This improves our ability to compare entities of different size as the empirical distribution for small entities relies on fewer observations than for large entities. Once we estimated the probability density function, we compute the SPEC index as follows.

$$SPEC_{ik} = \sum_{j=0:0.1:1} SRTA_j * \rho(SRTA_j)_{ik} \tag{3}$$

Our specialization index $SPEC_{ik}$ is the weighted sum of the probability ρ to observe SRTA values at the firm level reflecting comparative advantage in the given domain (i.e. SRTA>0). Indeed $\rho(SRTA_j)_{ik}$ is the probability to observe a given SRTA value j greater than zero (i.e. positive specialization) among the whole sample of SRTA values calculated for the area k for all firms belonging to the given country i. This probability is multiplied by the strength of specialization, namely by the value of the $SRTA_j$, which, ranging from 0 to 1, effectively serves as a weight for the sum. We limit the SRTA range to positive values because we are not interested in comparative disadvantage. In other words, a large value of the SPEC index means that, if we extract a firm at random out of the sample of firms from the given country, that firm has a high probability to be strongly specialized in the area under consideration. It is important to note that our index focus on the right tail of the distribution of SRTA. This is an improvement over traditional approaches that calculates the SRTA at the firm level and then averaged it at the country level. This approach fails to realize that comparative advantages are rarer than comparative disadvantages. Therefore calculating the average SRTA over the whole distribution hides the interesting signal contained in the data. Indeed, typically, the average SRTA would be negative. Given that observing values of the SRTA greater than zero is much less common than the opposite, the interesting information that the data provides with respect to comparison across groups is not provided by the mean. Rather, what really matters is how large the difference between the right tails of the distribution for the two groups is. Comparing the SPEC index across groups provides this information. Another popular choice in the literature is to calculate the SRTA for a given country as the aggregate of all of its firms. This approach is also unsatisfactory in the sense that the aggregate picture might be heavily influenced by a few large firms, washing away the information about comparative advantages or disadvantages of small firms. The SPEC index does not suffer from this problem either.

6 Findings

In the two following subsections, we present the findings that answer the two research questions raised in the introduction of this paper: (i) In which life-cycle stages new innovators have a comparative technological advantage over incumbents? (ii) Are there significant differences in the comparative technological advantage of new innovators from different countries? Before introducing the answers to these questions, we first describe the distribution of new and incumbent innovators in the NMPs sample. Table 4 reports the number of firms by geographic origin and type (new or incumbent innovators) across the five periods under consideration. To answer our two research questions, we merge the first and second component of the NMPs in the last period together, as explained in Subection 4.1.

All firms	1981-1985	1986-1990	1991-1995	1996-2000	2001-2006 (1st+2nd)	Total
US	61	92	62	75	80	370
JP	24	32	28	47	29	160
KR	0	2	5	7	5	19
TW	0	1	6	17	15	39
SG	0	0	1	4	3	8
KR/TW/SG	0	3	12	28	23	66
Total	85	127	102	150	132	596

New Innovators	1981-1985	1986-1990	1991-1995	1996-2000	2001-2006 (1st+2nd)	Total
US	35	50	20	40	48	193
JP	13	18	10	25	8	74
KR		2	3	2	3	10
TW		1	5	11	7	24
SG			1	2	1	4
KR/TW/SG	0	3	9	15	11	38
Total	48	71	39	80	67	305

Incumbents	1981-1985	1986-1990	1991-1995	1996-2000	2001-2006 (1st+2nd)	Total
US	26	42	42	35	32	177
JP	11	14	18	22	21	86
KR	0	0	2	5	2	9
TW	0	0	1	6	8	15
SG	0	0	0	2	2	4
KR/TW/SG	0	0	3	13	12	28
Total	37	56	63	70	65	291

Table 4: Number of firms by geographic origin and category.

6.1 Comparative technological advantage of new innovators and incumbents

In order to have a reliable estimation for the distribution of SRTAs for new and incumbent innovators we initially plot all five periods together. This returns 305 observations for the new innovators and 291 for the incumbents. Figure 6 shows the kernel smoothed cumulative distribution functions for the two categories of firms. The vertical axis reports the probability to observe, across the whole sample, values of the SRTA smaller or equal than those reported on the horizontal axis. Therefore if one distribution is "smaller"[4] than the other for positive values of the SRTA it means that the former shows a comparatively stronger specialization pattern in the given technology life cycle stage than the latter, as the probability to observe large SRTA values is higher. A first look at the figure reveals that the shape of the distributions changes across the different life cycle stages. However, in at least three cases, breakthrough, early growth and mature areas, the right tail of the distribution for both groups behaves quite similarly. The difference appears to be stronger in disruptive, renewing and exhausting areas. We test whether the behaviour of the two populations is statistically different by mean of the Anderson-Darling non-parametric two-sample test. The table riporting the results can be found in Supplemental Information S.6 (Table S.2). The test confirms that the distribution of SRTA for new and incumbent innovators is statistically different for all the life-cycle stages except for the exhausting one. New innovators seem to have a comparative advantage in disruptive areas (as predicted by Christensen), whereas incumbents seem to be comparatively stronger, for mild levels of the SRTA, in renewing and exhausting areas, in line with industry life-cycle theory. A clearer picture of these differences is shown in Figure 7, where we plot the SPEC index for new and incumbent innovators.

Our micro-founded specialization index confirms what we inferred from the visual inspection of the cumulative distributions. New innovators have a greater probability than incumbents to have a comparative advantage in all life-cycle stages up to maturity. These differences are all statistically significant based on the Anderson-Darling test. However only for disruptive domains the comparative advantage is considerably strong. For renewing and exhausting domains the opposite is true and the comparative advantage is hold by incumbents. Yet the difference is significant only for the former. Therefore, if we only distinguish firms based on whether they are new or incumbent innovators, without considering their country of origin, the semiconductor industry follow a recommended specialization pattern which is consistent with industry life-cycle theory, Christensen's notion of disruptive technologies and Levinthal and March's definition of incumbents' myopia (Christensen 1997; Levinthal and March 1993). Indeed our findings are consistent with the theoretical prediction that new innovators perform comparatively better in technology domains in the initial stages of their life-cycle because incumbents

[4]The correct terms would be first order stochastic dominance if one distribution were always below the other one and second order stochastic dominance if the two distributions cross at some point, meaning that one distribution is below the other only for values greater than a certain threshold. Stochastic dominance refers to the difference in probabilities to observe values of a given amount. If the distribution for one category is stochastically dominated (i.e. it falls below the other) for the whole or part of the range it means that the probability to observe large (small) values of the variable is higher (smaller) than for the other category.

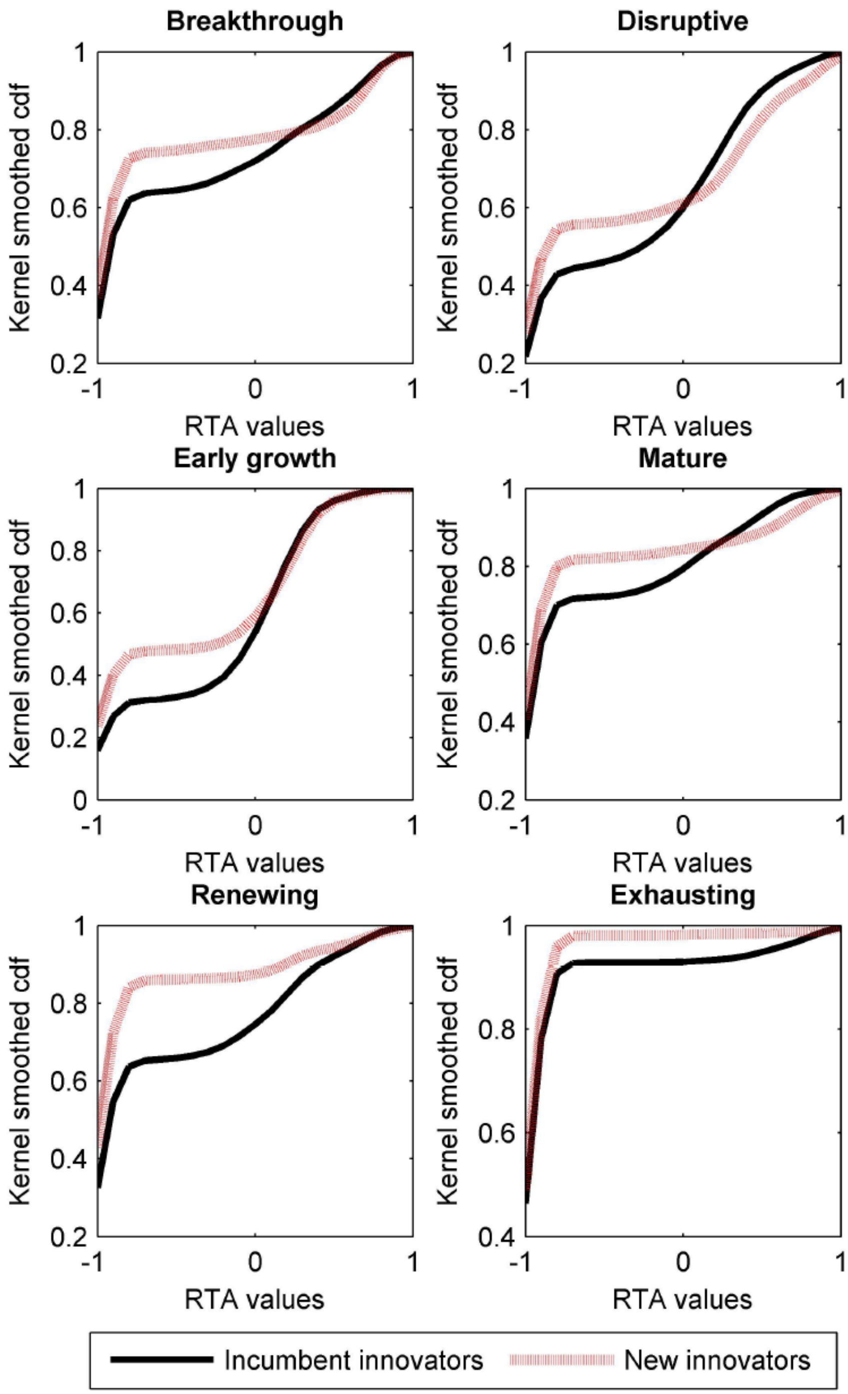

Figure 6: Estimated cumulative distribution functions for new and incumbent innovators

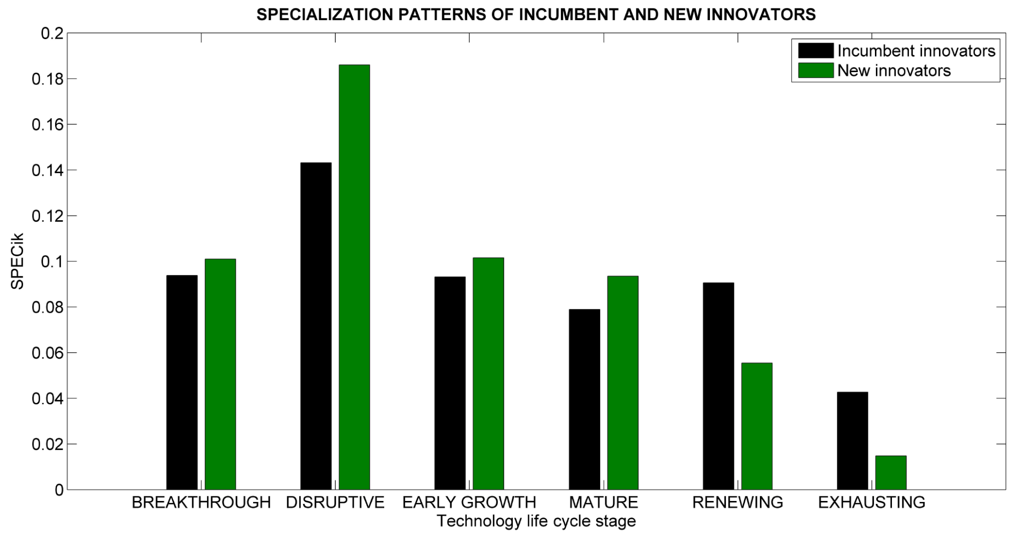

Figure 7: Micro-founded specialization index for new and incumbent innovators

are more likely to face learning traps that make them reluctant to explore new approaches to problem-solving. Our findings show that this is in general true but the comparative advantage is particularly strong only for disruptive domains. This answers our first research question. To tackle the second one we need to further distinguish firms based on their geographical origin. This is done in the next sub-section.

6.2 Comparative technological advantage breaked down by geographical origin

In Figure 8 we split new entrant innovators by geographical origin. Once again, in order to have enough observations for the estimation of the cumulative distribution function we plot all periods together (this constraint will be removed in the last part of the analysis). Furthermore, for the same reason, we need to group latecomer new innovators from Korea, Taiwan and Singapore into a single geographical area. This approach allows revealing the comparative technological advantages of new innovators from catching-up (i.e. Korea, Taiwan and Singapore), early entrant (i.e. Japan) and leader (i.e. US) countries. For the sake of further comparison, we also plot the distribution of SRTA for incumbent innovators. This distribution is the same shown in Figure 6.

US and Japanese new innovators follow the same pattern of comparative advantage. The

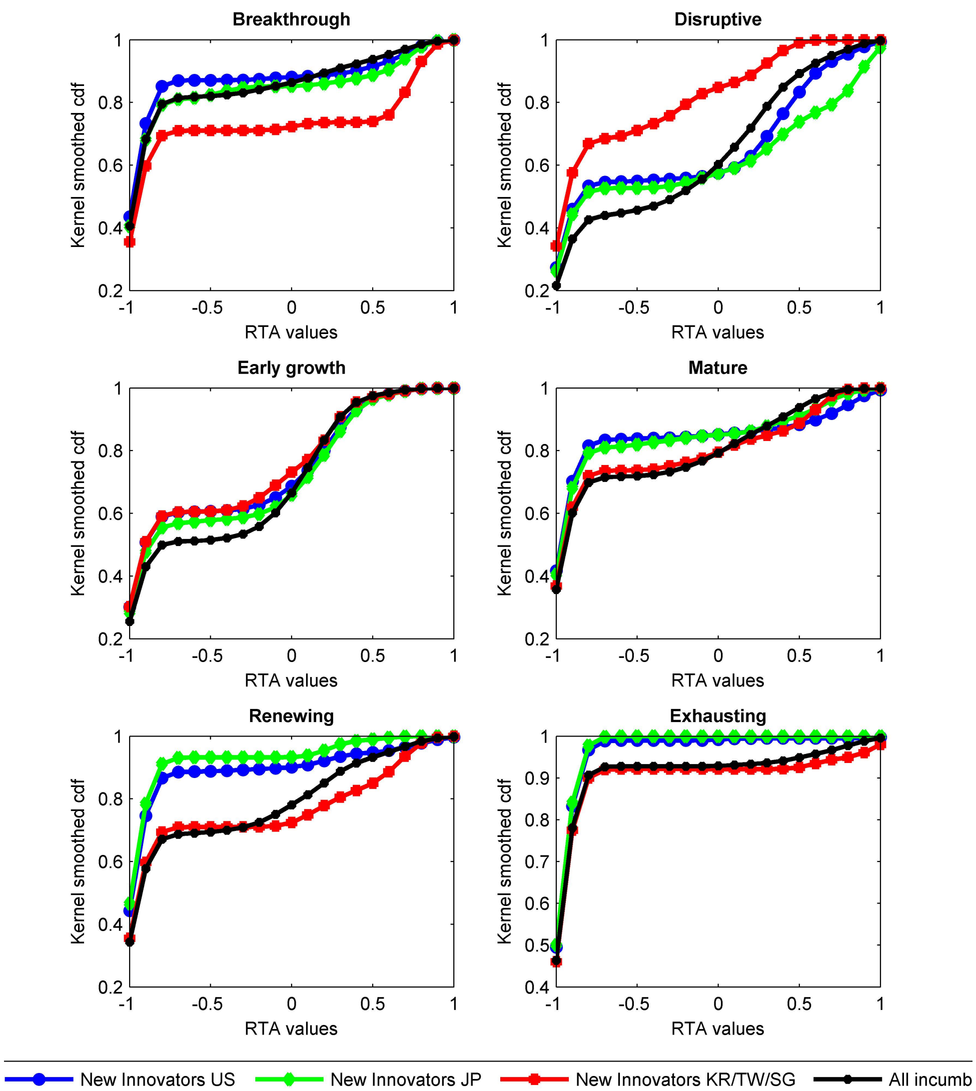

Figure 8: Estimated cumulative distribution functions for new innovators from the US, Japan, and the three Asian Tigers

kernel estimated cumulative distributions of the SRTA values for US's and Japan's new innovators are extremely close in all the life cycle stages with the exception of disruptive areas. To the contrary, there is a remarkable difference between the distributions of the three Asian tigers and those of US and Japan, especially at the extreme stages of the life cycle. In breakthrough, renewing and exhausting areas, the distribution of SRTA values for Korean, Taiwanese and Singaporean new innovators is always stochastically dominated by the distribution for US and Japanese new innovators. This means that Asian tiger's new innovators are comparatively more specialized in those areas that US and Japanese ones. The opposite is true for disruptive areas, whereas there is not much difference for early growth and mature ones. It is also interesting to compare specialization patterns between new innovators, now split by geographical origin, and incumbents. In technology domains in the early stages of their life-cycle, US and Japanese new innovators' specialization patterns closely follow incumbent innovators' one. On the other hand, for domains in the late stages (mature, renewing and exhausting), incumbents' distribution of SRTA values resembles more to the specialization patterns of new innovators from the three Asian tigers. This suggests that incumbent strategies are imitated more strongly by US and Japanese new innovators when it comes to specializing in emerging technologies, whereas they are followed more closely by Asian tigers' firms when the decision is about specializing in relatively older technologies.

As done in the previous section, to give a more precise answer to our second research question we look at the micro-founded specialization index for new innovators by geographical origin. This is reported in Figure 9. Once again, differences in the distributions plotted in Figure 8, which implies differences across SPEC indices, have been tested for statistical significance using the Anderson-Darling test (Supplemental Information S.6).

Let us first consider breakthrough, renewing and exhausting domains. If we pick a firm at random out of each of the samples of new innovators, there is a larger probability that the randomly selected firm has a strong comparative advantage in those areas if we sample it from the Asian tiger group rather than the US or Japanese ones. Yet differences across the related distributions are statistically significant only for renewing domains. They are close to be significant in breakthrough and exhausting domains, when we compare Asian tigers' new innovators against US ones for the former and against Japanese new innovators for the latter. They are not significant in when comparing Asian tiger's and Japanese new innovators in breakthrough and Asian tiger's and American new innovators in exhausting domains. When we look at disruptive areas, the pattern reverses. Japanese and US new innovators enjoy a strong comparative ad-

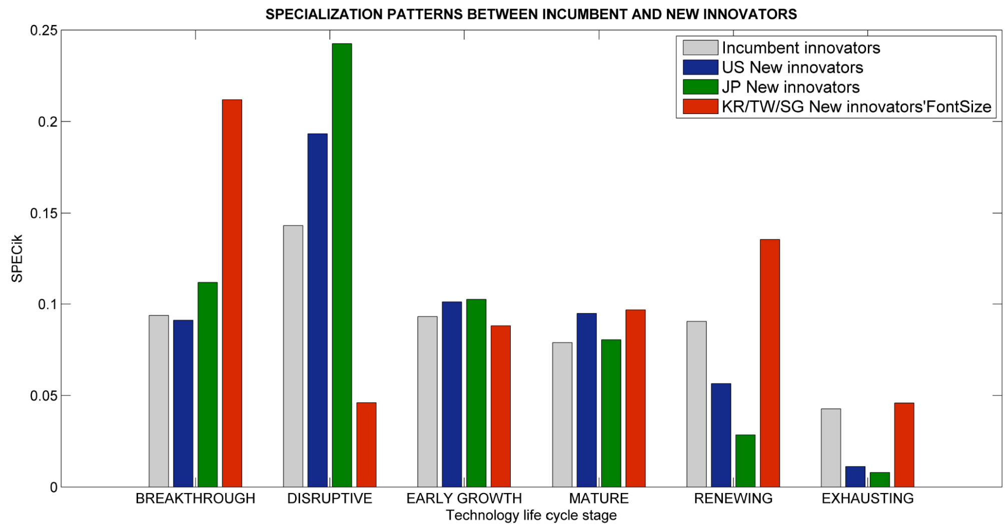

Figure 9: Micro-founded specialization index for incumbents and new innovators by geographic origin

vantage, whereas Asian tiger's ones have a clear disadvantage. Yet, the Anderson-Darling test reveals that the advantage over the Asian tigers is significant only for Japanese new innovators, albeit close to significance for American ones. Differences are very mild for early growth and mature areas, although statistically significant in the case of early development domains for Japan. The advantage enjoyed by Asian tiger's new innovators over US and Japanese ones is consistent with the anecdotic knowledge of the development of the Semiconductor industry in these countries. As shown by Mathews and Cho 1999, Chang et al. 1994 and Cho et al. 1998, the strategy adopted by firms from Taiwan and Korea consisted in accessing relatively obsolete foreign technologies and reverse-engineer them to start their learning path. To the contrary, their comparative advantage in breakthrough domains, although not significant, deserves more attention. In particular, from the point of view of catching-up and knowledge upgrading, it is interesting to know when this advantage started to emerge.

Thus far, we provided a static analysis, due to the lack of a sufficient number of observations to have period-by-period reliable estimations for the new innovators. We can overcome this constraint by looking at all firms together, regardless of whether they are new or incumbent innovators. This way we are able to show a dynamic picture of micro-founded specialization patterns at the country level. Figure 10 shows the trend of the SPEC index over time across geographic areas.

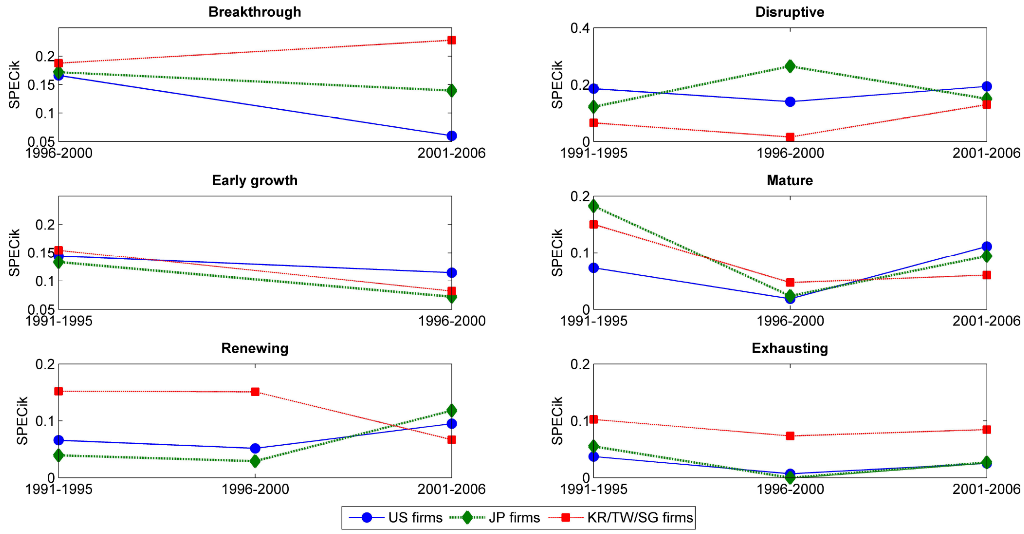

Figure 10: The evolution of the micro-founded specialization index over time

A dynamic look at specialization patterns reveals that the comparative strength of Asian tigers in breakthrough domains is recent and started in the 2000s. Up to the end of the 1990s, firms from Korea, Taiwan and Singapore, were comparatively more specialized in renewing and exhausting domains. Interestingly, an increase of the SPEC index for these firms can also be observed in the 2000s for disruptive areas. What is also striking is that US and Japanese firms' comparative technological advantage in breakthrough areas (and disruptive ones, for Japan only) is decreasing in the 2000s in favour of areas at later stages of their life cycle (mature, renewing and exhausting). More information on the technical nature of each of the technology domains identified in the 2001-2006 period is included in the Supplemental Information S.7.

These results shed light on the different strategies followed by the mayor players of the semiconductor industry. New entrants from emerging countries successfully catch-up with the leaders by initially specializing in renewing and exhausting technology domains. These areas of engineering research were left free by US and Japanese firms, which, up to the mid-1990s, were comparatively more specialized in disruptive and early growth areas. However, in the 2000s latecomer countries began to develop a distinct specialization in breakthrough areas and also an increasing focus on disruptive ones, though maintaining a comparative technological advantage in exhausting areas. A closer look at the data reveals that the large values of the SPEC index for Taiwan, Korea and Singapore in breakthrough and disruptive areas in the 2000s, is mainly due to their specialization in emerging areas belonging to the second component of the

NMPs, rather than the first one. This highlights their ability to anticipate a possible radical change in the trajectory (in favour of semiconductor applications for devices such as e-readers, tablets, LCD monitors) and testify the effort they devoted to build capabilities in the new frontier thin-film transistor LCD technologies (Hung 2006; Chang 2005). These findings describe a clear picture of the learning strategies followed by latecomers in the Semiconductor industry. As shown in Triulzi (2015, Chapter 3), up to the end of the 1990s, firms from Taiwan, Korean and Singapore were primarily focused on following well-established approaches to tackle central engineering problems in the semiconductors. However, the findings of the life-cycle analysis showed that, at the same time they were trying to renew these relatively older domains by mixing well-known approaches to problem solving with new ideas. These allowed latecomer firms building strong technological capabilities that quickly shift their comparative advantage to breakthrough areas in the early 2000s. This is confirmed by the ranking-changing strategies followed by some of these firms in the first half of the 2000s. Therefore, we can conclude that successful technological catching-up by firms from latecomer countries took a form that combined what Lee 2013 and Lee and Lim 2001 called path-creating and stage-skipping strategy. By focusing on renewing established engineering trajectories, they build sufficient technological capabilities to explore new ones. In contrast, for players from leading or early entrant countries (US and Japan), comparative advantage patterns reflect Klepper's industry life cycle theory. Entry focuses on emerging technologies, with a stronger advantage in disruptive domains, as predicted by Christensen 1997. For the sake of keeping the analysis concise, we did not show details on comparative advantage for individual firms. The interested reader can find a series of tables reporting SRTA indexes calculated for the mayor firms in the industry in the Supplemental Information S.8.

7 Discussion and Conclusions

Catching-up and leapfrogging in high-tech industries strongly depends on the direction of technological change and on the emergence of new technology domains and decline of old ones. In fast changing technical and business landscapes today's capabilities do not necessarily ensure long-run survival. This highlights the importance of studying the relationship between technology life cycle and the dynamic of comparative advantage patterns of new and incumbent innovators. Our study is one of the few empirical contributions, together with Lee 2013, to the discussion of technology life cycles at the domain level. Patent citation networks offer a fertile ground for such analysis. We theoretically defined the life-cycle of technology domains and its relation with product and industry life-cycles. Furthermore, we built a methodology to identify technology domains and trace their life-cycle by means of disentangling the complexity of large patent citation networks. This provided new insights on the dynamics of comparative advantage in the semiconductor industry.

First, we confirmed the empirical validity of entry and comparative advantage predictions from the theories of industry life-cycle and disruptive technologies. Second, we showed that, until the end of the 1990s, US and Japanese firms were comparatively better in emerging technology domains, whereas firms from Taiwan, Korea and Singapore, tended to specialize in relatively older domains, mainly in their mature, renewing and exhausting stages. These comparative advantage patterns changed strongly in the beginning of the 2000s, when firms from the three Asian tigers, next to their advantage in declining domains they also started developing a comparative advantage in emerging ones. This proves that latecomer firms from these countries have engaged in a mix between path-creating and stage-skipping catching-up, as theorized by Lee and Lim 2001. These results are also in accordance with the empirical analysis of technology cycle time and catching-up made by Lee 2013 in which the author shows that the successful catching-up of Korea and Taiwan built on upgrading the specialization pattern from older to newer technologies, exploiting short-life cycles. Our findings are also in line with the description of how Korean and Taiwanese firms managed to build their technological capabilities, as discussed by Chang et al. 1994, Mathews and Cho 1999, Cho et al. 1998, Chang and Tsai 2002, Bell Jr and Juma 2008 and Hobday 2000. These authors agree in highlighting the instrumental role played by Korean and Taiwanese firms' early specialization in old foreign licensed technologies to develop internal RD capabilities lately used to upgrade their specialization. The Asian tigers' relatively strong position in domains that were emerging in the early 2000s, testifies their ability to be forward-looking.

Yet, it is important to notice that in this work we did not assess the future impact of emerging domains. Our goal was to analyse whether new entrants' comparative advantage in those domains significantly differs from incumbents' one. It is needless to mention that emerging technologies are intrinsically risky and there is no guarantee that their development will be sustained in the future. A detailed analysis of how emerging areas affect the future direction of the technological trajectories goes beyond the scope of this paper. However, a preliminary analysis, that was not reported here, revealed that some areas did generate sustained new trajectories whereas others failed to do so. Since this has crucial implication for catching-up, a full analysis of the knowledge interaction between technology domains and the transferability of capabilities between areas is an open question for future research.

Finally, we want to praise the strength of using interdisciplinary approaches to disentangle today's technological and economic complexity. Several tools have been developed for this purpose, mainly at the intersection of economics with mathematics, physics and network science. The application of economic thinking to a combination of these tools, the community detection technique and the network of main paths, proved to be extremely insightful to analyse an economic question that occupied scholars at least since Vernon's seminal work (Vernon 1966), namely the one of the relationship between life cycles and comparative advantage. The correspondence of our findings with the extensive anecdotal knowledge of catching-up in the semiconductor industry contributes to validate our methodology to trace the life-cycle of technology domains and make a case for its use to study the technology dynamics of other high-tech industries or apply it at a wider scale to the question of the co-evolution of technologies.

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Supplemental Information

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1 Alternative beginning and end of the archetypal life-cycle of technology domains

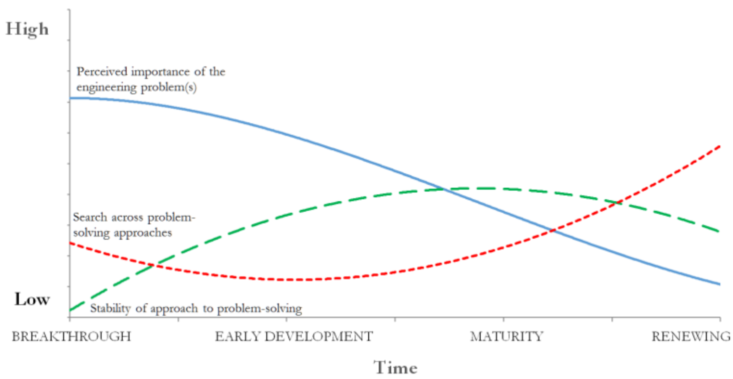

Figure S. 1: Archetypal life-cycle of a given technology domain with resistance to decline

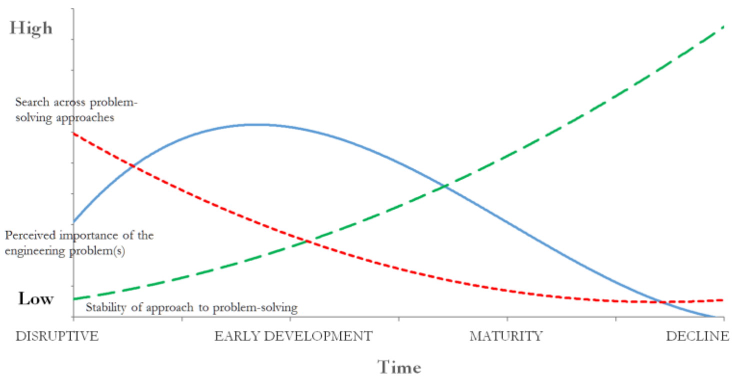

Figure S. 2: Archetypal life-cycle of a given technology domain starting with a disruption

2 Network Size over time

	76-80	76-85	76-90	76-95	76-00	76-06
Whole network - number of patents	2079	5631	12533	26853	54086	114097
Whole network - number of citations	2712	13310	40255	102957	272843	779076
Main component -number of patents	1703	5385	12348	26686	53874	113756
Main component -number of citations	2469	13164	40145	102864	272728	778890
Network of Main Paths - number of patents	1445	3490	6042	10107	15387	23428
Network of Main Paths - number of citations	1403	3291	5697	9489	14588	22077
Network of Main Paths -Main Component – number of patents	694	1540	2678	2043	4557	3544
Network of Main Paths - Main Component – number of citations	756	1597	2734	2064	4617	3562

Table S. 1: Basic network statistics

3 Plots of the main component of the network of main paths (NMPs)

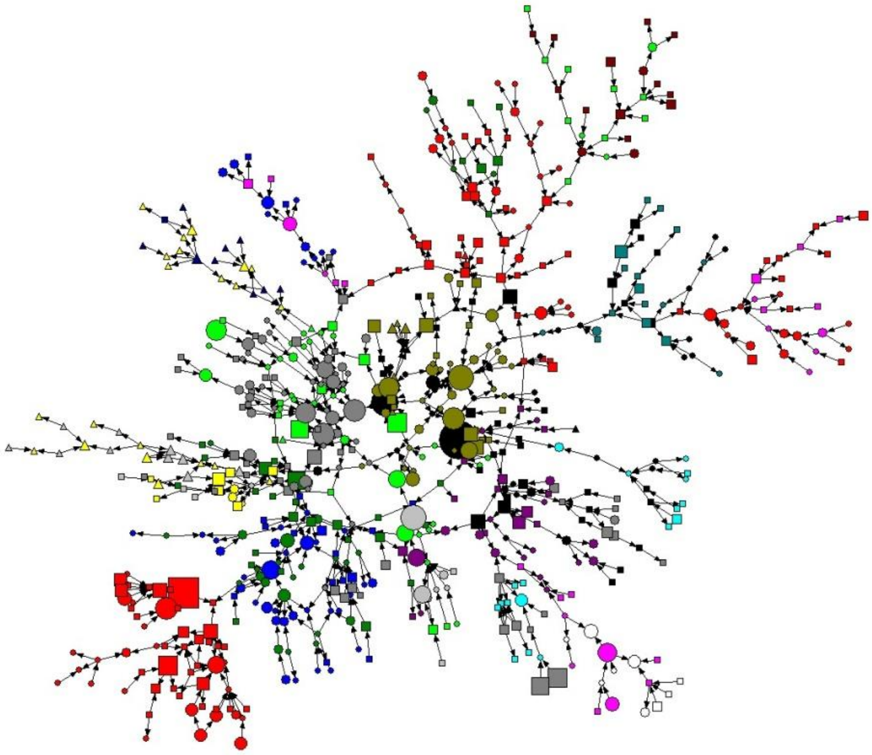

Figure S. 3: The space of technology domains between 1976 and 1980

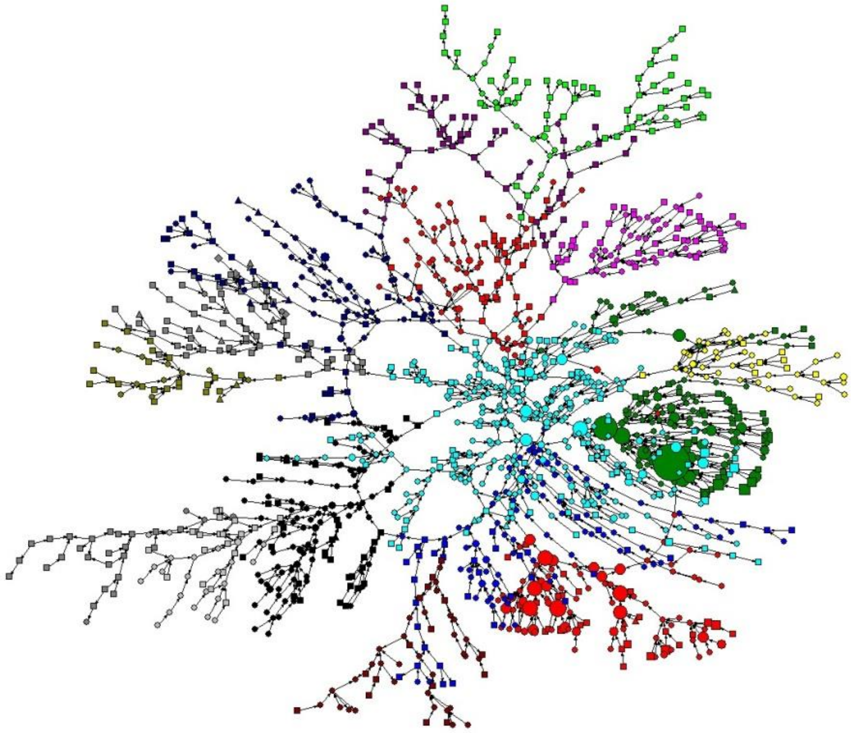

Figure S. 4: The space of technology domains between 1976 and 1985

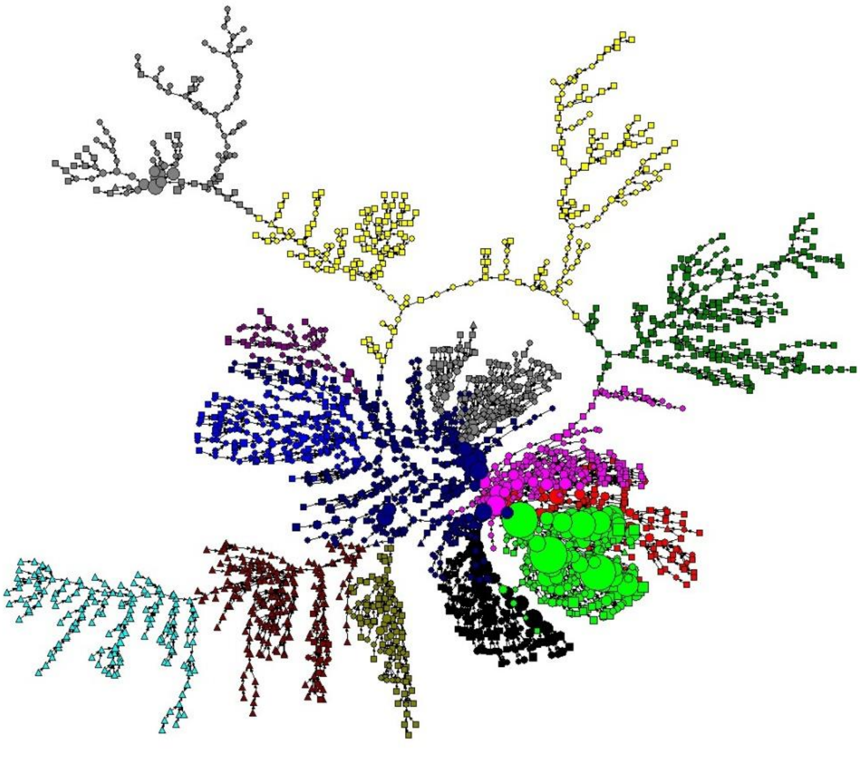

Figure S. 5: The space of technology domains between 1976 and 1990

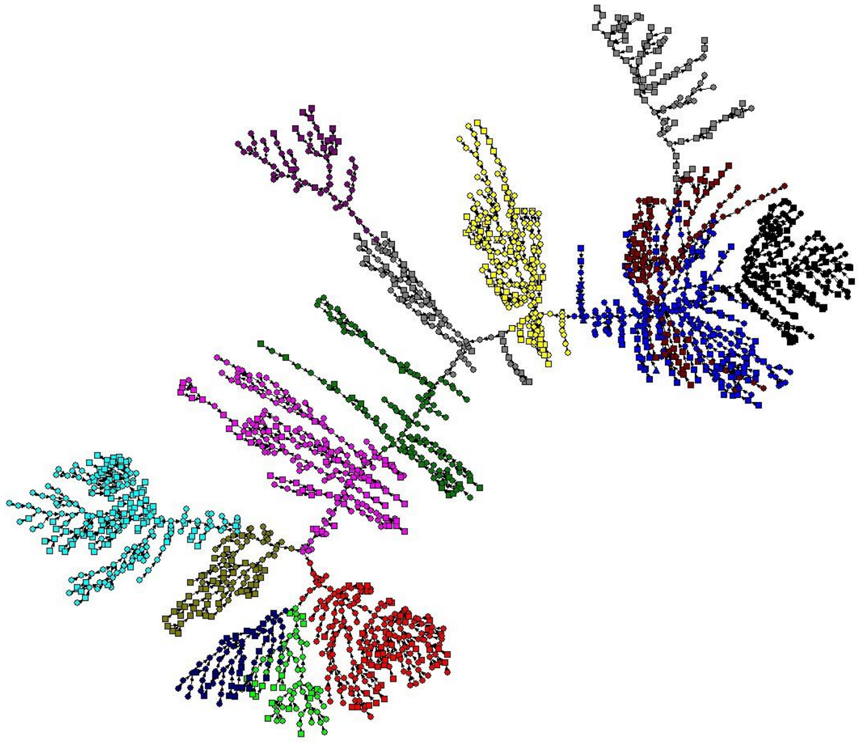

Figure S. 6: The space of technology domains between 1976 and 1995

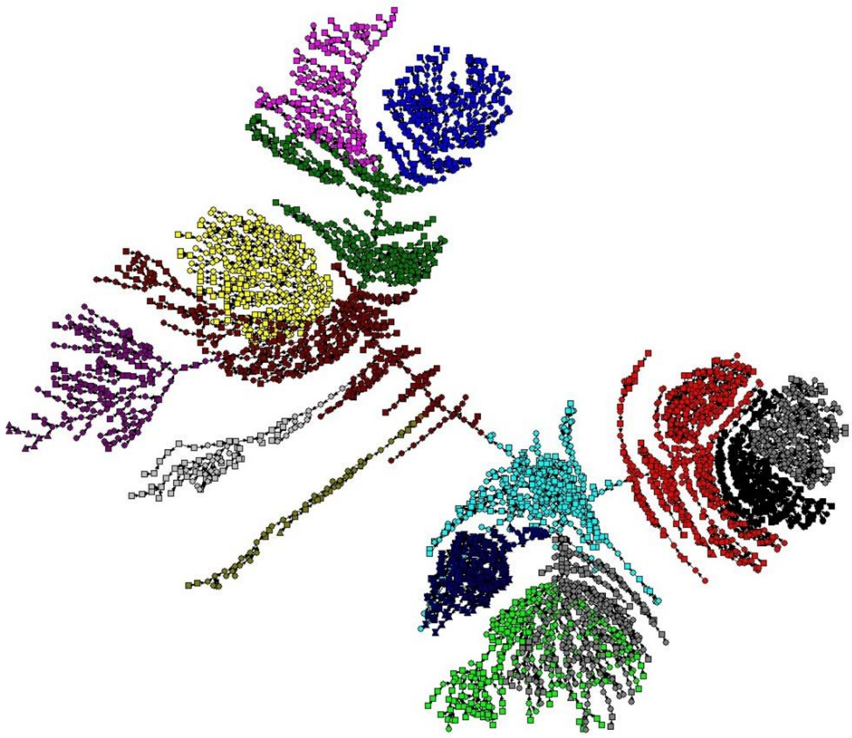

Figure S. 7: The space of technology domains between 1976 and 2000

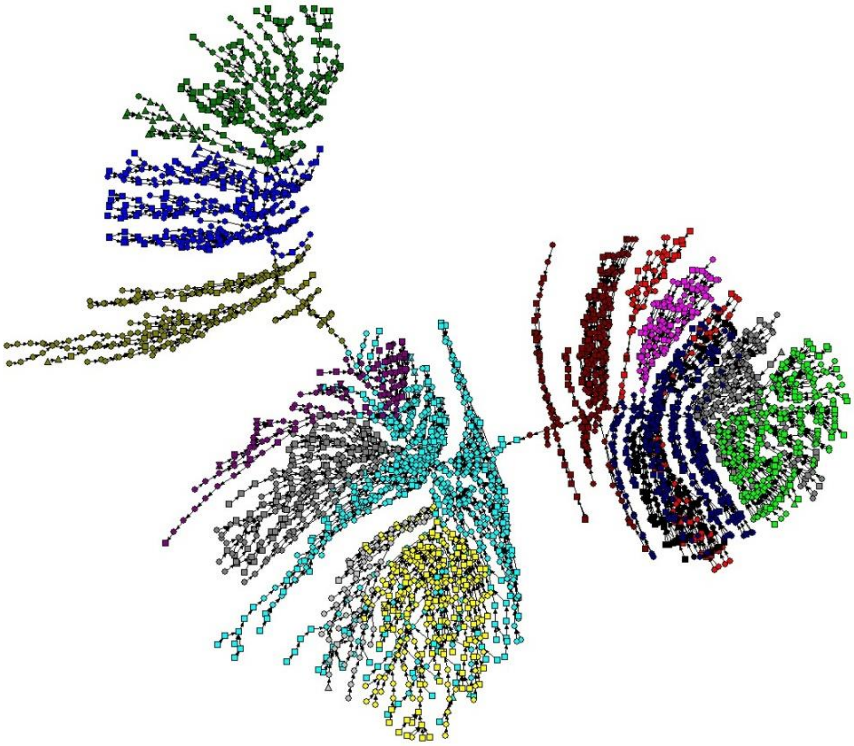

Figure S. 8: The space of technology domains between 1976 and 2006

4 Number of NMPs patents by new innovators and incumbents over time

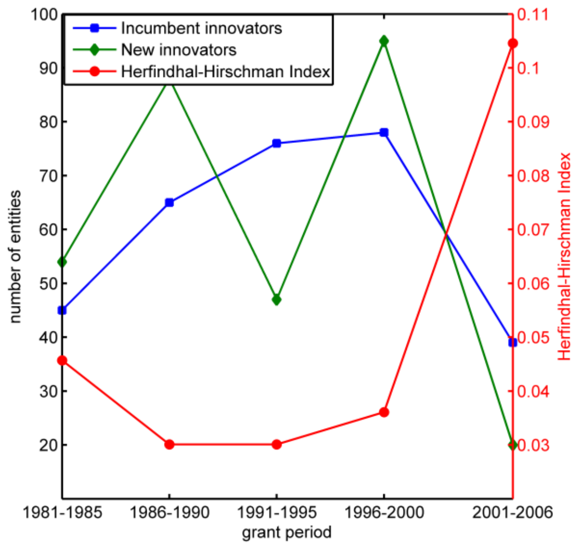

Figure S. 9: Number of new innovators and incumbentsand concentration index

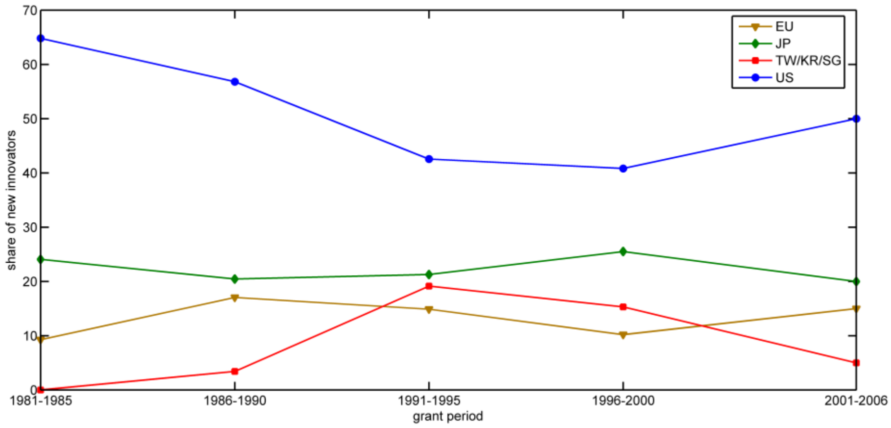

Figure S. 10: New entrant innovators by country of origin

5 Newman's community detection algorithm

To identify technology domains we used Newman' s algorithm (Newman, 2004). The algorithm maximizes modularity Q, which is defined as follows:

$$\boldsymbol{Q} = \sum_{i} (\boldsymbol{e}_{ii} - \boldsymbol{a}_{i}^{2}) \tag{S.1}$$

Where e_{ii} is the fraction of edges falling within community *i* and a_i^2 is equal to the squared sum of edges falling between communities, as $a_i = \sum_j e_{ij}$. Newman (2004) explains that modularity Q can be also calculated as the fraction of edges that fall within communities, minus the expected value of the same quantity if edges fall at random without regard for the community structure. The author highlights that if a particular division gives no more within-community edges than would be expected by random chance modularity Q would be equal to zero. This approach allows optimizing modularity Q without the need to try all possible partition combinations (which would take an amount of time exponential to the number of nodes in the network). The optimization approach starts from the worse possible combination. It then begins an iterative aggregation process that stops when the increase of modularity becomes negative. Obviously, as explained by Newman (2004), since the joining of a pair of communities between which there are no edges at all can never result in an increase in Q, one needs only consider those pairs between which there are edges. Then the change in Q upon joining two communities is given by:

$$\Delta\boldsymbol{Q} = \boldsymbol{e}_{ij} + \boldsymbol{e}_{ji} - 2\boldsymbol{a}_i\boldsymbol{a}_j = 2\,(\boldsymbol{e}_{ij} - \boldsymbol{a}_i\boldsymbol{a}_j) \tag{A.2}$$

One possible drawback of Newman' s algorithm is that it is not specifically thought for citations network, which have the peculiarity to be acyclical directed graphs. Yet, symmetrizing the adjacency matrix makes citations a univocal measure of relatedness from patent to patent. This allows using the algorithm. The second possible limitation consists in the fact that a real-world citation networks are sparser than the random counterparts that are used as benchmark to maximize modularity. This is due to the well-known shape of the distribution of citation-lags for patent networks. Jaffe and Trajtenberg (2002) showed that citations received by the average patent peaks after 3-4 years and then sharply decline. This is because constant streams of technical improvements make older patents irrelevant for the legal definition of the prior-art. Potentially this bias can identify communities on the network purely based on their age structure of patent citations, without considering the true relationship of similarity that might exist with older patents. To assess the strength of this bias we analysed the age structure of the communities (i.e. technology domains) identified by the algorithm. Results are shown in **Error! Reference source not found.**. The domains' density of patents for each time cohort is shown by mean of a density plot where darker colours represent higher density. We can clearly see that a few domains that are time dependent are visible only in the last period. Since there are few examples we cannot discard the possibility that these domains are indeed declining, i.e. their underlying engineering problems failed to attract further attention. The fact that age dependent communities are very rare proves that the potential bias in the algorithm does not affect the quality and validity of our results.

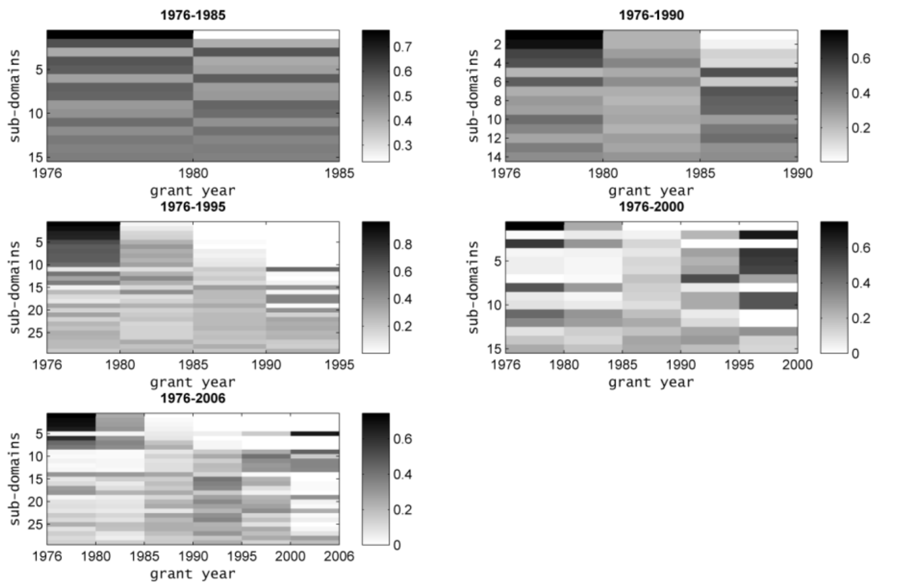

Figure S. 11: Age structure of technology domains

6 Anderson-Darling test results

In this section, we report the results of the non-parametric two-sample Anderson-Darling test for statistical difference.

Andersen-Darling test	Ninc	Nnew	Test result	p-value
Breakthrough	201	213	H1:Fnew(SRTA) ≠ Finc(SRTA)	0.0000
Disruptive	381	368	H1:Fnew(SRTA) ≠ Finc(SRTA)	0.0039
Early growth	266	287	H1:Fnew(SRTA) ≠ Finc(SRTA)	0.0000
Mature	381	368	H1:Fnew(SRTA) ≠ Finc(SRTA)	0.0000
Renewing	336	314	H1:Fnew(SRTA) ≠ Finc(SRTA)	0.0000
Exhausting	336	314	H0: Fnew(SRTA) = Finc(SRTA)	0.8460

Table S. 2: Anderson-Darling test for distributions in Figure 6

BREAKTHROUGH

	US new inn	JP new inn	KR/TW/SG new inn	All incumbent innov
	p-value	p-value	p-value	p-value
US new inn	--	0.8380	0.1495	0.0000
JP new inn	0.8380	--	0.3939	0.0009
KR/TW/SG new inn	0.1495	0.3939	--	0.1050

DISRUPTIVE

	US new inn	JP new inn	KR/TW/SG new inn	All incumbent innov
	p-value	p-value	p-value	p-value
US new inn	--	0.0000	0.1301	0.1856
JP new inn	0.0000	--	0.0000	0.0000
KR/TW/SG new inn	0.1301	0.0000	--	0.0545

EARLY GROWTH

	p-value	p-value	p-value	p-value
US new inn	--	0.0001	0.3999	0.0027
JP new inn	0.0001	--	0.0111	0.0000
KR/TW/SG new inn	0.3999	0.0111	--	0.0990

MATURE

	p-value	p-value	p-value	p-value
US new inn	--	0.8759	0.8773	0.0001
JP new inn	0.8759	--	0.8817	0.0037
KR/TW/SG new inn	0.8773	0.8817	--	0.0325

RENEWING

	p-value	p-value	p-value	p-value
US new inn	--	0.7154	0.0016	0.0000
JP new inn	0.7154	--	0.0009	0.0000
KR/TW/SG new inn	0.0016	0.0009	--	0.7093

EXHAUSTING

	p-value	p-value	p-value	p-value
US new inn	--	0.5527	0.6107	0.8625
JP new inn	0.5527	--	0.1360	0.5487
KR/TW/SG new inn	0.6107	0.1360	--	0.4532

Table S. 3: Anderson-Darling test for distributions in Figure 8

7 Topic analysis of the main technology domains of the Semiconductor Industry between 2001 and 2006

In this section, we report the title of the most central patents within each technology domain identified by the Newman' s modularity maximization algorithm.

Table S. 4: Topic analysis of the main technology domains of the Semiconductor industry between 2001 and 2006

Patent	grant year	Cluster	LC stage	NMP comp	PathC	Title	Assignee
6451641	2002	3	Exhausting	1	13.40	Non-reducing process for deposition of polysilicon gate electrode over high-K gate dielectric material	AMD
6297539	2001	3	Exhausting	1	2.49	Zicronium or hafnium oxide doped with calcium, strontium, aluminum, lanthanum, yttrium, or scandium	SHARP
6407435	2002	3	Exhausting	1	2.16	Because the layers reduce the effects of crystalline structures within individual layers, the overall tunneling current is reduced.	SHARP
6207589	2001	3	Exhausting	1	0.20	Method of forming a doped metal oxide dielectric film	SHARP
6297107	2001	6	Exhausting	1	12.96	High dielectric constant materials as gate dielectrics	AMD
6200865	2001	6	Exhausting	1	7.57	Use of sacrificial dielectric structure to form semiconductor device with a self-aligned threshold adjust and overlying low-resistance gate	AMD
6391785	2002	7	Mature	1	1.85	Method for bottomless deposition of barrier layers in integrated circuit metallization schemes	ASM/IM EC
6184128	2001	7	Mature	1	2.61	Method using a thin resist mask for dual damascene stop layer etch	AMD
6468924	2002	7	Mature	1	0.73	Methods of forming thin films by atomic layer	SAMSUN G

Patent	grant year	Cluster	LC stage	NMP comp	PathC	Title	Assignee
						deposition	
6750066	2004	7	Mature	1	2.32	Precision high-K intergate dielectric layer	AMD
6534395	2003	7	Mature	1	0.83	Method of forming graded thin films using alternating pulses of vapor phase reactants	ASM
6424001	2002	9	Renewing	1	1.34	Flash memory with ultra thin vertical body transistors	MICRON
6639268	2003	9	Renewing	1	0.61	Flash memory with ultra thin vertical body transistors	MICRON
6680508	2004	9	Renewing	1	1.36	Vertical floating gate transistor	MICRON
6903367	2005	9	Renewing	1	0.32	Programmable memory address and decode circuits with vertical body transistors	MICRON
6979857	2005	9	Renewing	1	0.32	Apparatus and method for split gate NROM memory	MICRON
6303523	2001	11	Exhausting	1	1.02	Plasma processes for depositing low dielectric constant films	APPLIED MATERIALS
6410462	2002	11	Exhausting	1	0.57	Method of making low-K carbon doped silicon oxide	SHARP
6287990	2001	11	Exhausting	1	0.90	CVD plasma assisted low dielectric constant films	APPLIED MATERIALS
6534397	2003	12	Disruptive	1	1.65	Pre-treatment of low-k dielectric for prevention of photoresist poisoning	AMD
6656837	2003	12	Disruptive	1	1.78	Method of eliminating photoresist poisoning in damascene applications	APPLIED MATERIALS
6406994	2002	12	Disruptive	1	1.79	Triple-layered low dielectric constant dielectric dual damascene approach	CHARTERED
6593247	2003	12	Disruptive	1	0.87	Method of depositing low k films using an oxidizing plasma	APPLIED MATERIALS

Patent	grant year	Cluster	LC stage	NMP comp	PathC	Title	Assignee
6784119	2004	12	Disruptive	1	0.37	Method of decreasing the K value in SIOC layer deposited by chemical vapor deposition	APPLIED MATERIALS
6979855	2005	15	Renewing	1	8.45	High-quality praseodymium gate dielectrics	MICRON
7045430	2006	15	Renewing	1	3.68	Atomic layer-deposited LaAlO3 films for gate dielectrics	MICRON
6767795	2004	15	Renewing	1	6.70	Highly reliable amorphous high-k gate dielectric ZrOXNY	MICRON
6921702	2005	15	Renewing	1	5.47	Atomic layer deposited nanolaminates of HfO2/ZrO2 films as gate dielectrics	MICRON
6660657	2003	15	Renewing	1	0.68	Methods of incorporating nitrogen into silicon-oxide-containing layers	MICRON
6429061	2002	16	Renewing	2	5.66	Complimentary metal oxide semiconductor (cmos); producing higher perfomance device; forming a relaxed silicon germanium layer with isolation and well implant regions	IBM
6291845	2001	16	Renewing	2	1.87	Fully-dielectric-isolated FET technology	STMICROELECTRONICS
6841457	2005	16	Renewing	2	1.42	Use of hydrogen implantation to improve material properties of silicon-germanium-on-insulator material made by thermal diffusion	IBM
6724008	2004	16	Renewing	2	1.07	Relaxed silicon germanium platform for high speed CMOS electronics and high speed analog circuits	AMBER WAVE
6713326	2004	16	Renewing	2	0.91	Process for producing semiconductor article using graded epitaxial growth	MIT
6524920	2003	17	Exhausting	2	22.14	Low temperature process for a transistor with	AMD INC

Patent	grant year	Cluster	LC stage	NMP comp	PathC	Title	Assignee
						elevated source and drain	
6300201	2001	17	Exhausting	2	6.20	Method to form a high K dielectric gate insulator layer, a metal gate structure, and self-aligned channel regions, post source/drain formation	CHARTERED
6194748	2001	17	Exhausting	2	4.46	MOSFET with suppressed gate-edge fringing field effect	AMD INC
6171910	2001	17	Exhausting	2	2.81	Method for forming a semiconductor device	MOTOROLA
6380043	2002	17	Exhausting	2	1.71	Low temperature process to form elevated drain and source of a field effect transistor having high-K gate dielectric	AMD INC
6933525	2005	18	Breakthrough	2	1.12	Display device and manufacturing method of the same	HITACHI
7084428	2006	18	Breakthrough	2	0.88	Transistor, integrated circuit, electro-optic device, electronic instrument and method of manufacturing a transistor	SEIKO EPSON CORP
6218219	2001	18	Breakthrough	2	0.60	Semiconductor device and fabrication method thereof	S.E.L
6407431	2002	18	Breakthrough	2	0.48	Semiconductor device and fabrication method thereof	S.E.L
6762468	2004	18	Breakthrough	2	0.21	Semiconductor device and method of manufacturing the same	TOSHIBA
6251738	2001	19	Exhausting	2	0.92	Process for forming a silicon-germanium base of heterojunction bipolar transistor	IBM
6521502	2003	20	Renewing	2	12.74	Solid phase epitaxy activation process for source/drain junction extensions and halo regions	AMD INC
6365476	2002	20	Renewing	2	8.07	Laser thermal process for fabricating field-effect transistors	ULTRATECH STEPPER

Patent	grant year	Cluster	LC stage	NMP comp	PathC	Title	Assignee
6660605	2003	20	Renewing	2	6.72	Method to fabricate optimal HDD with dual diffusion process to optimize transistor drive current junction capacitance, tunneling current and channel dopant loss	TEXAS INSTRU MENTS
6225173	2001	20	Renewing	2	5.80	Recessed channel structure for manufacturing shallow source/drain extensions	AMD INC
6218250	2001	20	Renewing	2	5.41	Method and apparatus for minimizing parasitic resistance of semiconductor devices	AMD INC
6440793	2002	21	Disruptive	2	6.47	Vertical MOSFET	IBM
6261894	2001	21	Disruptive	2	3.63	Method for forming dual workfunction high-performance support MOSFETs in EDRAM arrays	IBM
6964897	2005	21	Disruptive	2	2.28	SOI trench capacitor cell incorporating a low-leakage floating body array transistor	IBM
7122840	2006	21	Disruptive	2	1.23	Image sensor with optical guard ring and fabrication method thereof	TSMC
7098146	2006	21	Disruptive	2	1.11	Semiconductor device having patterned SOI structure and method for fabricating the same	TOSHIB A
6703648	2004	22	Disruptive	2	18.24	Strained silicon PMOS having silicon germanium source/drain extensions and method for its fabrication	AMD INC
6743684	2004	22	Disruptive	2	14.29	Method to produce localized halo for MOS transistor	TEXAS INSTRU MENTS
6881632	2005	22	Disruptive	2	10.56	Method of fabricating CMOS inverter and integrated circuits utilizing strained surface channel MOSFETS	AMBER WAVE
7074623	2006	22	Disruptive	2	8.70	Methods of forming strained-semiconductor-	AMBER WAVE

Patent	grant year	Cluster	LC stage	NMP comp	PathC	Title	Assignee
						on-insulator finFET device structures	
7122449	2006	22	Disruptive	2	7.24	Methods of fabricating semiconductor structures having epitaxially grown source and drain elements	AMBER WAVE
6190977	2001	24	Exhausting	2	28.94	Method for forming MOSFET with an elevated source/drain	TEXAS INSTRU MENTS - ACER
6303450	2001	24	Exhausting	2	8.48	CMOS device structures and method of making same	IBM
6284657	2001	25	Mature	2	1.52	Non-metallic barrier formation for copper damascene type interconnects	CHART ERED
7122442	2006	25	Mature	2	0.47	Method and system for dopant containment	TEXAS INSTRU MENTS
6611045	2003	25	Mature	2	0.17	Method of forming an integrated circuit device using dummy features and structure thereof	MOTOR OLA
6642579	2003	25	Mature	2	0.16	Method of reducing the extrinsic body resistance in a silicon-on-insulator body contacted MOSFET	IBM
6864155	2005	25	Mature	2	0.14	Methods of forming silicon-on-insulator comprising integrated circuitry, and wafer bonding methods of forming silicon-on-insulator comprising integrated circuitry	MICRON
6555839	2003	26	Renewing	2	1.43	Buried channel strained silicon FET using a supply layer created through ion implantation	AMBER WAVE
6350993	2002	26	Renewing	2	0.41	High speed composite p-channel Si/SiGe heterostructure for field effect devices	IBM
6207977	2001	26	Renewing	2	0.04	Vertical MISFET devices	IMEC
6204126	2001	27	Exhausting	2	2.52	Method to fabricate a new structure with multi-self-aligned for split-gate	TSMC

Patent	grant year	Cluster	LC stage	NMP comp	PathC	Title	Assignee
						flash	
6573126	2003	28	Renewing	2	0.81	Process for producing semiconductor article using graded epitaxial growth	MIT
6323108	2001	28	Renewing	2	0.24	Fabrication ultra-thin bonded semiconductor layers	US NAVY
6261929	2001	28	Renewing	2	0.23	Methods of forming a plurality of semiconductor layers using spaced trench arrays	NORTH CAR. ST. UNI.
6191007	2001	28	Renewing	2	0.12	Method for manufacturing a semiconductor substrate	DENSO CORP LTD
6235567	2001	28	Renewing	2	0.06	Silicon-germanium bicmos on soi	IBM
6413802	2002	29	Disruptive	2	29.61	Finfet transistor structures having a double gate channel extending vertically from a substrate and methods of manufacture	UNIV OF CALIFO RNIA
6214670	2001	29	Disruptive	2	18.48	Method for manufacturing short-channel, metal-gate CMOS devices with superior hot carrier performance	TSMC
6686231	2004	29	Disruptive	2	13.00	Damascene gate process with sacrificial oxide in semiconductor devices	AMD INC
7084018	2006	29	Disruptive	2	10.55	Sacrificial oxide for minimizing box undercut in damascene FinFET	AMD INC
6962843	2005	29	Disruptive	2	8.79	Method of fabricating a finfet	IBM

8 SRTA tables at the firm level

In this section we report the SRTA values calculated for a selection of firms from the US, Japan, Korea, Taiwan and Singapore. To keep the analysis short we do that only for the last three periods. Tables from Table S.5 to S.12 report the SRTA values for the main US, Japanese, Taiwanese, Korean and Singaporean players over time. We highlight values of the SRTA greater than 0.2 in bold. Firms are distinguished between new and incumbent innovators and also based on their business area (IDM=Integrated Device Manufacturer, GRO=Government Research Organization, NGRO=Non-Governmental Research Organization, Equipm.=Equipment supplier). The tables confirm comparative technological advantage patterns as discussed in Subsection 6.2. However, they provide further details for those interested to track comparative advantage trends for particular firms or research institutes.

Table S. 5: SRTA for the top Taiwanese, Korean and Singaporean firms (1991-1995)

Company	New Inn vs Inc	Type	#Patents	Disruptive	Early growth	Mature	Renewing	Exhausting
UMC (TW)	New innovator	Foundry	31	-0,477	0,230	-0,087	0,597	0,597
SAMSUNG (KR)	Incumbent	IDM	8	0,046	0,300	-0,365	-1,000	-1,000
TITRI (TW)	Incumbent	GRO	7	0,112	-0,171	-0,306	0,490	-1,000
HYUNDAI ELEC. (KR)	New innovator	IDM	7	-0,523	0,359	-0,306	0,708	-1,000
LG ELEC. (KR)	New innovator	IDM	7	-0,230	-0,171	0,360	-1,000	-1,000
TSMC (TW)	New innovator	Foundry	6	-0,155	0,245	0,107	-1,000	-1,000
CHARTERED (SG)	New innovator	Foundry	4	-1,000	0,664	-1,000	-1,000	-1,000
KETRI (KR)	Incumbent	GRO	3	0,188	-1,000	0,107	-1,000	-1,000
WINBOND (TW)	New innovator	IDM	2	-1,000	-1,000	0,576	-1,000	-1,000

Table S. 6: SRTA for the top US and Japanese players (1991-1995)

Company	New Inn vs Inc	Type	#Patents	Disruptive	Early growth	Mature	Renewing	Exhausting
TEXAS INSTR. (US)	Incumbent	IDM	39	-0,053	-0,223	0,177	-0,312	0,355
MOTOROLA (US)	Incumbent	IDM	38	-0,040	-0,211	-0,010	0,235	0,623
MICRON (US)	New innovator	IDM	38	0,096	0,132	-0,546	0,235	0,037
IBM (US)	Incumbent	IDM	35	0,159	-0,005	-0,221	-1,000	-1,000
MITSUBISHI	Incumbent	IDM	33	-0,073	-0,052	0,189	-0,234	-1,000

Company	New Inn vs Inc	Type	#Patents	Disruptive	Early growth	Mature	Renewing	Exhausting
(JP)								
TOSHIBA (JP)	Incumbent	IDM	33	-0,202	-0,538	0,340	0,301	-1,000
NEC (JP)	Incumbent	IDM	22	-0,335	-0,052	0,375	-1,000	-1,000
AT&T (US)	Incumbent	IDM	17	0,016	0,186	-0,207	0,093	-1,000
SONY CORP (JP)	Incumbent	IDM	17	-0,051	-0,264	0,273	-1,000	-1,000
FUJITSU (JP)	Incumbent	IDM	13	0,083	-0,135	-0,076	0,223	-1,000
HITACHI (JP)	Incumbent	Equipm.	11	0,089	-0,052	0,007	-1,000	-1,000
NATIONAL SEMICOND. (US)	Incumbent	IDM	11	-0,002	-1,000	0,340	-1,000	-1,000
HARRIS (US)	Incumbent	User	7	0,374	-1,000	-1,000	-1,000	-1,000
LSI LOGIC (US)	Incumbent	Fabless	7	0,305	-0,171	-1,000	-1,000	-1,000
APPLIED MATERIALS (US)	Incumbent	Equipm.	6	0,188	0,245	-1,000	-1,000	-1,000
HUGHES (US)	Incumbent	User	6	-0,465	-1,000	0,425	0,547	-1,000
MATSUSHITA (JP)	Incumbent	IDM	6	-0,465	0,245	0,107	-1,000	0,744
OKI ELECTRIC (JP)	Incumbent	IDM	6	-1,000	0,245	0,425	-1,000	-1,000
SHARP (JP)	Incumbent	IDM	6	0,046	-0,096	-0,234	0,547	-1,000
SIEMENS (DE)	Incumbent	IDM	6	0,046	-0,096	0,107	-1,000	-1,000
HONEYWELL (US)	Incumbent	IDM	5	0,274	-0,005	-1,000	-1,000	-1,000
SEIKO EPSON (JP)	Incumbent	IDM	5	-0,390	0,597	-1,000	-1,000	-1,000
SEMICOND. ENERGY (JP)	Incumbent	NGRO	5	-0,065	0,329	-0,147	-1,000	-1,000

Table S. 7: SRTA for the top Taiwanese, Korean and Singaporean players (1996-2000)

Company	New Inn vs Inc	Type	#Patents	Break-through	Disruptive	Early growth	Mature	Renewing	Exhausting
TSMC (TW)	Incumbent	Foundry	92	-0,429	-0,310	-0,018	0,004	0,361	-1,000
UMC (TW)	Incumbent	Foundry	77	-0,725	-0,653	0,089	-0,248	0,101	0,748
SAMSUNG (KR)	Incumbent	IDM	31	-0,117	-1,000	0,029	0,636	-0,033	-1,000
CHARTERED (SG)	Incumbent	Foundry	29	-0,224	-0,284	-0,151	0,231	0,385	0,804
VANGUARD (TW)	New innovator	Foundry	25	-1,000	-1,000	0,160	-1,000	0,075	-1,000
LG ELEC. (KR)	Incumbent	IDM	21	0,187	-0,130	-0,122	0,377	0,161	-1,000
HYUNDAI ELEC. (KR)	Incumbent	IDM	17	-0,470	-1,000	0,184	-1,000	-0,402	-1,000

ACER (TW)	New innovator	IDM	13	-1,000	0,426	0,065	-1,000	0,055	-1,000
TITRI (TW)	Incumbent	GRO	9	-0,190	-1,000	-0,045	-1,000	0,415	-1,000
MOSEL VITELIC (TW)	New innovator	IDM	6	0,011	-1,000	-0,098	-1,000	0,415	-1,000
WINBOND (TW)	Incumbent	IDM	5	0,102	-1,000	-0,007	-1,000	0,184	-1,000

Table S. 8: SRTA for the top US and Japanese players (1996-2000)

Company	New Inn vs Inc	Type	#Patents	Break-through	Disruptive	Early growth	Mature	Renewing	Exhausting
AMD (US)	Incumbent	IDM	93	-0,117	-0,704	0,029	0,332	0,111	-1,000
MICRON (US)	Incumbent	IDM	66	0,011	-0,606	0,068	0,169	-0,205	-1,000
NEC (JP)	Incumbent	IDM	49	0,239	-0,504	-0,031	-0,027	-0,059	-1,000
IBM (US)	Incumbent	IDM	37	0,140	-0,392	0,053	0,113	-0,436	-1,000
TEXAS INSTR. (US)	Incumbent	IDM	36	-0,190	-1,000	0,086	0,126	0,004	-1,000
MOTOROLA (US)	Incumbent	IDM	35	0,102	-1,000	-0,007	0,598	-0,093	-1,000
TOSHIBA (JP)	Incumbent	IDM	25	-0,010	-1,000	0,084	-1,000	-0,069	-1,000
MITSUBISHI (JP)	Incumbent	IDM	21	0,078	-1,000	0,046	-1,000	0,018	-1,000
MATSUSHITA (JP)	Incumbent	IDM	18	0,463	-1,000	-0,098	0,441	-1,000	-1,000
NATIONAL SEMICOND. (US)	Incumbent	IDM	17	0,433	-1,000	-0,128	-1,000	-0,079	-1,000
LSI LOGIC (US)	Incumbent	Fabless	16	-1,000	-1,000	0,244	-1,000	-1,000	-1,000
SHARP (JP)	Incumbent	IDM	15	0,241	-1,000	-0,007	-1,000	-0,016	-1,000
INTEL (US)	Incumbent	IDM	12	0,343	-1,000	-0,292	-1,000	0,415	-1,000
LUCENT (US)	New innovator	User	12	-1,000	-1,000	0,202	-1,000	-0,246	-1,000
SONY CORP (JP)	Incumbent	IDM	11	0,252	-1,000	0,023	0,617	-1,000	-1,000
HITACHI (JP)	Incumbent	Equipm.	10	-0,240	0,236	0,070	-1,000	-0,159	-1,000
VLSI TECH (US)	Incumbent	IDM	9	0,154	-1,000	0,046	-1,000	-0,107	-1,000
SEMICOND. ENERGY (JP)	Incumbent	NGRO	7	-1,000	-1,000	0,244	-1,000	-1,000	-1,000
YAMAHA (JP)	Incumbent	IDM	7	-0,066	-1,000	-0,031	-1,000	0,349	-1,000

Company	New Inn vs Inc	Type	#Patents	Break-through	Disruptive	Early growth	Mature	Renewing	Exhausting
SIEMENS (DE)	Incumbent	IDM	6	0,508	0,459	-0,570	0,771	-1,000	-1,000
APPLIED MATERIALS (US)	Incumbent	Equipm.	5	0,421	-1,000	-0,007	-1,000	-1,000	-1,000
UNIV CALIFORNIA (US)	Incumbent	University	5	-1,000	0,528	-0,007	-1,000	0,184	-1,000
SANYO ELECTRIC (JP)	Incumbent	IDM	5	0,102	0,732	-0,207	-1,000	-1,000	-1,000
AMERICAN SUPERCOND.(US)	New innovator	User	5	-1,000	0,883	-1,000	-1,000	-1,000	-1,000
FOVEONICS (US)	New innovator	User	5	-1,000	-1,000	0,244	-1,000	-1,000	-1,000

Table S. 9: SRTA for the top Taiwanese, Korean and Singaporean players (2001 2006 Main component of the network of main paths)

Company	New Inn vs Inc	Type	#Patents	Disruptive	Mature	Renewing	Exhausting
TSMC (TW)	Incumbent	Foundry	13	0,196	0,397	-0,165	-1,000
SAMSUNG (KR)	Incumbent	IDM	9	-1,000	0,540	0,095	-1,000
CHARTERED (SG)	Incumbent	Foundry	4	-0,017	0,580	-0,125	-1,000
UMC (TW)	Incumbent	Foundry	4	0,318	-1,000	-0,125	-1,000
HYUNDAI ELEC. (KR)	Incumbent	IDM	3	-1,000	-1,000	0,217	-1,000
VANGUARD (TW)	Incumbent	Foundry	1	0,589	-1,000	-1,000	-1,000
HYNIX (KR)	New innovator	IDM	1	-1,000	-1,000	0,217	-1,000

Table S. 10: SRTA for the top US and Japanese players (2001 2006 Main component of the network of main paths)

Company	New Inn vs Inc	Type	#Patents	Disruptive	Mature	Renewing	Exhausting
MICRON (US)	Incumbent	IDM	75	-0,276	-0,666	0,133	-1,000
AMD (US)	Incumbent	IDM	31	-0,068	0,489	-0,141	0,509
IBM (US)	Incumbent	IDM	22	-0,175	0,345	0,029	-1,000
APPLIED MATERIALS (US)	Incumbent	Equipm.	17	0,494	-1,000	-0,691	0,578
TEXAS INSTR. (US)	Incumbent	IDM	15	0,015	-1,000	0,065	-1,000
MOTOROLA (US)	Incumbent	IDM	14	-0,567	0,036	0,142	-1,000
SHARP (JP)	Incumbent	IDM	11	-1,000	-1,000	-0,005	0,841
INFINEON (DE)	Incumbent	IDM	4	-0,017	-1,000	0,077	-1,000
NOVELIUS SYSTEMS (US)	New innovator	Equipm.	4	0,487	-1,000	-0,440	-1,000
LAM (US)	Incumbent	Equipm.	3	0,589	-1,000	-1,000	-1,000
MATSUSHITA (JP)	Incumbent	IDM	3	0,126	-1,000	0,018	-1,000
GENUS (US)	New innovator	Equipm.	3	-1,000	-1,000	0,217	-1,000

Table S. 11: SRTA for the top Taiwanese, Korean and Singaporean players (2001 2006 Second component of the network of main paths)

Company	New Inn vs Inc	Type	#Patents	Breakthrough	Disruptive	Mature	Renewing	Exhausting
TSMC (TW)	Incumbent	Foundry	40	-0,700	0,100	-0,131	0,000	0,084
SAMSUNG (KR)	Incumbent	IDM	18	0,594	-0,347	-1,000	-0,091	-1,000
LG PHILIPS (KR)	New innovator	IDM	13	0,752	-1,000	-1,000	-1,000	-1,000
UMC (TW)	Incumbent	Foundry	10	-1,000	0,024	-1,000	0,333	-1,000
HYUNDAI ELEC. (KR)	Incumbent	IDM	9	-1,000	0,152	0,262	-0,286	-1,000
CHARTERED (SG)	Incumbent	Foundry	7	-1,000	-0,001	0,374	-0,167	0,742
HANN STAR (TW)	New innovator	IDM	5	0,752	-1,000	-1,000	-1,000	-1,000
KETRI (KR)	Incumbent	GRO	3	-1,000	0,076	-1,000	0,250	-1,000
MACRONIOX (TW)	Incumbent	IDM	3	-1,000	0,076	-1,000	0,250	-1,000
CHUNGHWA (TW)	New innovator	IDM	3	0,752	-1,000	-1,000	-1,000	-1,000
HYNIX (KR)	New innovator	IDM	3	-1,000	-0,264	0,673	0,250	-1,000
TITRI (TW)	Incumbent	GRO	2	0,559	-1,000	-1,000	-1,000	0,919
VANGUARD (TW)	Incumbent	Foundry	2	-1,000	0,272	-1,000	-1,000	-1,000
AU OPTRONIC (TW)	New innovator	IDM	2	0,752	-1,000	-1,000	-1,000	-1,000

Table S. 12: SRTA for the top US and Japanese players (2001 2006 Second component of the network of main paths)

Company	New Inn vs Inc	Type	#Patents	Breakthrough	Disruptive	Mature	Renewing	Exhausting
AMD (US)	Incumbent	IDM	81	-1,000	0,038	-0,026	0,152	0,401
IBM (US)	Incumbent	IDM	73	-0,348	0,118	-0,226	-0,187	0,129
TOSHIBA (JP)	Incumbent	IDM	33	-0,218	0,003	-1,000	0,250	-1,000
TEXAS INSTR. (US)	Incumbent	IDM	23	-1,000	-0,046	0,335	0,270	-1,000
SEMICOND. ENERGY (JP)	Incumbent	NGRO	18	0,725	-0,823	-1,000	-0,565	-1,000
MICRON (US)	Incumbent	IDM	17	-1,000	0,061	-0,050	0,190	-1,000
NEC (JP)	Incumbent	IDM	13	-0,296	0,193	0,084	-1,000	-1,000
AMBERWAVE SYSTEMS (US)	New innovator	Equipm.	13	-1,000	0,147	-1,000	0,071	-1,000
INTEL (US)	Incumbent	IDM	12	-1,000	0,186	-1,000	-0,412	0,595
MITSUBISHI (JP)	Incumbent	IDM	9	0,404	-0,264	0,547	-0,286	-1,000
SHARP (JP)	Incumbent	IDM	9	-0,120	-0,675	-1,000	0,591	-1,000
MATSUSHITA (JP)	Incumbent	IDM	7	-1,000	0,272	-1,000	-1,000	-1,000
FUJITSU (JP)	Incumbent	IDM	6	0,082	-0,264	0,673	-0,091	-1,000
LSI LOGIC (US)	Incumbent	Fabless	6	-1,000	0,076	0,673	-1,000	-1,000
MIT (US)	Incumbent	University	6	-1,000	-0,067	-1,000	0,429	-1,000
CANON (JP)	Incumbent	User	5	-1,000	0,272	-1,000	-1,000	-1,000
HITACHI (JP)	Incumbent	Equipm.	5	0,171	0,024	-1,000	0,000	-1,000
HUGHES (US)	Incumbent	User	5	-1,000	0,272	-1,000	-1,000	-1,000
MOTOROLA (US)	Incumbent	IDM	5	-1,000	0,024	0,509	-1,000	0,809
FREESCALE (US)	New innovator	IDM	5	-1,000	0,166	-1,000	0,000	-1,000
INFINEON (DE)	Incumbent	IDM	4	-1,000	0,134	0,587	-1,000	-1,000

APPLIED MATERIALS (US)	Incumbent	Equipm.	3	0,650	-0,264	-1,000	-1,000	-1,000
OKI ELECTRIC (JP)	Incumbent	IDM	3	-1,000	-0,264	-1,000	0,538	-1,000
SONY CORP (JP)	Incumbent	IDM	3	-1,000	0,076	-1,000	0,250	-1,000
AGERE SYSTEM (US)	New innovator	Fabless	3	-1,000	0,076	-1,000	0,250	-1,000
E INK (US)	New innovator	IDM	3	0,752	-1,000	-1,000	-1,000	-1,000
HONEYWELL (US)	Incumbent	User	3	-1,000	0,272	-1,000	-1,000	-1,000
RENESAS ELECTR. (JP)	New innovator	IDM	3	-1,000	-0,264	0,673	0,250	-1,000