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EVOLUTION OF INNOVATION IN INDUSTRY LIFE CYCLES: A COMPLEX NETWORK PERSPECTIVE

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ABSTRACT

Technological life cycles are driven by the changes in the shape and level of innovation, yet innovation rate is not directly observable and is difficult to trace. Innovation measured by patent-citation networks (PCN) cannot be estimated solely by quantity, whereas quality-adjusted quantity measurements are still prone to bias. Our paper complement PCN data analysis with an agent-based simulation (ABS) on networks to uncover the latent innovation that automatically accounts for the quality and quantity components instead of decoupling them. We build dynamic PCN for radio frequency 'CMOS' technology and subsequently develop ABS to replicate underlying innovation network formation. Comparing the real and synthetic data, we isolate latent innovation rate in PCN and by mapping pivotal patent assignees — innovators, we calculate the diversity of innovators in the technology market. Identifying innovation patterns, we show that, early on, innovation structures are less diverse and exploratory, but this grows and matures eventually until value creation become an expensive endeavor. Contrary to what is observed, we show how the abundance that appears are less significant publications mostly driven by exploitation in the technology market.

Keywords: Innovation, Design management, Organisation of product development, Latent Innovation Rate, Patent-Citation Networks

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1 INTRODUCTION

Assessment of innovation in technological life cycles is valuable for a variety of commercial, economic, and social reasons. Previously, many researchers have utilized technological life cycles to study innovation structures (Dosi, 1982), patterns of knowledge development and diffusion (Malhotra et al., 2019) But it is not easy to identify innovation rate and forecast patterns of innovation. This is because growth of innovation structure is dynamic and endogenous to maturity level of the technology under consideration (Lee et al., 2012); resource allocation dilemma like exploration versus exploitation also play significant role in determining innovation, and ultimately, R&D trajectory which leads to complex evolution of innovation and heterogeneity of technological life cycles.

1.1 Prior approaches

Complex evolution of innovation is strongly influenced by both rate of innovation and state of technology, the former being more difficult to determine. Firstly, innovation rate is not only determined by quantity of innovation, but also by quality. Breakthrough innovations considered as high-quality innovations, are more significant than multiple low quality or incremental innovations. However, the value of innovation is indeterminate at its early stage until it gains acceptance, usability, and validity. Innovations thought to be breakthrough from the start are evidently so based on the gap they fill in knowledge, but potential uncertainty associated with them ex-ante do not reveal innovation quality until they are fully realized. Therefore, the quality component of rate of innovation is often hidden and requires other proxy variables (Lanjouw and Schankerman, 2004; Bekkers and Martinelli, 2012) to measure and establish relationship with stage of technological life cycle (Redelinghuys, 2000). Next, state of technology is also difficult to identify due to multiple aperiodic market shocks and hidden proprietary information, hindering the prediction and forecasting of technological life cycle.

Researchers have estimated innovation using quality-adjusted quantity measurements (Peri, 2005; Roach and Cohen, 2013) by using empirical methods where they identify attributes that significantly explain quality of innovation. These models, however, might not be applicable in all fields and are prone to confusion regarding causality (see Moser et al. (2018) for a detailed discussion). Alternatively, innovation rate can also be analyzed if we can uncover latent innovation metric that accounts for combined effect of quantity and quality. Taking this approach, instead of isolating the quality and quantity components of the innovation rate and weighing their effects separately, we identify the rate of innovation by replicating naturally occurring level of interactions, citations, and edges between published patents, which automatically predict the resource allocation in innovation by firms to ensure a balance between quality and quantity. Interestingly, patent-citation networks (PCNs) can provide evidence to measure resource allocation since they log associations as well as contain information about innovation structures, quality and their archival footprint (Jiang and Luo, 2022).

1.2 Overview of new approach

In this paper, we complement patent-citation data analysis with an agent-based simulation on networks to uncover the latent innovation that automatically accounts for the quality and quantity components instead of decoupling them. As a first step, we build a dynamic citation network for radio frequency CMOS technology and develop an agent-based simulation to replicate underlying innovation network formation mechanisms to examine age-dependent bias and isolate latent innovation rates in PCN. Later, mapping pivotal patent assignees — innovators, we calculate the diversity of innovators in the technology market throughout the technological lifecycle.

Previous research have already adopted multiple metrics from PCN that offer multiple solutions to the associated measurement problems. There is generally a positive correlation between citations received by a specific patent and other indicators of economic and technological importance, according to empirical studies. However, it is worthy to note that even though PCN fix assessments of innovation (Galen Russell Hancock, 2016), naive implementations of centrality-based classifications favor older patents, adding intrinsic “age-dependent bias” on patents. In the simplest case, even when we account for a uniform likelihood of citation regardless of innovativeness, considering the fact that quality of innovation is a hidden attribute, early mover patents are more likely to be cited more owing to the higher citation opportunities merely based on age. Therefore, most of the centrality-based classifications inflate rate of innovation at the outset and understate the same eventually at later stages. Since prediction of future

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technological developments critically depend on current state of dependencies, any error or bias at this stage hinder the prediction and forecasting effort due to the uncertainty and lack of complete information available to innovation stakeholders. It is commendable, however, that centrality-based methods are fundamentally simple to adapt and use to capture the quality of innovation.

So, instead of utilizing centrality-based methods to estimate only quality of innovation, we use them to identify latent innovation rate by isolating inherent age-dependent bias and analyze the dynamic evolution of underlying technological life cycles. We start by building a PCN associated with radio frequency 'CMOS' technology, one of the key enablers of Smart Phones, and show the impact of inherent bias on innovation structure. Next, to isolate the heterogeneous rate of innovation and uncover latent rate of innovation, we utilize agent-based modeling to emulate the underlying mechanism of citation formation in PCN and draw parallel from real data to partition heterogeneous rate of innovation at various stages of technological evolution. We build a hyper-parameters based agent-based simulation (ABS) with birth rate of patents, innovative patents rate (or merely incremental patents), boundations for age of citations, and out-degree distribution and proportions to calibrate heterogeneous innovation rate in evolution of technological life cycle. We observe that certain functional forms of hyper-parameters explain perceivable heterogeneity in rate of innovation, both in case of real data and simulated data. We emulate time trends for innovation rate by comparing the final simulation results, defined as synthetic data, with real data obtained from the patent-citation network and correlate the underlying mechanisms at different stages of technological development. As a result, latent innovation rate is uncovered and tuned, alleviating distortion in technological life cycle curves.

In the final step, we use the PCN to identify influential patents discounted with the weighted value of latent innovation rate. It opens numerous possibilities for centrality based network analysis citation networks and gives us the ability to trim and peel large scale innovation networks layer by layer to reach the desired level of influence in a precise manner. The classification methodology provides novel approach for large patent citation network as it helps penetrate to the significant and important innovation structure of technology under consideration, as per requirement, to reduce noise in accessing rate of innovation metrics at lower quality levels. Our final results come from assignee networks as we map pivotal patent assignees — innovator, which adds much wider scope to identify innovation patterns in the evolving technology. We hypothesize that innovators publish patents of various influence level in the dynamic citation network structure and then, using a normalized entropy measure calculate the diversity of innovators in the technology market. We demonstrate how patterns of innovation correspond to stages in the development of the underlying focal technology.

We observe that, early on, innovation structures are less diverse and innovating firms mostly strategizing exploration aim for high value break though innovation, but this gradually changes, and a lot of new innovators try to capitalize on extensive research collaborations. This grows and matures eventually until value creation and commercialization become an expensive endeavor. Therefore, only a few prominent players stay in the market publishing valuable patents and in contrast when, an abundance of less significant publications continues to crop up majorly from exploitation strategy in the technology market. Through our methodology, we reveal underlying innovation structures in PCN and enable study of the strategic cooperation and competition structures that occur. In addition to confirming the stages of technological life cycle in formal literature, our research contributes to established techniques for examining development in the context of innovation structure that is driven by both the demand and supply sides. In the subsequent sections, we describe details of citation network and focal technology, agent-based simulation and bias in measuring innovation and finally, temporal diversity in innovator market and results.

2 METHODOLOGY

Technological development is a gradual multi-dimensional process that involve multiple participants. In general, the inherent complex relationship between the root and branches of innovation pedigree is difficult to classify definitively. Therefore, classifying patents by technology is a common necessity in patent empiric. Previous literature have used multiple approaches to address issues of patent selections and size selection. They use a technological position attribute which maps to a category of patents, and a cluster of assigned patents preliminarily based on the technological category from which relevancy is already established. But we use a common technique of classification by creating communities of congenial patents by using keywords to break patents into natural groups and then regulating connections by

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developing predetermined trimming thresholds (Valverde et al., 2017). We use expert level knowledge to determine few key identifying features of a technology like keywords, eminent authors, firms and academic institutions which help screen patents. Even though, the screening process does not provide us with a comprehensive subset of all relevant patents, interconnected citation network linked with patents and precise filtering thresholds for connections automate our selection of patents to desired size.
Also, another comparatively minor issue is that since innovation process is gradual and seamless, clearly distinguishing a group of innovations which indicate the start or end of innovation is also difficult. Fuzzy starting and end points can largely change the memberships of technological lineages and alter the potency of analysis to inherent aperiodic shocks. To navigate around the existing restrictions for distinct start and end points such that focal technology is immune to small market shocks, we choose such a technology to analyze technological lifecycle so that active span of lifecycle is hardly one to two decades as explained is the next subsection.

2.1 Choosing focal technology and generation of innovation network structure

In this research, we study the technology innovation of CMOS radio frequency chips. CMOS (Complementary metal–oxide–semiconductor), the building block of the modern communication age, are based on a particular transistor type that was originally developed for digital application at Fairchild Semiconductor, which also sparked a several-decade long scaling race, generally known as the Moors law. In the first decades of its development, CMOS was not considered suitable for wireless applications that required operations at Radio Frequency modulation, due to its poor high-frequency performance (Abidi, 1999). Therefore, wireless modules, which were built using other available technologies, were bulky, expensive, and not reliable, limiting the integration of advanced multiple-function modules similar to those of today's smartphones. Although, this wireless transmission components bottleneck persisted, simultaneous upstream technology development continued, mainly thanks to transistor scaling according to Moors law expectations (Schaller, 1997). Scaling provided a side benefit of increasing the frequency of operation of CMOS, eventually making it possible to explore using this technology in wireless applications. Consequently, the first RF-CMOS modules were developed by researchers at Berkeley and UCLA in the early 90s (Lee, 2003) pushing the operation of CMOS-based wireless systems to 10s of Gigahertz in less than a decade (Heydari et al., 2007). Gradual innovation and continuous improvement to integrate already existing similar complementary technologies accelerated the evolution of the technology uninhibitedly until faster system-level integration of RF-CMOS modules help launch first iPhone in 2007. As a result, overall, the span of evolutionary trajectory was attenuated to a decade or so, making technology immune to shocks from market conditions compared to other long duration technological life cycles. In other words, RF-CMOS modules have a clearly identifiable start date; denoted by the development of first module, and maturity date; corresponding to the point the product was first launched commercially.
We build PCN using patents relevant to focal technology. The sequence of these relevant patents is a representation of the central technological trajectory and provides insights into how the focus of innovative activity changed as the technology evolved over time. Linking cited and citing edge of patents, a comprehensive network is finally defined by a graph G(V,E) consisting of V patents and E links. The citation network includes 3195 patents published by 429 assignees as shown in Figure 1b and 1c. In fact, the 429 assignee have published many more patents besides 3195 patents, but the selection pool of 3195 patents in PCN is determined by keyword selection, because emphasis has been placed specifically on including only those patents which seem very relevant to the associated technology. PCN membership can be easily manipulated by expanding the subset of keywords — the catchment area of technology. PCN Network structure facilitates the identification of key players in technology fields, competitors or potential partners for collaboration and many more. It can be used, for instance, to identify key patents based on the fact that the more a patent is cited by other patents, the higher the valuation it has (Von Wartburg et al., 2005).

3 MODELING AGENT-BASED SIMULATION FOR MEASURING INNOVATION

PCN, so created, can use page rank centrality to access innovation structures at multiple levels of importance as per requirement. But, naive implementations of such methods favor older patents, adding intrinsic "age-dependent bias" on innovation rate. It can very well seen that due to a higher number of citation opportunities associated with older patents, early mover patents are more likely to be cited

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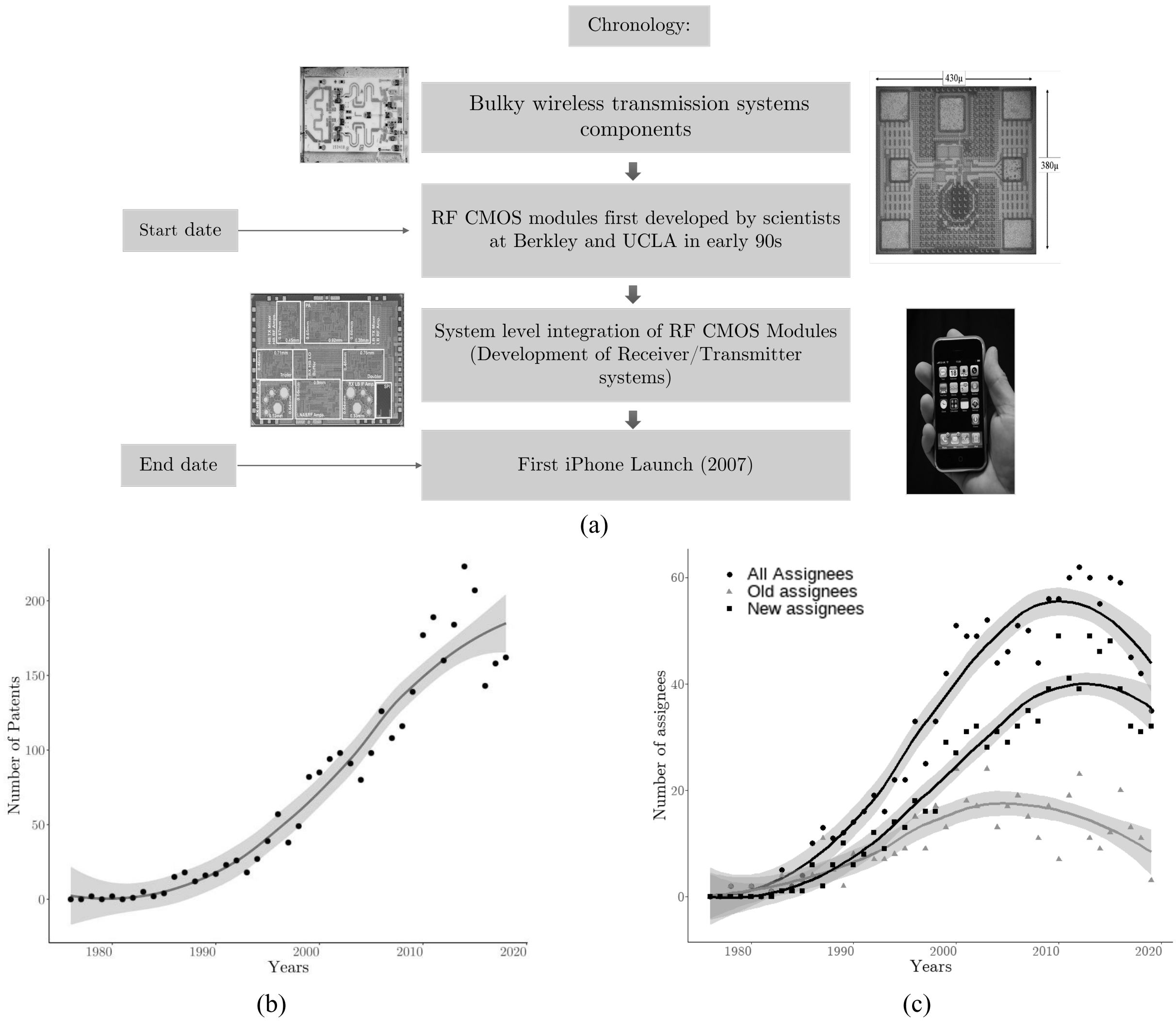

Figure 1. (a) Evolution of 'RF CMOS' technologies (b) Annual frequency of patents in citation network, (c) Annual assignee activity over years.

compared to newly published patents with similar levels of innovation merely because of age alone. Therefore, most of the centrality-based classifications inflate rate of innovation at the outset and understate the same eventually at later stages, exposing final interpretation to other types of bias and reducing prediction reliability. That said, it does not discredit the usefulness of the methods for capturing the quality of innovation. We hypothesize that, if we can isolate the degree of inherent bias and refine the signals of dynamic evolution associated with rate of innovation, we could still invigorate the simplicity. We substantiate the existence of age-dependent bias and utilize agent-based modeling to emulate the underlying mechanism of the bias in order to understand the significant impact of each of the relevant hyper-parameters associated with the simulation model.

To do that, firstly, we create temporal trends for frequency of patents as proxy for rate of innovation across life cycle. Distinguishing patent based on centrality measures like page rank; we classify patents based on their influence in the evolution of technology and plot the frequency of various levels of influential patents over the technological lifecycle of almost two decades as shown in Figure 1b. Next, we trim technological life cycle at different time point thresholds and repeat the process to examine difference between innovation trend plots of diverse influences across various time point thresholds. It is observed that innovation trend plots show identical tracks for various level of influence irrespective of the time point thresholds across technological life cycle. All frequency trends follow an inverted 'U' shape curves indicating that the rate of innovation rises rapidly until a peak and gradually subsides close to the time point thresholds. Consequently, when studying the evolution of the lifecycle of a technology, differences in innovations at across technological stages are of little value if we cannot

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distinguish any discernible differences in trends with various trimming time thresholds over the life cycle. Therefore, we utilize agent-based modeling (ABM) to emulate the underlying mechanism of age-dependent bias in patent citation method and draw parallel from real data to dissociate the effect of bias and indicators of heterogeneous innovation rate at various stages of technological evolution in the form of heterogeneous innovation rate. In order to substantiate the existence of the heterogeneous rate of innovation, we use ordinary linear simple regression to compare the relationship between time point threshold and difference between frequency of various types of influential patents in the form of Inter-Quartile-Range (IQR);

$$IQR_{y,t} = \beta_0 + \beta_y \cdot years_y + \epsilon_{y,t} \tag{1}$$

Where, $IQR_{y,t} =$ represent Inter-Quartile-Range ($\#patents_{quartile3} - \#patents_{quartile1}$) of patent frequency at year $'y'$, with the citation network trimmed at year $'t'$ and β_y is the coefficient vector of length $y-1$ years. The coefficients of OLS regression show that patent frequency IQR are significantly explained by specific years in the life cycle and IQR distributions across threshold years can be used to identify variations in innovation rates.

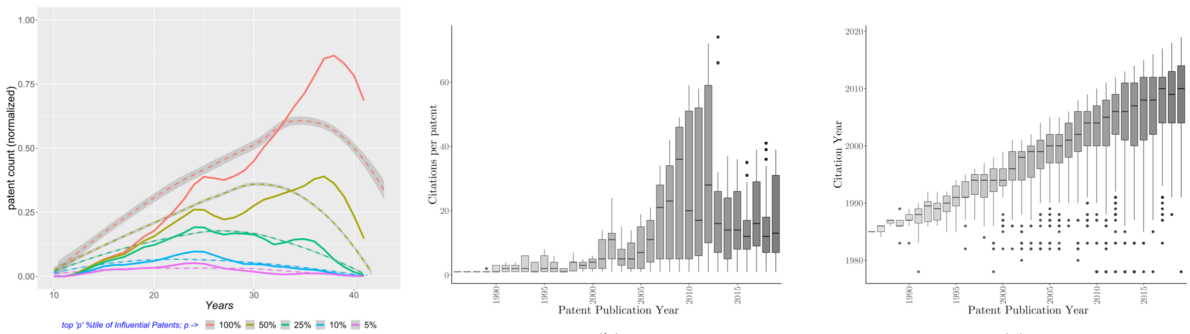
3.1 Agent based model

Agent-based modeling mimic PCN dynamics with patents represented by agents. It discretely simulates the evolution of innovation over time steps to observe knowledge transfer over an arbitrary period of time T, discretized as t, where $t \in \{0,1,2,3......,T\}$ and T matches current age of focal technology. The first aim of the model is to emulate the evolution mechanism, while the second objective is to calibrate the hyper-parameters from the real data, and finally tune itself with as few variables as possible that are not calibratable to uncover the latent innovation rate in presence of known age-dependent bias. Modeling of technological evolution starts with few spontaneous breakthrough patents inspired by few of the previously existing patents which we define as *'seed patents'* in the citation network. As new patents are added to the citation network, the network grows over time following a birth-rate function, $M(t)$, calibrated from the real data based on the age of evolution. There are two types of patents: i) Innovative patents – epiphanic discoveries contributing significantly to the technology, mostly results of radical breakthrough innovations, ii) Incremental patents – less insightful discoveries compared to innovative patents but they fill in technological gaps and have commercial value. $IR(t)$, determines proportion of innovative patents every year – the innovation rate – and similarly, $[1 - IR(t)] \cdot M(t)$ is frequency of incremental patents.

The out-degree of new generation patents are represented by two components: out-degree to patents of just previous year $O_{-1}(t)$ and out-degree of patents of patents older than one year $O_{old}(t)$. All new generation patents follow calibrated out-degree distribution for both types, each of which is represented as a random distribution with a mean and variance $U[O_i(t), O_i(t)_\sigma]$ (Figure 2b). These patents independently cite previous innovative patents and incremental patents based on p_1 and p_2 ($p_1 > p_2$) respectively, such that existence of an out-degree depends on respective binomial realizations dependent on in-degree of citations with binomial event probability of $p_i^{\sqrt{indegree}}$, $i \in 1,2$. This helps mimic the underlying age-dependent bias phenomenon where patents with higher number of citations are more likely to be referred by newer patents compared to patents with less citations. Following the realization citation set, a subset is trimmed using random choices to match $O_{old}(t)$ number of out-degrees. The fact that p_1 is greater than p_2 ensures that on an average innovative patents are preferred over incremental ones, even if random choices are made. Furthermore, we also introduce bounds for maximum age of citations, defined as the lag in technological reliance $TR(t)$, in order to test the robustness of simulation results and calibrate them later as shown in Figure 2c. We test multiple functional forms of $IR(t)$ starting from a constant over t to p.d.f function of a β distribution[1] with the aim to match the trajectory of real data.

Once simulated PC network is built, we rank patents (agents) based on page rank centrality, classify them with decreasing value of influence and plot patent frequency across lifetime of simulation for various levels of influence. Since most of the variables are either normalized or calibrated from real data,

[1] $IR(t) = \frac{t_{norm}^{\alpha-1}(1-t_{norm})^{\beta-1}}{B(\alpha,\beta)}$, where $B(\alpha,\beta)$ is the Gamma function and $t_{norm} = \frac{t}{T}$.



(a) (b) (c)

Figure 2. (a) real data from patent-citation network fitted with synthetic data generated by agent-based modeling with tuned hyper-parameters and functions. Dotted lines are from synthetic data and solid lines are from real data. (b) Out-degree distribution across years (c) Lag in technological reliance of patents published in respective years.

there are four variables representing degrees of freedom that govern the shape of innovation rate function $IR(t)$ viz. α, β – hyper-parameters of β–distribution, binomial event probabilities p_1 and $p_2 = 1 - p_1$. We verify degree to which tunable hyper-parameters of agent-based modeling play roles in explaining presence of heterogeneous innovation rate in evolution of technological lifecycle.

We compare final simulation results, defined as synthetic data, with real data from PC network to validate tolerance intervals for hyper-parameters that generate the least difference (Root Mean Squared Error) on average to emulate the underlying mechanism at various stages of technological evolution. It is observed that certain functional forms of hyper-parameters explain perceivable heterogeneity in rate of innovation in real data better than others. Based on the observations, we step up our approach, tune hyper-parameters of simulation to match innovation rate in both the data sets in order to check such methodological feasibility shown in Figure 2a. Despite the presence of age-dependent bias, innovation rate is characterized by simple patent count measure, and we observe that centrality-based classification of influence traces the trajectory of evolution in technological lifecycle very well once the bias is isolated. In the subsequent sections of the paper, we capitalize on newly uncovered latent innovation rate and use to study evolution of technology innovation. We use tuned ABM hyperparameters and subsequently the innovation rate $IR(t)$ to generate weighted level of influence metric of patents to classify patents in real data. We calculate weighted page ranks of patents with respect to annual innovation rates to generate new influence of patents. Using this, we map pivotal patent assignees — innovators and calculate the diversity of innovators in the technology market by using a normalized entropy measure in Section 4.

4 TEMPORAL DIVERSITY IN INNOVATOR MARKET

The view of innovation is based on the flow of patents and citations that link one invention with another. Yet, in order to visualize the cascading flow of innovation in the form of the innovation structure of assignees, the composition and diversity of the innovation market are crucial. Innovation structures tend to be more about patent ownership than patents themselves due to competition and collaboration among firms and PCN literature have emphasized that innovators' knowledge bases are of considerable value. Since it is important to understand how firms capture value from innovation given the structure of the innovation market (James et al., 2013), we explore firms and institutions based on innovation value or so to say the influence of their published patents using latent innovation rate uncovered previously.

We hypothesize that diversity of innovators and distribution of innovation value are indicators of innovation network(Wang et al., 2011). To map annual assignee activity in terms of patent publication, we build a network of assignee based on patents citations, and then analyze it. As we dig deeper, it is observed that number of assignees tends to increase from year to year and reaches a saturation point around year 2010 and then begins to decline as seen in Figure 1. In the assignee network, there are old assignees that publish patents continuously, while a continuous increase in new assignees also take place throughout the period. Around year 2010, despite the fact that the number of old assignees remained unchanged, the number of new assignees start waning which can be a distinctive property of stage of

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the technological lifecycle. As we explore the underlying innovation structure further, we investigate the diversity of innovators in order to better understand the innovation strategies of assignee firms in patent market.

To measure diversity of patent market publications in a given year, we define a measure called "Entropy". Shannon Entropy acts a proxy to measure diversity in the publication market of focal technology. Mathematically, entropy E for all assignee in a year is defined as E_y. Suppose, patent 'P' published in year 'y' has an assignee 'a'. $N_{a,y}$ is the number of patents published by assignee 'a' in year 'y and $P_{a,y}$ represents proportion of patents published by assignee 'a' in year 'y'; $\frac{N_{a,y}}{\Sigma_a N_{a,y}}$. Thus, E_y = Entropy of all Assignees in year 'y'.

$$E_y = \sum_{a \,\in\, Assignees\ in\ y} P_{a,y} \cdot -log(P_{a,y}) \tag{2}$$

The fantastic property of citation networks is that we can trim networks based on centrality criteria and selectively penetrate deeper into the innovation structure. As we plot normalized entropy measure of the innovation market, we use weighted page-rank centrality to differentiate influential assignee and examine composition of innovation market at various levels of influential patents as seen in Figure 3. The market entropy curve takes on an S-shaped shape when we consider the diversity of all patent assignees (100%) across the years, whereas the curve gradually transforms into an inverted U-shape when we consider assignee diversity only for highly influential patents (top 5 & 10 percentile of patents). It is noteworthy that PC networks alone, however, cannot help distinguish various levels of innovative structures solely based on their citations, and a "S" shape growth in the number of published patents in Figure 1b infers a different story, however, by utilizing the assignee structure we can classify patent-citation network, visualize diversity of assignee of patents for varying level of influential patents and eventually analyze innovation structure and firm positions in technology market as a whole.

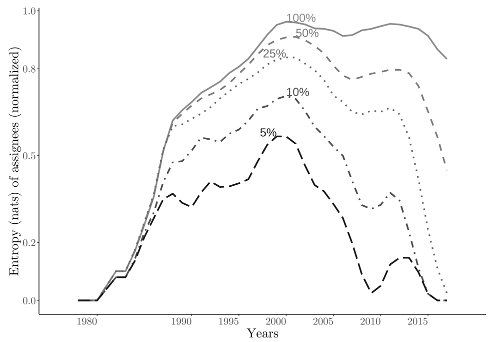

Figure 3. Normalized entropy of assignees of core patents of RFID-CMOS patents across years.

Figure 3 shows two things: (1) Diversity of innovation market measured by entropy in vertical axis and (2) differentiation of various assignees based on respective patent influence in the PCN by spacing between various bands of curves. Diversity in the innovation market starts small because of fewer patents at the start, but as time progresses more and more innovators enter the market and differentiate their strategy to publish patents that are both breakthroughs and incremental innovations until technological innovation reaches a peak as observed in Figure 3. Broadly speaking, at the onset, there is a race between advanced technologically leading firms to publish the first of the breakthrough patents, so even though market diversity gradually increases, differentiation of type of patents is not that different, and we see that the craze for new innovation draws more and more firms into the market publishing similar type of patents. Firms that know more are more likely to be able to learn more. It is no coincidence that the peak market diversity and separation between various types of patent published by assignees is intensified at the same time (year 1995 onward). Particularly with patents related to RF-CMOS technology, both the market diversity and differentiation of various assignees is highest around the time when U-Berkeley and UCLA researchers first developed patents for RF-CMOS modules in the early 1990s. Later in the technological life cycle even though innovation market diversity increases continuously, frequency of high value innovation decreases, and innovators start publishing only low value patents by upholding exploiting strategy.

Therefore, we observe an inverted ’U’-shaped diversity of influential innovators during the life cycle, rather than an ’S’-shaped diversity for less influential innovators. Early on, innovation structures are less diverse, but this gradually changes, and a lot of new innovators try to capitalize on extensive research collaborations. This grows and matures eventually until the value creation and commercialization becomes an expensive endeavor. Therefore, only a few prominent players stay in the market publishing valuable patents, however, in contrast, an abundance of less significant incremental publications also continues to crop up.

In the early phases of breakthrough technologies, similar to product innovation in AU models, firms are more willing to allocate higher resources because the ‘winner takes most’ principle is at play. Furthermore, firms use exploration strategies when they have excess resources. Gradually, increasing firm entry into the innovation market results in increased diversity because dominant designs continue to become more imminent. The rate of change of product innovation is also high with increasing marginal reward until dominant design is prototyped. At the outset, the primary objective is not state-of-the-art but to develop insights and competencies. Since breakthrough innovations are usually productivity enhancing, only innovative firms with advanced performance maximizing capabilities are expected to be in the market as a result of the high degree of uncertainty, high risk and only high expected downstream potential of innovation markets. Superior firms emphasize unique products and indulge in exploration rather than exploitation or imitation often in the anticipation of expanding existing competencies (also studied in Steinberg et al. (2022)). As technological superiority is critical, the types of patents that assignees target at this stage before the peak of diversity aren’t very different.

Later, when dominant designs are available thereby reducing uncertainty, (Teece, 2008) influential patent market are already saturated with few of superior firms like oligopolies (Burnap et al., 2017). However, low influential — incremental patents still continue to maximize returns from newer innovations following exploitation and cost minimizing strategy where even though products are standardized, and newer innovation mainly satisfy price competition objectives.

5 CONCLUSION

This paper presents a methodology that uses publicly available patent metadata creating multiple levels of citation networks to identify and analyze innovations. There are two main contributions that we believe our paper offers. Firstly, as with all patent-citation studies that use centrality-based network tools, our paper modifies the standard method by isolating intrinsic age-dependent bias and uncovering latent innovation metrics within the data at the desired levels of granularity. Secondly, we show that although patents differ greatly qualitatively in terms of their value, the analysis of essential patents used to measure evolution of innovation does not reveal actual firm strategies. Rather, the network of patent assignees classified based on quality of published patents provides a true picture of firm strategy and diversity of innovation networks at various stages of its life cycle. Usually, studies involving assignee network and firm strategy in innovation are time-consuming (Valencia-Romero and Grogan, 2020) rely on primary and secondary data limited to few clusters of firms in specific industries, but with the said methodology, large amounts of publicly available data can be used to reveal expected firm strategies based on respective technological applications.

It is worth noting that the evolution of innovation involves both the flow of knowledge and the isolation of searches among innovators within the same design community, working on related technologies. In addition to the way they behave (strategize), invent and interact by relying on one another’s search collectively shapes the performance of the design community. By examining the diversity of such single-objective oriented communities at different stages of technology, we can gain insight into the state of the design community as a whole. The fact that this can be done by utilizing publicly available patent citation data is of great value.

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