Literature Review Sheet

**Papers on general purpose technologies**

Bresnahan (2010)

Chapter 18 - General Purpose Technologies

<https://www.sciencedirect.com/science/article/pii/S0169721810020022>

This chapter selectively surveys the literature on general purpose technologies (GPTs), focusing on incentives and aggregate growth implications. The literature on classical GPTs (steam, electricity, computers) and on classical great economic transformations (industrial revolutions, the information age) are linked to the theoretical and empirical literatures. The implications of GPT analysis for understanding the history of productivity growth in the late twentieth century are taken up on the concluding remarks.

Moser & Nicholas (2004)

Was Electricity a General Purpose Technology? Evidence from Historical Patent Citations

<https://pubs.aeaweb.org/doi/pdf/10.1257/0002828041301407>

This paper uses historical patent citation data to test whether electricity, as the canonical example of a General Purpose Technology, matches the current criteria of GPTs. We use a sample of American patents assigned to publicly traded companies in biennial years of the 1920's to check which of four industry categories (electricity, chemicals, mechanical, and other) most closely matches the key elements of GPTs. We analyze the characteristics of our patents at their grant date and trace knowledge embodied in these patents through citations in patent grants between 1976 and 2002. Our sample consists of 1,867 U.S. patents from the 1920's, and 3,400 forward citations to these patents. Our aim is both to help inform the way that growth theorists model the development of GPTs and to enhance our understanding of technological progress in the last century more generally.

Jovanovic & Rousseau (2005)

Chapter 18 - General Purpose Technologies

<https://www.sciencedirect.com/science/article/pii/S157406840501018X>

A general purpose technology or GPT is a term coined to describe a new method of producing and inventing that is important enough to have a protracted aggregate impact. Electricity and information technology (IT) probably are the two most important GPTs so far. We analyze how the U.S. economy reacted to them. We date the Electrification era from 1894 until 1930, and the IT era from 1971 until the present. While we document some differences between the two technologies, we follow David [In: Technology and Productivity: The Challenge for Economic Policy (1991) 315–347] and emphasize their similarities. Our main findings are:

1. Productivity growth in the two GPT eras tended to be lower than it was in other periods, with productivity slowdowns taking place at the start of the two eras and the IT era slowdown stronger than that seen during Electrification.
2. Both GPTs were widely adopted, but electricity’s adoption was faster and more uniform over sectors.
3. Both improved as they were adopted, but measured by its relative price decline, IT has shown a much faster improvement than Electricity did.
4. Both have spawned innovation, but here, too, IT dominates Electricity in terms of the number of patents and trademarks issued.
5. Both were accompanied by a rise in “creative destruction” and turbulence as measured by the entry and exit of firms, by mergers and takeovers, and by changing valuations on the stock exchange.

In sum, Electrification spread faster than IT has been spreading, and it did so more evenly and broadly over sectors. Also, IT comprises a smaller fraction of the physical capital stock than electrified machinery did at its corresponding stage. On the other hand, IT seems to be technologically more dynamic; the ongoing spread of IT and its continuing precipitous price decline are reasons for optimism about productivity growth in the 21st century.

Hall & Trajtenberg (2006)

Uncovering General Purpose Technologies with Patent Data

<https://ideas.repec.org/h/elg/eechap/3286_14.html>

Our modest goal in this chapter is to see what might be learned about the existence and technological development of general purpose technologies (GPTs) through the examination of patent data, including the citations made to other patents. Such measures would be useful both to help identify GPTs in their early stages of development and also as proxies for the various rates of technical change called for in a fully developed growth model such as that in Helpman and Trajtenberg (1998b). In doing this exploration we are also motivated by the observation that not all technologies or, indeed, R&D dollars are equal, but that economists too often ignore that fact, primarily because of data limitations. As has been pointed out by others before us patenting measures have the potential to allow more detailed analysis of the ‘direction’ as well as the ‘rate’ of technical change.

Petralia (2020)

Mapping general purpose technologies with patent data

<https://www.sciencedirect.com/science/article/pii/S0048733320300925>

This article develops a three-dimension indicator to capture the main features of General Purpose Technologies (GPTs) in patent data. Technologies are evaluated based on their scope for improvement and elaboration, the variety of products and processes that use them, and their complementarity with existing and new technologies. Technologies’ scope for improvement is measured using patenting growth rates. The range of its uses is mapped by implementing a text-mining algorithm that traces technology-specific vocabulary in the universe of all available patent documents. Finally, complementarity with other technologies is measured using the co-occurrence of technological claims in patents. These indicators are discussed and evaluated using widely studied examples of GPTs such as Electric & Electronic (at the beginning of the 20th century) and Computer & Communications. These measures are then used to propose a simple way of identifying GPTs with patent data. It is shown there exist a positive association between the rate of adoption of GPTs in sectors, measured in terms of the number of GPT patents, and their growth.

Hötte, Tarannum, Verendel, & Bennett (WP)

Exploring Artificial Intelligence as a General Purpose Technology with Patent Data -- A Systematic Comparison of Four Classification Approaches

<https://arxiv.org/abs/2204.10304>

Artificial Intelligence (AI) is often defined as the next general purpose technology (GPT) with profound economic and societal consequences. We examine how strongly four patent AI classification methods reproduce the GPT-like features of (1) intrinsic growth, (2) generality, and (3) innovation complementarities. Studying US patents from 1990-2019, we find that the four methods (keywords, scientific citations, WIPO, and USPTO approach) vary in classifying between 3-17% of all patents as AI. The keyword-based approach demonstrates the strongest intrinsic growth and generality despite identifying the smallest set of AI patents. The WIPO and science approaches generate each GPT characteristic less strikingly, whilst the USPTO set with the largest number of patents produces the weakest features. The lack of overlap and heterogeneity between all four approaches emphasises that the evaluation of AI innovation policies may be sensitive to the choice of classification method.

**Disruptive Innovation**

Govindarajan & Kopalle (2005)

Disruptiveness of innovations: measurement and an assessment of reliability and validity

<https://onlinelibrary.wiley.com/doi/abs/10.1002/smj.511>

Strategic management scholars have long explored the broad topic of innovation, a cornerstone in creating competitive advantage. Any attempt at theory construction in this area must encompass reliable and valid measures for key innovation characteristics. Yet, with respect to an important construct, i.e., disruptiveness of innovations, there has been relatively little academic research. Without formalizing the disruptiveness concept with a reliable and valid measure, it is difficult to conduct rigorous research to uncover the causes of the innovator's dilemma and identify mechanisms to help incumbents develop such innovations. In this paper, we develop a scale for the disruptiveness of innovations. We collected data from senior executives (vice president or general manager level) at 199 strategic business units (SBUs) in 38 Fortune 500 corporations and performed a series of analyses to establish the reliability and validity of the disruptiveness scale. The reliability measures, exploratory factor analysis, confirmatory factor analysis, and subsequent statistical tests strongly support our measure. Further, we also present nomological validity of the disruptiveness construct, thus establishing its predictive validity. Thus, this paper distinguishes the disruptiveness concept from other established innovation constructs, such as radicalness and competency destroying. Finally, we discuss the significance of our results and how this study might be useful to other researchers.

Nagy, Schuessler, & Dubinsky (2016)

Defining and identifying disruptive innovations

<https://www.sciencedirect.com/science/article/pii/S0019850115300110>

Three essential questions about innovations prevent academics from helping managers determine if a new technology is a disruptive innovation to their organization. First, what is a disruptive innovation? Second, how can a disruptive innovation be disruptive to some and yet sustaining to others? Third, how can disruptive innovations be identified before a disruption has occurred in an organization? This paper proposes answers to these three questions by redefining disruptive innovations through use of innovation adoption characteristics. Through the relative nature of innovation characteristics, a heuristic, or Baedeker, to better determine if an innovation could be disruptive to an organization is proposed. Illustration of the approach is presented to show how potentially disruptive innovations could be identified before an organizational disruption has occurred.

Guo, Pan, Guo, Gu, & Kuusisto (2019)

Measurement framework for assessing disruptive innovations

<https://www.sciencedirect.com/science/article/pii/S0040162518306656>

Assessing potential disruptiveness of innovations is an important but challenging task for incumbents. However, the extant literature focuses only on technological and marketplace aspects, and most of the documented methods tend to be case specific. In this study, we present a multidimensional measurement framework to assess the disruptive potential of product innovations. The framework is designed based on the concept that the nature of disruptive innovations is multidimensional. Three aspects are considered, i.e., technological features, marketplace dynamics and external environment. Ten indicators of the three categories are proposed and then connected based on the conceptual and literature analysis. Three innovations, namely, WeChat (successful), Modularised Mobile Phone (failed) and Virtual Reality/Augmented Reality (ongoing), are selected as case studies. A panel of industrial experts with PhD degree in engineering is surveyed. The survey results are calculated and analysed according to the framework and then compared against the developments of the innovations. We also check the robustness of this framework by surveying other groups of people, and the results are nearly identical to the previous findings. This study enables a systematic assessment of disruptive potential of innovations using the framework, providing insights for decisions in product launch and resource allocation.

Si & Chen (2020)

A literature review of disruptive innovation: What it is, how it works and where it goes

<https://www.sciencedirect.com/science/article/pii/S0923474820300163>

The disruptive innovation theory, proposed and developed by Christensen over 20 years ago, has been widely discussed and applied. However, there are still serious misunderstanding and misusing of the concept and connotation of disruptive innovation. Doubts about its practical significance and predictability also remain. In this paper, we attempt to further clarify the concept and emphasize its important role in guidance in practices through reviewing relevant literatures published in SSCI journals. Furthermore, we propose a multilevel theoretical framework to examine the influence factors of disruptive innovation by integrating various research results. We also provide suggestions and implications for future research.

Bhatt, Lai, Drave, Lu, & Kumar (2023)

Patent analysis based technology innovation assessment with the lens of disruptive innovation theory: A case of blockchain technological trajectories

<https://www.sciencedirect.com/science/article/pii/S0040162523005498>

The technological innovation period has reduced drastically in the current era giving rise to constantly new disruptive technologies, which may seem discreet; however, their evolution is also derived from the previous technological path. This study aims to identify the technology trajectory and evolution phases of disruptive technology, Blockchain, with respect to its predecessor technologies. Within the context of disruptive innovation theory, patent citation analysis employing the key-route main path method was utilized for this study. The data collection was based on keywords and IPC codes to retrieve US patents from the webpat database. The data obtained included 10,919 initial patents and 6206 final patents after simple family merge. The results acquired ranged from the year 1974 to 2021. The study identified five significant technology clusters based on the key-route main path analysis and framed the evolution path of the technology. The findings reveal the technological path dependence and knowledge flow of technological innovation. The novelty of this study lies in its approach to mapping DI theory characteristics with patent analysis to identify the path dependence of disruptive innovations, which aids researchers and decision-makers in understanding and assessing their innovation strategies.

Momeni & Rost (2016)

Identification and monitoring of possible disruptive technologies by patent-development paths and topic modeling

<https://www.sciencedirect.com/science/article/pii/S0040162515004072>

Understanding current technological changes is the basis for better forecasting of technological changes. Because technology is path dependent, monitoring past and current trends of technological development helps managers and decision makers to identify probable future technologies in order to prevent organizational failure. This study suggests a method based on patent-development paths, k-core analysis and topic modeling of past and current trends of technological development to identify technologies that have the potential to become disruptive technologies. We find that within the photovoltaic industry, thin-film technology is likely to replace the dominant technology, namely crystalline silicon. In addition, we identity the hidden technologies, namely multi-junction, dye-sensitized and concentration technologies, that have the potential to become disruptive technologies within the three main technologies of the photovoltaic industry.

Park, Leahey, & Funk (2023)

Papers and patents are becoming less disruptive over time

<https://www.nature.com/articles/s41586-022-05543-x>

Theories of scientific and technological change view discovery and invention as endogenous processes1,2, wherein previous accumulated knowledge enables future progress by allowing researchers to, in Newton’s words, ‘stand on the shoulders of giants’3,4,5,6,7. Recent decades have witnessed exponential growth in the volume of new scientific and technological knowledge, thereby creating conditions that should be ripe for major advances8,9. Yet contrary to this view, studies suggest that progress is slowing in several major fields10,11. Here, we analyse these claims at scale across six decades, using data on 45 million papers and 3.9 million patents from six large-scale datasets, together with a new quantitative metric—the CD index12—that characterizes how papers and patents change networks of citations in science and technology. We find that papers and patents are increasingly less likely to break with the past in ways that push science and technology in new directions. This pattern holds universally across fields and is robust across multiple different citation- and text-based metrics1,13,14,15,16,17. Subsequently, we link this decline in disruptiveness to a narrowing in the use of previous knowledge, allowing us to reconcile the patterns we observe with the ‘shoulders of giants’ view. We find that the observed declines are unlikely to be driven by changes in the quality of published science, citation practices or field-specific factors. Overall, our results suggest that slowing rates of disruption may reflect a fundamental shift in the nature of science and technology.

Wang, Liang, Ye, Chen, & Liu

Disruptive development path measurement for emerging technologies based on the patent citation network

<https://www.sciencedirect.com/science/article/pii/S1751157724000063>

Studying disruptive innovation development paths for emerging technologies helps trace and grasp key core technologies development, promoting innovation and development in emerging technologies and industries. This paper measures the innovation development path for emerging technology, including: (1) improving the triple citation network and quantifying disruptive measurement by designing a technological disruption model; (2) proposing a contraction method for the citation network from the dataset perspective; (3) proposing a method to extract the main path using technology disruption degree as a criterion for citation networks importance; (4) taking the sintering technology in 3-D printing technology as the empirical object with 12,662 patent families from 1997 to 2019. The empirical results indicate that the disruption degree value is determined by the transitive citation relationship without the co-citation relationship, and the closed-loop structures are effectively removed, thereby reducing the size of the dataset. The proposed disruption quantification method can support effective evaluation of technological innovation levels and decision-making for the research and development (R&D) direction and resource allocation.

**Radical and Breakthrough Innovation**

Stiller, van Witteloostuijn, & Cambré (2020)

Do current radical innovation measures actually measure radical drug innovation?

<https://link.springer.com/article/10.1007/s11192-020-03778-x#Sec12>

To date, there has been little agreement in the literature on what exactly constitutes radical drug innovation and how to properly measure this important construct. Without a validated measure, our ability to understand radical drug innovations, explain their origins, and demonstrate their implications for management and health policy is limited. This paper addresses the problem of radical drug innovation measurement, provides evidence of the limitations associated with the current state of the art, and offers a new method based on German health technology assessments (HTA). Data was obtained for 147 drugs authorized by the European Medicines Agency from 2011 to 2016. The innovativeness of these drugs was assessed using current measures of radical drug innovation compared with the newly developed measure. Findings indicate that current measures of radical drug innovation are associated with very inconsistent outcomes and do not appear to measure what they purport to measure. This study argues that assessing therapeutic value (as measured by the German HTA) is particularly important, given that drug novelty alone does not conclusively indicate whether a drug will deliver therapeutic value.

Green, Gavin, & Aiman-Smith (1995)

Assessing a multidimensional measure of radical technological innovation

<https://ieeexplore.ieee.org/abstract/document/403738/authors#authors>

For almost 30 years, innovations have been characterized as radical or incremental. Nevertheless, the construct has not been precisely defined and ad hoc measures have been the norm in the literature. This paper describes the development of measures which address multiple dimensions of the concept of innovation radicalness and treat it as a continuous variable. A rigorous process of item development, reliability analysis, and both exploratory and confirmatory factor analysis was used. The developed measures meet psychometric standards, demonstrate criterion-related validity, and capture four dimensions of radicalness: technological uncertainty, technical inexperience, business inexperience, and technology cost. Findings support the conceptualization of radicalness as a continuum with multiple dimensions, and suggest that those dimensions may be differentially related to project characteristics and outcomes. The utility of these measures and dimensions as diagnostic tools in project management is discussed. Radicalness as a multidimensional concept is also discussed as a valuable tool in project planning, project evaluation, and understanding the strategic implications of pursuing radical innovation.

Dahlin & Behrens (2005)

When is an invention really radical?: Defining and measuring technological radicalness

<https://www.sciencedirect.com/science/article/pii/S0048733305000764>

We develop a valid definition of technological radicalness which states that a successful radical invention is: (1) novel; (2) unique; and (3) has an impact on future technology. The first two criteria allow us to identify potentially radical inventions ex ante market introduction; adding the third condition, we can ex post determine if an invention served as an important change agent. Empirically testable condition selected 6 of 581 tennis racket patents granted between 1971 and 2001. Two of the identified patents – the oversized and the wide-body rackets – are considered radical inventions by industry experts. Applying our definition and operationalization would allow researchers to achieve greater generalizability across studies, avoid endogenous definitions of radicalness, and study predictors of market success for radical inventions.

Briggs & Buehler (2018)

An Analysis of Technologically Radical Innovation and Breakthrough Patents

<https://www.tandfonline.com/doi/full/10.1080/13571516.2018.1438873>

Breakthrough innovations – commonly defined by innovations with patents surpassing a critical threshold of forward citations – generate benefits for innovators, businesses, and society. Analyzing more than five million patents and citations from 1976 to 2017, this paper adds to the existing literature by examining whether the radicalness of a patented good – that is, the more technology classes cited as contributing prior arts not identified in the patent’s own technology identity – impacts the likelihood an innovation is a breakthrough. In essence, the paper tests the common belief that it is beneficial to “think outside the box” when innovating. The results show that increased radicalness increases the likelihood of a breakthrough up to a certain threshold, after which increased radicalness decreases the likelihood of a breakthrough. Additionally, established innovators and university ownership of a patent each extend the range for which increased radicalness increases the probability of a breakthrough, while joint patent ownership decreases the range.

Katila (2000)

Using patent data to measure innovation performance

<https://www.inderscienceonline.com/doi/epdf/10.1504/IJBPM.2000.000072>

Technologically radical innovations are a key success factor in many high technology industries. This study examines how firms can measure performance on this key dimension. I ask two questions; 1, how can patent data be used to measure innovation and its radicalism, and 2, what are some of the empirical shortcomings with the current methods using patent data? These research questions are examined through a longitudinal data of 100 biopharmaceutical companies. Two main conclusions are drawn. First, patents and the subsequent patents that cite them provide a useful way to measure innovation performance. Patent data can be used to monitor activities of competitors, form a performance evaluation system in R&D organisations, and identify a specific technological trend. Second, in prior research, patent citation lags used to distinguish between innovations of different quality have been too short to distinguish between incremental and radical innovations. Lags of ten years and longer are recommended. Short lags may obscure patent-based comparisons of firm innovativeness.

Schoenmakers & Duysters (2010)

The technological origins of radical inventions

<https://www.sciencedirect.com/science/article/pii/S004873331000137X>

This paper aims to trace down the origins of radical inventions. In spite of many theoretical discussions on the effect of radical inventions, the specific nature of radical inventions has received much less attention in the theoretical and empirical literature. We try to fill that void by an empirical investigation into the specific origins of radical inventions. We explore this issue by a close examination of 157 individual patents, which are selected from a pool of more than 300,000 patents. In contrast to the conventional wisdom that radical inventions are based less on existing knowledge, we find that they are to a higher degree based on existing knowledge than non-radical inventions. A further result that follows from our analysis is that radical inventions are induced by the recombination over more knowledge domains. The combination of knowledge from domains that might usually not be connected seems to deliver more radical inventions.

Feng & Han (2023)

Radical innovation detection in the solar energy domain based on patent analysis

<https://www.frontiersin.org/articles/10.3389/fenrg.2022.1056564/full>

In this paper, a new framework to identify radical innovations in the solar energy domain is proposed by combining a technological convergence study and scientific relation analysis, and the link prediction method is utilized to detect potential radical innovations in this domain.

Kelly, Papanikolaou, Seru, & Taddy (2021)

Measuring Technological Innovation over the Long Run

<https://www.aeaweb.org/articles?id=10.1257/aeri.20190499>

We use textual analysis of high-dimensional data from patent documents to create new indicators of technological innovation. We identify important patents based on textual similarity of a given patent to previous and subsequent work: these patents are distinct from previous work but related to subsequent innovations. Our importance indicators correlate with existing measures of patent quality but also provide complementary information. We identify breakthrough innovations as the most important patents—those in the right tail of our measure—and construct time series indices of technological change at the aggregate and sectoral levels. Our technology indices capture the evolution of technological waves over a long time span (1840 to the present) and cover innovation by private and public firms as well as nonprofit organizations and the US government. Advances in electricity and transportation drive the index in the 1880s, chemicals and electricity in the 1920s and 1930s, and computers and communication in the post-1980s.

Summary

GPT: General Purpose Technology

* Three main features of GPTs outlined by the literature (Bresnahan & Trajtenberg, 1995; Bresnahan, 2010)

1. Pervasiveness: a GPT is used in a wide array of application sectors
2. Improvement: a GPT undergoes technical improvement over time
3. Innovation-spawning: a GPT enables innovation in its application sectors (AS)

* Efforts to measure/identify GPTs also rely on these characteristics
  + Hall & Trajtenberg (2006)
    - Focuses on extremely highly cited (>3 times the number of cites received by the 99th percentile) patents
    - Looks at generality, patenting growth, and citation lags
    - Constructs 5 generality measures based on different technological and industry classifications
    - Identified those high in the metrics (top 20% for generality, citing patent generality, and subsequent five-year growth of patent class) as GPT patents
    - Suggestion for generality measure: construct a weighted generality measure that accounts for the overall probability that one class cites another
  + Moser & Nicholas (2004)
    - Looks at old patents (granted in even years between 1920-1928)
    - Measures originality, longevity, and generality
    - Originality: binary, whether the focal patent is the earliest citation of a forward citation patent
    - Longevity: mean and maximum lag between grant and citation
    - Generality: 1 – HHI for three-digit citing classes
    - Compares electricity, chemical, mechanical, and other
    - Electricity patents do not show typical GPT characteristics: they score high in originality, but low in number of citations, longevity, and generality
  + Petralia (2020)
    - Proposes an alternative text-based measure of pervasiveness
    - Extract keywords representative of the technology from USPTO class and subclass descriptions, and count the number of different technological categories that use the keywords
    - Also looks at innovation complementarity: the number of classes that co-occur in a patent with the focal class
* Summary of the empirical literature
  + Citations-based measures such as generality are widely used
  + Some text-based measures
  + Although some aspects of the GPT-ness of a patent can be calculated, other aspects like growth cannot be determined on a patent level

Disruptive Innovation

* Efforts to identify/measure disruptive innovations can largely be sorted into
  + Developing survey scales (Govindarajan & Kopalle, 2006; Lin et al., 2015)
  + Developing analytic framework for managers (Nagy et al., 2016; Guo et al., 2019)
  + Analyzing patent citation networks (Wang et al., 2024; Park et al., 2023; Momeni & Rost, 2016; Bhatt et al., 2023)
* Patent citation network
  + Main path analysis (MPA): algorithmically identifies significant chains in a citation graph. MPA can be used to filter out “unimportant” patents or to identify important patents located at converging positions of multiple technological trajectories.
  + Momeni & Rost (2016) uses MPA + k-core clustering + topic modeling to identify potential disruptive technologies
  + Citation-based measures of disruptiveness focus on the discontinuity of the citation chain
    - Funk & Owen-Smith’s (2017) CD index: a patent is considered disruptive if its citing patent cites only the focal patent and not its predecessors
    - Wang et al. (2024) proposes a modified measure, but the underlying idea is the same.
* Summary of empirical literature
  + Mostly focus on identifying the technological trajectory in a specific field
  + Patent-based measures of technological discontinuity are used to determine disruptiveness

Radical and Breakthrough Innovation

* Novel and valuable solution that substantially improves products/services and exerts tremendous influence on industries and markets

Measures

* Citations (Ahuja & Lampert, 2001; Schoenmakers & Duysters, 2010; Briggs & Buehler, 2018)
* Breakthrough innovation: forward citations (sometimes binary, top n%)
* Radicalness: backward citations (number of backward citations in different technological classes, etc.), sometimes measured by forward citations
* Dahlin & Behrens (2005): constructs an overlap measure between patents by looking at overlapping backward citations. A patent is considered radical if overlap is low with past and present patents, and high with future patents
* Kelly et al. (2021) revisits this idea using text-based similarity measure (modified TF-IDF): the more dissimilar to past patents and the more similar to future patents, the more valuable the patent is.