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A Dynamic Network Measure of Technological Change

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Abstract. This article outlines a network approach to the study of technological change. We propose that new inventions reshape networks of interlinked technologies by shifting inventors' attention to or away from the knowledge on which those inventions build. Using this approach, we develop novel indexes of the extent to which a new invention consolidates or destabilizes existing technology streams. We apply these indexes in analyses of university research commercialization and find that, although federal research funding pushes campuses to create inventions that are more destabilizing, deeper commercial ties lead them to produce technologies that consolidate the status quo. By quantifying the effects that new technologies have on their predecessors, the indexes we propose allow patent-based studies of innovation to capture conceptually important phenomena that are not detectable with established measures. The measurement approach presented here offers empirical insights that support theoretical development in studies of innovation, entrepreneurship, technology strategy, science policy, and social network theory.

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> Economic progress, in capitalist society, means turmoil . . . . New products and new methods compete with the old products and old methods not on equal terms but at a decisive advantage that may mean death to the latter. (Schumpeter 1942, p. 32)

1. Introduction

Foundational theories of technological change distinguish between two types of new technologies. The first "come to exist as entities that depart in some deep sense from what went before" (Arthur 2007, p. 274; Mokyr 1990). Recombinant DNA made a radical departure from existing drug discovery methods that had relied on massive screening of potentially therapeutic compounds (Henderson and Cockburn 1996, Gambardella 1995). Inventions like this can transform the fortunes of organizations and industries. A second type of new technology builds on and enhances its predecessors and therefore has the result of consolidating (not challenging) the status quo. In one classic study, Enos (1962) describes four waves of improvements in processes for manufacturing gasoline. Although new technologies of this type are sometimes dubbed "incremental," they may make substantial improvements over their predecessors and they account for the lion's share of economic and social welfare returns from technological progress (Enos 1958, Rosenberg 1982, David 1990).

Despite the substantive and theoretical importance of differentiating between these two types of technologies, no quantitative measure exists to capture this distinction. Systematic explanations for why, when, and how particular inventions have differential effects on their environment remain elusive. Assessments of technological dynamics traditionally relied on detailed case studies of particular technologies (Dosi 1982, Bresnahan and Greenstein 1996, Goldfarb 2005, Arthur 2009). Quantitative studies exploded with the introduction of the National Bureau of Economic Research (NBER) U.S. Patent Citations Data File in the late 1990s (Hall et al. 2002) and led to many productive insights. However, the patent literature's focus on citation counts and forward-citation-based measures of impact has become a limitation, because many dimensions of technological change cannot be seen by observing the simple magnitude of an invention's later use. Attending to the impact of a new invention without also considering how it relates to already extant technologies creates bias and ambiguity in analyses.

The inability to systematically measure fundamental concepts has made theoretical development challenging in many areas. Consider work on university research commercialization. Since the 1980 passage of the Bayh–Dole Act (Public Law 96-517, 94 Stat. 3015), a law that allowed organizations to seek patents and issue licenses on inventions made with federal funding, scholarly debate has raged over the consequences of commercial activity for university science. Although proponents emphasize universities' ability to make transformative discoveries, detractors worry that commercial engagement pushes campuses to focus on narrow pursuits that are attractive to industry. Empirical research has been unable to adjudicate between these positions. Part of the challenge is that forward-citation-based measures of universities' patent impact are unable to determine whether corporate engagement results in greater alignment between industrial interests and academic priorities. Indeed, studies find that both industrial and more traditional academic funding sources yield higher-impact patents (e.g., Owen-Smith and Powell 2003). Such findings help to establish that public and corporate partners both select high-quality projects, but they do little to adjudicate the key substantive question for studies of academic commercialization.

Computational advances are creating opportunities for extracting deeper insights from large-scale databases like the U.S. Patent Citations Data File. In the area of technological change, a quantitative measure that leverages these advances to distinguish between technologies that depart from or reinforce established trajectories would allow empirical studies to better match foundational theories and may facilitate new conceptual development. To create such a measure, we begin with a network conception of technological change. New discoveries are additions to preexisting networks of complementary or substitutable components. Inventions alter the structure of these networks by creating relationships among technologies and changing the way subsequent additions connect. Networks of technologies evolve as inventions consolidate or destabilize the status quo by increasing or decreasing the use of incumbent technologies.

We build on studies that distinguish between technologies that render firm capabilities obsolete (and therefore are competency destroying) and those that improve the value of capabilities (and therefore are competency enhancing) (Abernathy and Clark 1985, Tushman and Anderson 1986, Christensen 1997). However, our approach differs from these works. First, studies of competency-enhancing and competency-destroying inventions focus on major changes, i.e., discontinuities that fundamentally break with existing standards (Tripsas 1997, Kaplan et al. 2003, Feldman and Yoon 2012). By contrast, we suggest that a new technology's influence on the status quo is a matter of degree, not categorical difference, and we make this observation a focal point of our indexes. Second, our approach decouples the consolidating or destabilizing effects of new technologies from organizations' competencies. Although the implications of new inventions are felt forcefully in terms of how they influence incumbents' capabilities (Benner 2007; Sosa 2009, 2011), their effects ripple more broadly through dynamic networks of prior and subsequent technologies.

Using our network model of technological change, we propose a measure, the CD_t index, that quantifies the extent to which an invention consolidates or destabilizes the subsequent use of the components on which it builds. Combining our CD_t index with an impact weight yields an additional mCD_t index that characterizes the magnitude of an invention's consolidation or destabilization of the status quo. These indexes are sensitive to the enhancing and destructive effects of important new technologies.

Applying these measures to the context of university research commercialization, we find clear evidence that, when universities have greater commercial engagement, they tend to create technologies that consolidate the status quo but, when they receive more federal funding for academic research, they tend to produce more destabilizing inventions. Commercial engagement and federal support are both positively associated with forward citations of university patents. This important finding points to the challenge of relying on forward-citation-based impact measures to distinguish among patents.

In what follows, we first review existing measures. Next, we present our CD_t and mCD_t indexes. Subsequent sections use patent data in four validation exercises. First, we demonstrate that our indexes discriminate among patents along dimensions that are known to be associated with the destabilizing or consolidating nature of technologies. Second, we present case studies that illustrate core features of our indexes while attesting to their ability to identify recognized breakthroughs. Third, we demonstrate the usefulness of our approach with regressions that compare patents' impact with their scores on the CD_t and mCD_t indexes. Finally, we present several different aggregate versions of our measures and evaluate their potential for organizational-level analyses in models that examine how features of the academic research enterprise explain characteristics of university patents.

2. Measuring the Effects of Technologies

2.1. Existing Measures

Many quantitative metrics treat technologies as variable in their impact, i.e., the extent to which they are later used. Although the true impact of a technology is difficult to measure, citations of papers and patents are a common proxy (Griliches 1990, Trajtenberg 1990, Harhoff et al. 1999, Hall and Trajtenberg 2004, Lanjouw and Schankerman 2004, Wuchty et al. 2007, Schoenmakers and Duysters 2010). Impact measures are attractive because they correspond to the intuitive idea that new technologies that offer improvements over the state of the art should become more widely used than less valuable inventions. However, because they focus on the magnitude of future use, impact measures of technologies miss the key substantive distinction between new things that are valuable because they reinforce the status quo and new things that are valuable because they challenge the existing order. In short, impact measures are good for evaluating the extent to which new inventions are used, but they are limited because they offer no insight into how they are used and what those uses do to shape future trajectories, a central objective of evolutionary theories of change (Arthur 2007, 2009; Dosi 1982; Nelson and Winter 1982; Verspagen 2007). This ambiguity makes it problematic to use impact measures to develop and test such theories.

We argue that, to understand a new technology's effects, it is necessary to look not only at its impact, but also how the technology fits into existing trajectories. Measures that consider only the magnitude of a technology's later use miss the crucial point that new technologies emerge in environments that are comprised of other technologies (Arthur 2007, 2009). Existing approaches are therefore unable to describe the substantial effects that inventions may have on the subsequent use of their technological predecessors or the evolution of broader technological trajectories. We describe a new measure designed to capture these very effects by appeal to network science.

2.2. Consolidating and Destabilizing Technologies

Our measure has four core features. First, and most important, it is structural in a network sense, able to capture the extent to which future inventions that build on a technology also rely on that technology's predecessors. This second-order view of impact implies that an invention's importance stems both from how it influences the use of other technologies and its own direct use. Second, the measure is dynamic, able to account for variation in the extent to which an invention alters the use of its predecessors over time. Third, the measure is continuous, able to capture degrees of consolidation and destabilization ranging from large-scale transformations to smaller-scale, incremental shifts. Finally, the measure is valenced, able to distinguish between consolidating and destabilizing technologies that may have similar impact but different consequences for the status quo.

We developed our measure using utility patents granted by the U.S. Patent and Trademark Office (USPTO). Utility patents cover the majority of patented inventions. They include any new or improved method, process, machine, manufactured item, or chemical compound. Although other categories exist for design patents, which are granted for ornamental designs of functional items, and plant patents, which cover plant breeds, most patents granted in the United States are in the utility category, over 90% in 1999 (Hall et al. 2002). We focus on utility patents to help to avoid complexities that arise from differences in citation practices across categories.

Patents are attractive for our purposes because the USPTO requires inventors to include citations of relevant technological predecessors (known as "prior art") in their patent documents. Before being granted, all patents go through an evaluation process in which examiners review these citations for comprehensiveness. Applicants have incentives to make accurate citations: listing irrelevant predecessors weakens a patent's enforceability, but failing to acknowledge related work can invalidate a patent.[1]

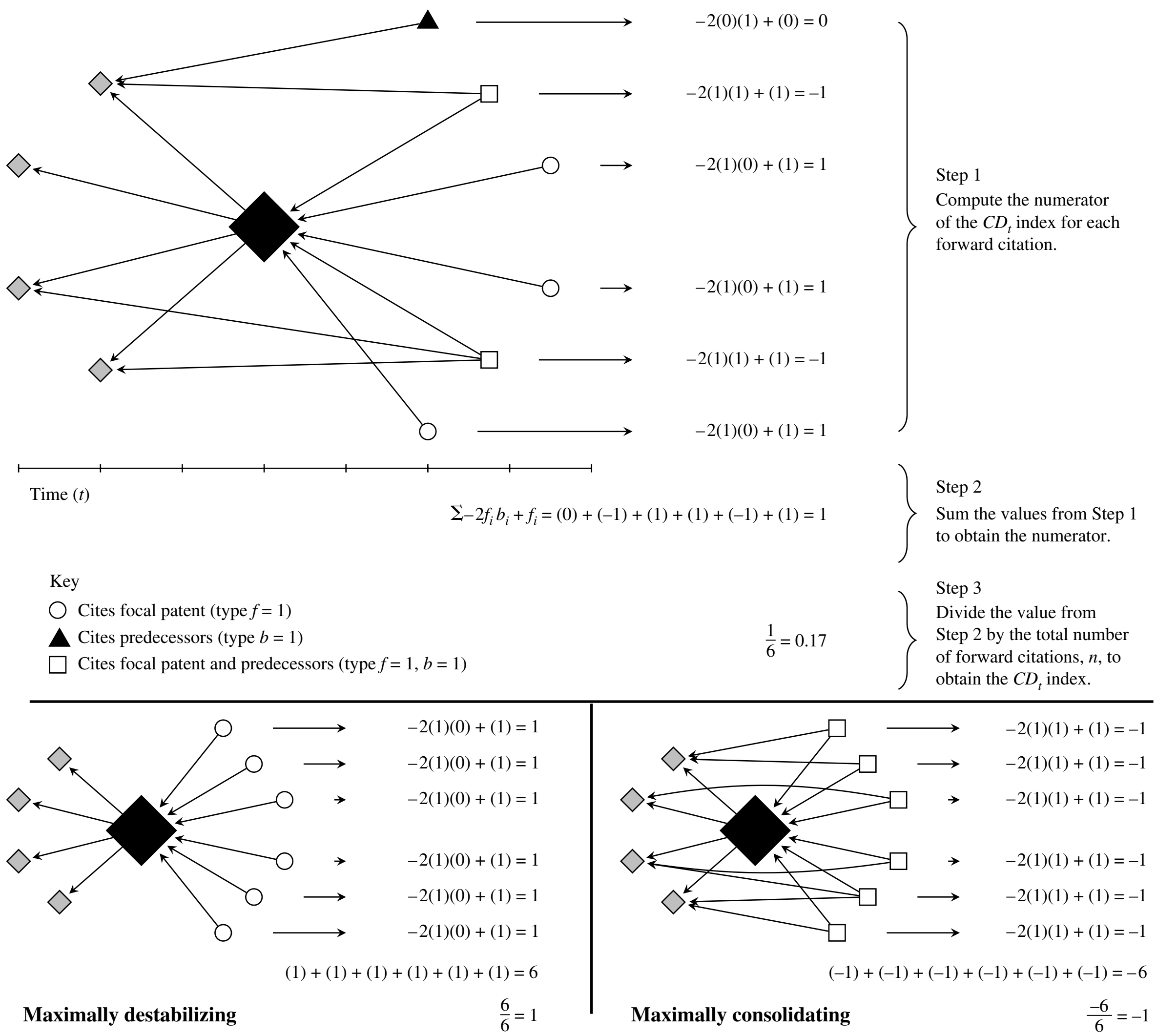
2.3. Measure Development

The CD_t index characterizes how future inventions make use of the technological predecessors cited by a focal patent. Our intuition is that citations of predecessors should decrease after a destabilizing invention is introduced because the technology entails a break with past ways of thinking. By contrast, consolidating inventions should be cited together with their predecessors and therefore increase citations of technologies on which they build. The networks in the bottom left and right panels of Figure 1 illustrate this idea.

The bottom left panel of Figure 1 depicts a hypothetical patent that is maximally destabilizing. The focal invention (black diamond) cites four predecessor technologies (gray diamonds). These citations contribute to the impact of earlier inventions and indicate the focal patent's technological lineage. On the right side of the panel, six subsequent patents (white circles) cite the focal invention, but note that none of these future patents (or "forward citations") also cite the focal invention's technological predecessors. The focal patent is destabilizing because it directs the attention of subsequent inventors and examiners away from technologies that were relevant to its conceptualization. The bottom right panel of Figure 1 shows a focal patent that has identical impact to the one in the left panel (as measured by forward citations) but is maximally consolidating. As illustrated by the white squares, each future patent also cites at least one of the focal patent's predecessors, and therefore this hypothetical patent appears to consolidate the use of these earlier technologies.[2]

Drawing on the tools of network science, we developed our measure by conceptualizing patents as nodes in tripartite networks (or "graphs").[3] A tripartite graph, denoted $G = (V_1, V_2, V_3, E)$, is a network with three generic types or categories of nodes, V_1, V_2,

Figure 1. Illustrative Calculations of the CD_t Index for Three Patents



Note. For simplicity, we eliminate the weighting parameter w_{it} by setting it to 1.

and V_3, and ties (or "edges") E that connect nodes of different types. The edges in our graphs are directed because citations point from one patent to another, and our graphs are acyclic because patents only cite inventions that are temporally prior and therefore there are no paths that begin and end with the same patent (or "node").

Using this notation, let V_1 consist of a focal patent, f, that we seek to evaluate; V_2 consist of predecessor inventions, b, cited by the focal patent; and V_3 consist of a set of future patents, i, that eventually cite the focal patent and/or its predecessors. Types f and b are fixed at focal patent's issue date, but i can grow as time passes and the patent and/or its predecessors accrue new citations. Our objective is to characterize how a new patent, i, joins the network defined by the ties (citations) between patents of type b and f. New patents may join in one of three ways: (1) i can cite the focal patent's predecessors (type b), (2) i can cite the focal patent (type f), or (3) i can cite the focal patent and its predecessors (both types f and b). For a focal patent and vector $\mathbf{i} = (i_1, i_2, \ldots, i_{n-1}, i_n)$ of future patents that cite the focal patent and/or its technological predecessors at time t, we define the CD_t index as

$$CD_t = \frac{1}{n_t} \sum_{i=1}^{n} \frac{-2 f_{it} b_{it} + f_{it}}{w_{it}}, \quad w_{it} > 0, \tag{1}$$

where

$$f_{it} = \begin{cases} 1 & \text{if } i \text{ cites the focal patent (type } f\text{)}, \\ 0 & \text{otherwise}, \end{cases} \tag{2}$$

and

$$b_{it} = \begin{cases} 1 & \text{if } i \text{ cites any focal patent predecessors (type } b\text{)}, \\ 0 & \text{otherwise}, \end{cases} \tag{3}$$

where n_t is the number of forward citations in $\mathbf{i}$, and w_{it} indexes a matrix $\mathbf{W}$ of weights for patent i at time t.[4]

We emphasize that n_t is the number of forward citations of both the focal patent and/or its technological predecessors and therefore this quantity differs from a traditional measure of patent impact. The multiplication by −2 in the numerator of Equation (1) ensures that the measure ranges from −1 to 1, with positive values representing inventions that are more destabilizing and negative values highlighting inventions that are more consolidating. Figure 1 gives examples of how to calculate the CD_t index for three different patents.

The CD_t index captures the direction of an invention's effects on existing technologies, not the magnitude; therefore the measure does not discriminate among inventions that influence a large stream of subsequent work and those that shape the attention of a smaller number of later inventors. By introducing a weighting parameter to Equation (1), the magnitude of a focal invention's future use can be incorporated. Formally,

$$mCD_t = \frac{m_t}{n_t} \sum_{i=1}^{n} \frac{-2 f_{it} b_{it} + f_{it}}{w_{it}}, \quad w_{it} > 0, \tag{4}$$

where m_t is a parameter that captures the magnitude of use of f at time t. In this formulation, m_t differs from n_t in that the former counts only citations of the focal patent, whereas the latter includes citations of both the focal patent and its predecessors. This measure differs from the CD_t index by distinguishing among inventions according to their overall effect on a network of interlinked technologies. The CD_t index captures the direction of an invention's effects, whereas the mCD_t index mixes both direction and magnitude.

In cases where neither the focal patent nor its technological predecessors receive any citations from future patents during the measurement interval, the value of n_t is 0 and the indexes are undefined. When calculated five years after the focal patent's issue date, undefined values of the CD_t and mCD_t indexes were rare, occurring in only 82,572 cases of 2.9 million, a rate of 2.8%. Empirical analyses in later sections examine the implications of these undefined values more closely.[5]

3. Assessments of Face Validity

3.1. Descriptive Statistics and Correlations

Using data on the 2.9 million U.S. utility patents granted between 1977 and 2005, we examine the ability of our indexes to discriminate among inventions along dimensions that are known from previous work to have associations with the destabilizing or consolidating nature of new technologies. Our analyses exclude 34,889 patents that were outside the scope of the National Bureau of Economic Research's (NBER's) technology categorization system and 177 patents with substantial missing data. The basic covariates were obtained from the Patent Network Dataverse (Li et al. 2014) and supplemented with data taken from the USPTO.

For simplicity, we set the weighting parameter w_{it} in Equations (1) and (4) to 1 so that each future patent i that eventually cites the focal patent and/or its predecessors contributes equally. Most of our analyses in this and later sections evaluate impact and the CD_t and mCD_t indexes using forward citations made during the first five years after the focal patent's issue, because annual citations of most patents reach their peak within this time frame (Jaffe and Trajtenberg 2002). We denote these quantities as I_5, CD_5, and mCD_5, respectively. In a small number of cases, we use all citations made through the year 2010, regardless of the focal patent's issue date. For clarity, we label these values I_{2010y}, CD_{2010y}, and mCD_{2010y} to indicate the different approach to calculation.

Table 1 reports descriptive statistics and correlations. Values of the CD_5 index roughly approximate a normal distribution with a mode of 0, mean of 0.07, standard deviation of 0.23, and a range from −1 to 1. The distribution leans slightly to the right, which suggests that modestly destabilizing inventions may be more common than slightly consolidating ones. This runs counter to prior research, which shows that destabilizing technologies are rare. However, existing literature does not account for the possibility that destabilization is a matter of degree. Given that patents are somewhat costly to obtain and applicants are required to demonstrate how their invention is nonobvious, useful, and novel, this distributional skew may be expected. Moreover, when interpreting the distribution, it is useful to observe that the measure is only modestly correlated with impact ($r = 0.03$, $p < 0.001$). The distribution of the mCD_5 index is similar to the CD_5 index, with a mode of 0, mean of 0.31, standard deviation of 1.75, and a range from −127.84 to 222.67, but the tails are longer.

Other estimates in Table 1 also add support that our indexes function as intended. First, consider the correlations between assignee type and the CD_5 index. The (small) negative correlation between the CD_5 index and firm assignee ($r = -0.00$, $p < 0.01$) suggests that firms tend to produce more consolidating inventions, whereas universities ($r = 0.02$, $p < 0.001$) and government laboratories ($r = 0.02$, $p < 0.001$) generate more destabilizing ones. These correlations are consistent with previous observations about the differences between these types of organizations. Companies tend to specialize in shorter-term, application-oriented development whereas public sector organizations more often focus on longer-term, fundamental research (Dasgupta and David 1994, Rosenberg and Nelson 1994). Consistent with these observations, the CD_5 and mCD_5 indexes are also positively correlated with acknowledgement of a "government interest" ($r = 0.02$, $p < 0.001$, and $r = 0.01$,

Table 1. Descriptive Statistics and Correlations

Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12
1. CD_5 index	0.07	0.23	1.00											
2. mCD_5 index	0.31	1.75	0.53	1.00										
3. *Impact* (I_5)	3.60	5.92	0.03	0.20	1.00									
4. *Government interest*	0.02	0.14	0.02	0.01	−0.00	1.00								
5. *Nonpatent predecessors cited* (log)	0.44	0.82	0.00	0.01	0.13	0.13	1.00							
6. *Predecessor patents cited*	8.86	13.14	−0.17	−0.11	0.19	−0.01	0.26	1.00						
7. *Claims*	14.21	12.32	−0.04	0.00	0.19	0.01	0.19	0.20	1.00					
8. *Distinctiveness*	0.69	0.46	0.03	0.03	0.05	0.01	0.03	0.02	0.02	1.00				
9. *NBER—Chemical*	0.18	0.38	0.01	−0.01	−0.07	0.02	0.07	−0.03	−0.02	0.06	1.00			
10. *NBER—Computers*	0.14	0.35	−0.01	0.05	0.18	−0.01	0.05	0.03	0.09	−0.01	−0.19	1.00		
11. *NBER—Drugs*	0.09	0.29	0.02	−0.01	0.02	0.05	0.30	0.03	0.05	−0.04	−0.15	−0.13	1.00	
12. *NBER—Electrical*	0.19	0.39	0.03	0.04	0.04	0.03	−0.03	−0.03	0.00	0.01	−0.22	−0.20	−0.16	1.00
13. *NBER—Mechanical*	0.20	0.40	−0.01	−0.03	−0.07	−0.03	−0.16	−0.02	−0.06	−0.03	−0.23	−0.21	−0.16	−0.24
14. *NBER—Others*	0.19	0.40	−0.05	−0.04	−0.07	−0.04	−0.14	0.02	−0.05	0.00	−0.23	−0.20	−0.16	−0.24
15. *Government*	0.02	0.14	0.02	0.00	−0.03	0.28	0.03	−0.03	−0.03	0.01	0.03	−0.01	0.01	0.02
16. *Firm*	0.79	0.41	−0.00	0.02	0.08	−0.17	0.02	0.04	0.07	0.01	0.07	0.12	−0.07	0.08
17. *University*	0.02	0.13	0.02	0.01	0.01	0.29	0.22	−0.01	0.04	0.01	0.02	−0.03	0.14	−0.01
18. *Median assignee experience* (log)	4.43	3.35	0.03	0.05	0.09	0.06	0.09	−0.02	0.04	0.02	0.08	0.21	−0.08	0.15
19. *Median team distance* (log)	1.56	2.19	0.00	0.01	0.06	0.04	0.14	0.05	0.09	0.02	0.08	0.02	0.08	−0.01
20. *Median team experience* (log)	1.26	1.14	−0.02	−0.00	0.08	−0.02	0.10	0.10	0.10	−0.02	0.08	0.04	0.04	0.05
21. *Inventors*	2.15	1.55	0.02	0.03	0.09	0.02	0.17	0.06	0.10	0.02	0.11	0.03	0.09	−0.01
22. *Examiner experience* (log)	5.09	2.60	0.00	−0.01	−0.05	−0.02	−0.10	−0.03	−0.05	−0.03	0.02	−0.12	−0.04	−0.00
23. *Examiner workload*	579.68	528.19	−0.03	0.00	0.07	−0.01	0.02	0.05	0.07	0.00	−0.08	0.12	−0.01	0.10
24. *Grant lag*	2.08	1.97	−0.00	0.01	0.04	0.02	0.10	0.05	0.06	0.02	−0.02	0.10	0.04	−0.01
25. *Application year*	1,991.84	8.14	−0.08	−0.02	0.13	−0.01	0.17	0.16	0.21	−0.04	−0.09	0.13	0.05	0.06
26. *Grant year*	1,993.92	8.10	−0.09	−0.02	0.14	−0.01	0.20	0.17	0.23	−0.03	−0.10	0.15	0.06	0.05

Variable	13	14	15	16	17	18	19	20	21	22	23	24	25	26
13. *NBER—Mechanical*	1.00													
14. *NBER—Others*	−0.25	1.00												
15. *Government*	−0.02	−0.03	1.00											
16. *Firm*	−0.02	−0.19	−0.26	1.00										
17. *University*	−0.05	−0.05	−0.01	−0.25	1.00									
18. *Median assignee experience* (log)	−0.08	−0.28	0.07	0.51	0.01	1.00								
19. *Median team distance* (log)	−0.06	−0.10	0.03	0.16	0.06	0.17	1.00							
20. *Median team experience* (log)	−0.05	−0.14	−0.05	0.22	−0.03	0.34	0.06	1.00						
21. *Inventors*	−0.07	−0.12	0.03	0.19	0.04	0.25	0.49	0.07	1.00					
22. *Examiner experience* (log)	0.07	0.06	−0.00	−0.03	−0.03	−0.06	−0.04	−0.02	−0.05	1.00				
23. *Examiner workload*	−0.02	−0.10	−0.01	0.04	−0.00	0.07	0.02	0.05	0.03	0.29	1.00			
24. *Grant lag*	−0.04	−0.05	0.02	0.02	0.03	0.03	0.04	−0.00	0.04	−0.13	0.10	1.00		
25. *Application year*	−0.06	−0.06	−0.04	0.07	0.04	0.15	0.11	0.20	0.15	−0.07	0.19	−0.14	1.00	
26. *Grant year*	−0.07	−0.07	−0.04	0.08	0.05	0.16	0.12	0.20	0.16	−0.10	0.22	0.10	0.97	1.00

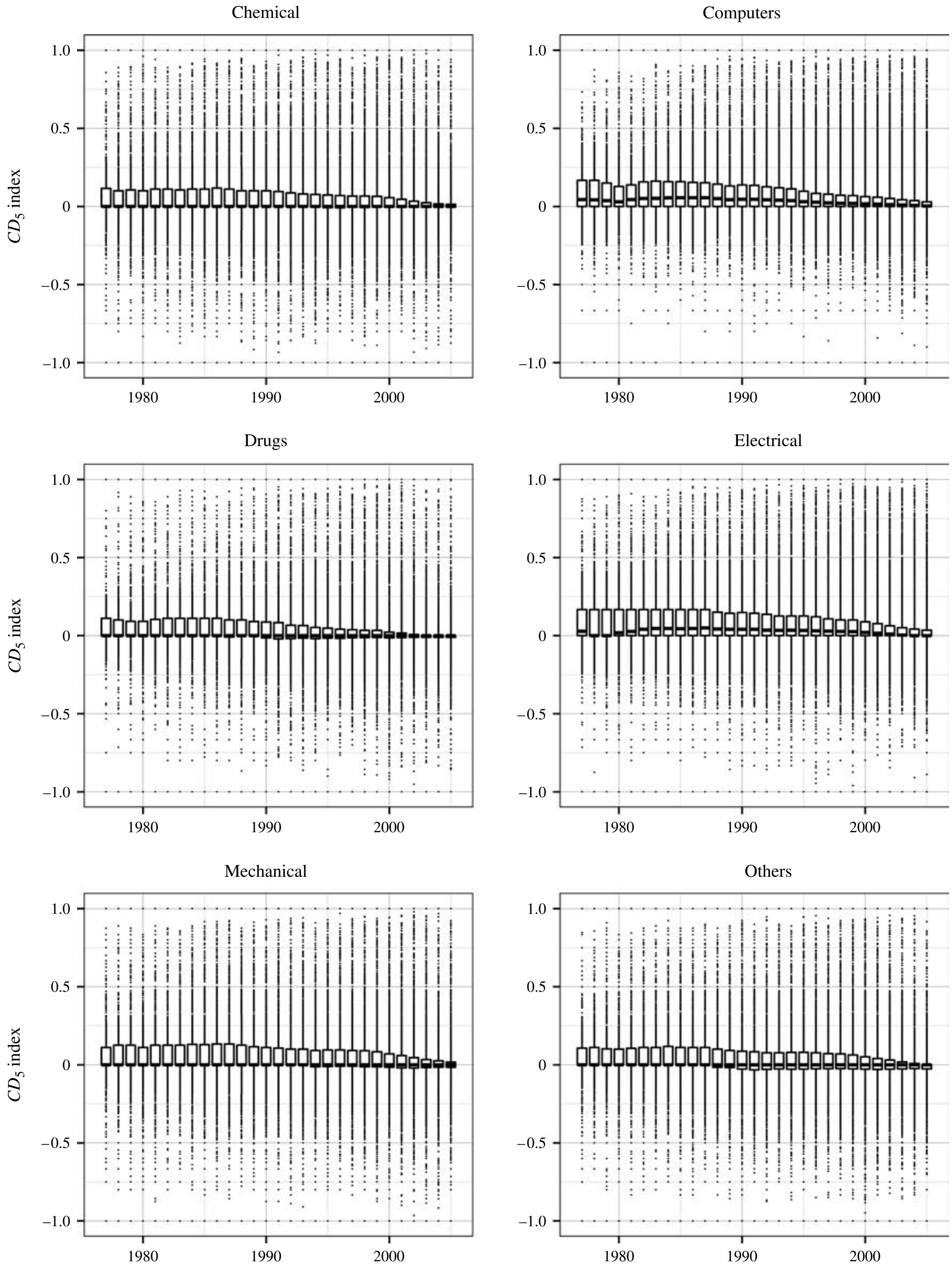
$p < 0.001$, respectively).[6] Government interest patents result from federally funded research programs that have been vetted by peer review and are oriented toward more fundamental discoveries. Finally, the small positive correlation between the number of inventors and the CD_5 ($r = 0.02$, $p < 0.001$) and mCD_5 ($r = 0.03$, $p < 0.001$) indexes implies that larger teams may produce more destabilizing technologies, a potentially noteworthy addition to research on scientific collaboration (Wuchty et al. 2007, Singh and Fleming 2010).

Figure 2 shows the within-year variability of the CD_5 index by NBER category. Consistent with critiques about the exploding volume of patenting and perceived lowering of quality thresholds required for obtaining a successful grant (Jaffe and Lerner 2004), the figure suggests that, across technology categories, the average patent of today is less destabilizing than those of the late 1970s and early 1980s. We also find significant (all $p < 0.001$) negative correlations across categories between application and grant year and the CD_5 index. However, Figure 2 also shows more outliers on the positive end of the CD_5 index in later years.[7]

3.2. Case Studies

Quantitative descriptions of our indexes are consistent with established findings about the correlates of various types of inventions. We next examine how well they are able to identify and classify particular breakthroughs. Table 2 reports the impact and CD_t and mCD_t indexes measured five years after issue (I_5, CD_5, and mCD_5) and as of 2010 (I_{2010y}, CD_{2010y}, mCD_{2010y}) for

Figure 2. Distribution of the CD_5 Index Among U.S. Utility Patents Granted Between 1977 and 2005



select inventions that have had a significant influence on their fields.

Several patents on enhancements in oil and gas drilling are notable among inventions that have consolidated the use of their predecessors. These inventions do not establish new methods; they refine already widely used technologies. For example, patent 4,573,530, "In-Situ Gasification of Tar Sands Utilizing a Combustible Gas," assigned to Mobil Oil Corporation, describes an improved process for extracting carbon monoxide and hydrogen from tar sands. Process inventions like this have become important in recent years because con-

Table 2. Illustrative Patents

Patent	CD_5 index	mCD_5 index	I_5	I_{2010y}	Predecessors cited	App. year	Grant year	Title	Assignee
4,637,464	−0.20	−0.20	1	194	7	1984	1987	In Situ Retorting of Oil Shale with Pulsed Water Purge	Amoco Corp.
4,573,530	0.17	0.17	1	192	6	1983	1986	In-Situ Gasification of Tar Sands Utilizing a Combustible Gas	Mobil Oil Corp.
4,658,215	0.29	0.57	2	200	4	1986	1987	Method for Induced Polarization Logging	Shell Oil Co.
4,928,765	0.00	0.00	0	195	10	1988	1990	Method and Apparatus for Shale Gas Recovery	Ramex Synfuels, International, Inc.
6,958,436	−0.85	−127.84	150	150	5	2002	2005	Soybean Variety SE90346	Monsanto Co.
5,015,744	−0.46	−17.12	37	173	4	1989	1991	Method for Preparation of Taxol Using an Oxazinone	Florida State University
6,376,284	−0.30	−33.04	111	175	19	2000	2002	Method of Fabricating a Memory Device	Micron Technology, Inc.
6,063,738	−0.01	−0.39	51	178	12	1999	2000	Foamed Well Cement Slurries, Additives and Methods	Halliburton Co.
4,724,318	0.09	3.57	42	145	2	1986	1988	Atomic Force Microscope and Method for Imaging Surfaces with Atomic Resolution	IBM Corp.
5,016,107	0.06	1.65	28	163	17	1989	1991	Electronic Still Camera Utilizing Image Compression and Digital Storage	Eastman Kodak Co.
6,285,999	0.16	5.22	33	193	7	1998	2001	Method for Node Ranking in a Linked Database	Stanford University
4,356,429	0.00	0.00	2	408	4	1980	1982	Organic Electroluminescent Cell	Eastman Kodak Co.
4,445,050	0.20	0.20	1	150	4	1981	1984	Device for Conversion of Light Power to Electric Power	None
5,010,405	0.60	5.40	9	159	2	1989	1991	Receiver-Compatible Enhanced Definition Television System	MIT
4,237,224	0.81	46.77	58	282	1	1979	1980	Process for Producing Biologically Functional Molecular Chimeras	Stanford University
4,399,216	0.70	11.13	16	339	2	1980	1983	Processes for Inserting DNA Into Eucaryotic Cells and for Producing Proteinaceous Materials	Columbia University
4,343,993	1.00	5.00	5	169	0	1980	1982	Scanning Tunneling Microscope	IBM Corp.
4,683,202	1.00	42.00	42	2,209	0	1985	1987	Process for Amplifying Nucleic Acid Sequences	Cetus Corp.

ventional gasification methods are difficult to use in remote regions like Northern Alberta, Canada, where the largest tar sands deposits are located.

The measure also identifies technologies that are known to have destabilized the use of their predecessors. Patents 4,237,224, 4,399,216, and 4,683,202 (the Cohen–Boyer patent on recombinant DNA, the Axel patent on eukaryotic cotransformation, and the Mullis patent on polymerase chain reaction (PCR), respectively) are at the bottom of Table 2.[8] These three inventions from the late 1970s and early 1980s set the stage for the molecular biology revolution in pharmaceutical R&D by making techniques for targeted in vitro drug discovery possible (Powell and Owen-Smith 1998). That technological shift altered the international pharmaceutical industry in the 1980s and 1990s by challenging traditional organic-chemistry-based drug discovery methods (Henderson and Cockburn 1996, Powell et al. 1996). These patents were also lucrative for their assignees. The Cohen–Boyer patent generated some $255 million in licensing royalties for Stanford University over its lifetime (Hughes 2001). A more aggressive licensing policy at Columbia University led the Axel patent to yield some $790 million in revenues (Colaianni and Cook-Deegan 2009). Finally, some estimates place the total royalties for the Mullis patent at $2 billion (Fore et al. 2006).

The scanning tunneling microscope (STM, patent 4,343,993) and the atomic force microscope (AFM, patent 4,724,318) together enabled the development of nanotechnology. Both instruments image and move individual atoms on material surfaces, which allows electronics, medications, and other products to be designed and built atom by atom. Although both inventions are destabilizing on our measure (i.e., they have positive scores), the AFM is less so than the STM. This relative ranking accords with nanotechnology's evolution. Although the STM was introduced five years before the AFM, the AFM offered several major improvements, including three-dimensional renderings and the ability to image living organisms (Youtie et al. 2008). The AFM was a radical improvement over prior microscopes, but it was less destabilizing because it built on (and cited) the more transformative STM.

Finally, consider patent 5,016,107, for an "Electronic Still Camera Utilizing Image Compression and Digital Storage." This is an Eastman Kodak patent for an early digital camera that employed novel techniques for image processing, compression, and recording on a removable storage medium (Lucas and Goh 2009). Relative to the perceived destabilization of digital photography for silver halide imaging, this patent ranks low on the CD_5 index with a score of 0.06. One explanation is that, unlike the technologies discussed above, a single patent did not cover the advent of digital photography (Christensen 1997).[9]

The examples described above cover well-known breakthroughs from multiple industries and technology classes. They demonstrate that our approach distinguishes between destabilizing and consolidating inventions, as well as among degrees within each category. We now turn to a more detailed consideration of three inventions—glyphosate-resistant soybeans, a method of ranking of online search results, and a eukaryotic cotransformation technique—that occupy different locations on the consolidating–destabilizing spectrum.

Consider Monsanto's patent 6,958,436, titled "Soybean Variety SE90346." This invention illustrates the core premise of a consolidating invention. The patent describes a genetically engineered soybean that is resistant to glyphosate, an herbicide patented by Monsanto in the 1970s. Glyphosate is the active ingredient in Monsanto's Roundup product line, the best-selling herbicide worldwide. In addition to glyphosate tolerance, the seed integrates other desirable plant traits, including improved yield, immunity to various diseases, and resistance to shattering, by using genetic sequences owned by Monsanto. Genetically engineered seeds increase the value of the earlier patented chemical and biological technologies by broadening potential application areas and excluding competitors (Graff et al. 2003, Pollack 2009). In this particular case, Monsanto has developed a plant variety engineered to resist damage from its market-leading herbicide.

The top panel in Figure 3 plots citations between the Monsanto soybean patent, its predecessors, and subsequent inventions. The line graph below the figure tracks the patent's annually updated CD_5 index. In the network diagram, as in the measure, forward citations are divided into three types. Triangles are patents that cite the focal patent's predecessors but not the focal patent. Circles represent patents that cite only the focal invention and not its predecessors. Squares indicate patents that cite both the focal patent and its predecessors.

The figure shows interesting features of this consolidating invention. Note that, although the soybean patent has received 150 total citations (as of 2010), it has never been cited independently of the technologies on which it builds. The patent's introduction also virtually eliminated independent citations of its predecessors (i.e., triangles).

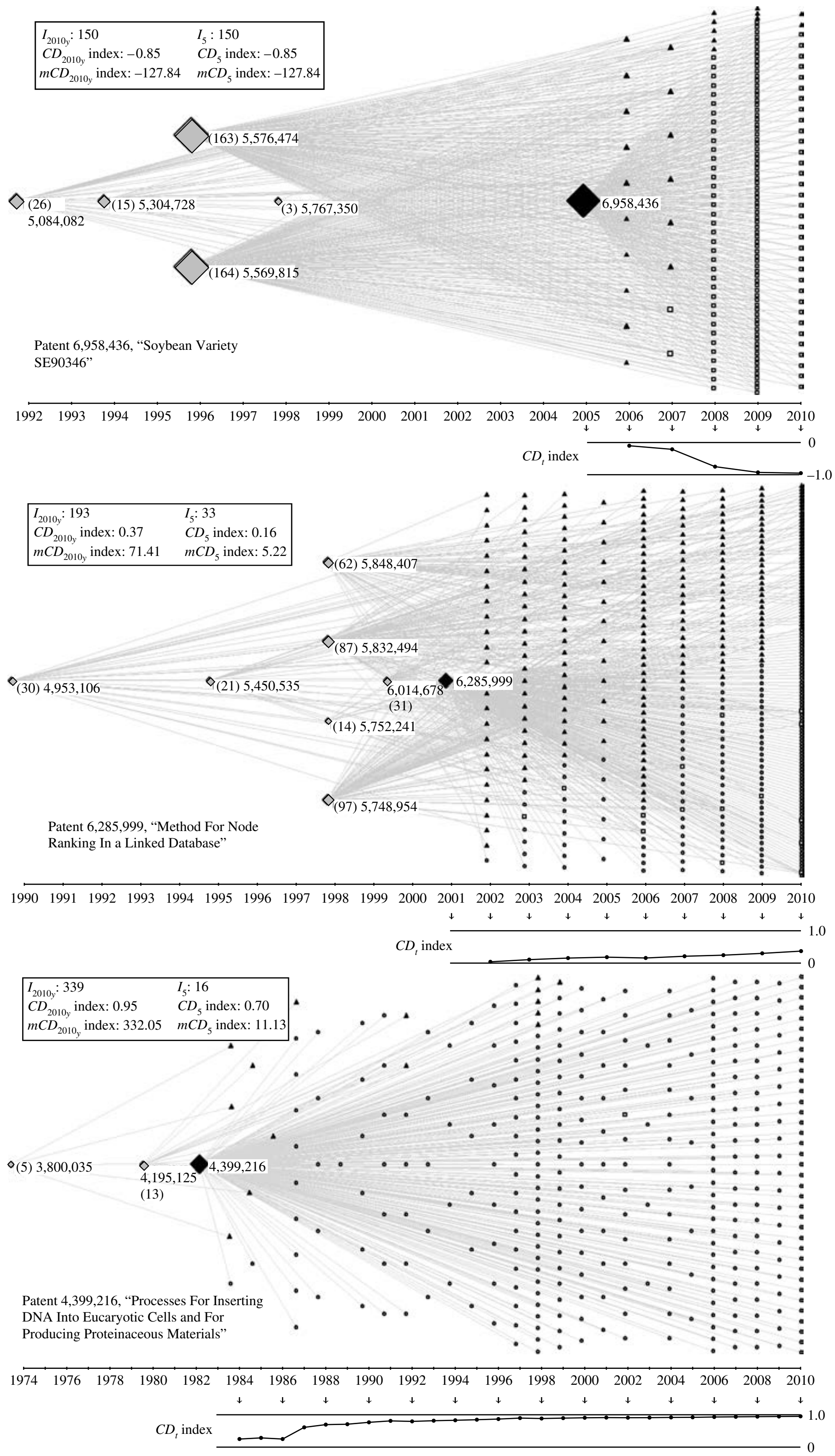
The line graph that tracks the patent's CD_5 index starts at 0 but rapidly approaches −1. This pattern implies that the focal patent and its predecessors are complementary in a way that would not be expected if this invention had, for instance, opened a new method of plant engineering.

Although not revealed in the figure, two additional features of the Monsanto soybean patent are suggestive. First, consider raw citation counts. In the five years before the focal patent was granted, the five technological predecessors received a total of 61 citations, or 2.44 citations per patent per year on average. In the five years following the soybean patent grant, citations of the predecessors increased by more than 600%, to an average of 15.28 per patent per year.[10]

The second suggestive feature is the antecedent technology's ownership. By the time of application, Monsanto had acquired the firms that owned all but one of the predecessors cited by the focal patent.[11] This observation fits with theories of technological innovation that argue that incumbent firms strive to enhance the value of their knowledge bases (Sosa 2011). It also suggests interesting possibilities for using this approach to examine corporate decisions about when to litigate competitor's intellectual property. We would predict that the most likely patents to be challenged in established industries are those that consolidate the technological position of a significant competitor. A similar logic might be used in explanations of merger and acquisition activities in technologically intensive fields, where complementary patent portfolios loom large.

Next, we examine patent 6,285,999, titled "Method for Node Ranking in a Linked Database." This invention, referred to as PageRank, covers the core algorithm used by Google to measure the importance of web

Figure 3. Network Diagrams for the Monsanto (Top), PageRank (Middle), and Axel (Bottom) Patents



Notes. Black diamonds are focal patents, gray diamonds are predecessors, triangles cite predecessors but not the focal patent, squares cite the focal patent and predecessors, and circles cite the focal patent but not predecessors. Node sizes are proportional to degree centrality, given in parentheses. The CD_t index over time appears below each network.

pages. Before PageRank, search engines used largely ineffective strategies to rank search results (Brin and Page 1998). PageRank, which is owned by Stanford University but licensed exclusively to Google, proposed a new method that drew on insights from social network theory to rank web pages by the number of links they receive from other sites. PageRank's destabilizing effects are evident in Yahoo!'s June 2000 agreement to make Google its default search engine. Prior to the implementation of Google's search technology, Yahoo! was the market-leading search engine. After the introduction of this invention, Yahoo! could only maintain its position by adopting its competitor's technology.

The middle panel of Figure 3 presents the network of citations involving the PageRank patent, its predecessors, and subsequent patents. The figure is instructive when compared to the Monsanto soybean patent above it. Unlike the soybean patent, which quickly garnered a substantial number of citations, PageRank appears to have been overlooked in years immediately following its 2001 publication.[12] Most citations between 2002 and 2007 cite PageRank's technological predecessors, but not the patent itself. This changes between 2007 and 2010, when more subsequent inventions cite PageRank without its predecessors. During this period, PageRank increasingly destabilizes its predecessors' use. This pattern of change is also visible in the CD_5 index trend line, which begins near 0 and rises to 0.37.

For our final case, we turn to the Axel patent on eukaryotic cotransformation, in the bottom panel of Figure 3. This destabilizing discovery is one of the foundational inventions of biotechnology. The patent covers a method for inserting foreign genes into cells that then produce associated proteins. Along with the bacteriological method of recombinant DNA invented by Cohen and Boyer, cotransformation is a fundamental tool in biologically based drug development. In contrast to both Monsanto's soybean and Google's PageRank, citations of the predecessors cited by Columbia's Axel patent effectively cease within two years of its publication. Of nearly 340 citations of the Axel patent, only one subsequent invention cites it together with its predecessors and only 14 cited the predecessors on their own.[13] Indeed, the trend line below this panel suggests that a swift change in the CD_5 index happened three years after issue and was followed by a smooth rise to a maximum value of 0.95.

The juxtaposition of the cotransformation and soybean patents is interesting when viewed in light of research on technology paradigms and industry life cycles. If the Axel invention and similar technologies laid the foundations for molecular biology in the late 1970s and early 1980s, then subsequent breakthroughs that follow much later but operate within the same paradigm should be more consolidating, as is the case with the Monsanto patent. Tracing changes in the CD_t index of inventions that belong to particular lineages over time might offer new means to evaluate industry evolution and the process by which knowledge paradigms and technology standards coalesce, expand, and are swept away.

3.3. Regression Analyses

Our analyses so far have looked at the face validity and discriminatory power of the CD_t and mCD_t indexes relative to patent impact. We found that (1) the CD_t index is essentially uncorrelated with impact, and (2) the technologies our approach identifies as consolidating or destabilizing are sensible and echo published evaluations of high-profile technologies.

In this section, we begin to explore the value of the CD_t and mCD_t indexes for substantive research. We do this by considering the CD_t and mCD_t indexes alongside impact in sets of regressions that explore arguments from current literature about the determinants of important new technologies. We begin by presenting models at the patent level and then consider adaptations of the CD_t and mCD_t indexes at the organization level in analyses of university patenting.

3.3.1. Patent-Level Analyses.

Sample. Our data consisted of the 2.9 million U.S. utility patents that (1) were granted after 1976 but before 2006, (2) were available in full-text form from the USPTO (this criterion eliminated a small number of patents, most of which had been withdrawn from issue), and (3) were assigned to one of the six NBER technology categories. For each patent, we collected covariates at the patent, assignee, team, and examiner levels.

Patent Importance. We measured our three indicators of patent importance—the CD_5 and mCD_5 indexes and impact (I_5)—using citations received during the first five years after being granted. As noted previously, the CD_5 and mCD_5 indexes are undefined when neither a focal patent nor its predecessors receive any citations. To better understand the behavior of the indexes, we therefore also considered models where we replaced these undefined values with 0.

Patent Covariates. One alternative interpretation of our indexes is that, rather than capturing differences in the effects of new technologies, they record variation in opportunity. As a focal patent cites more predecessors, it also makes it easier for future patents to cite those predecessors, which in turn may cause the focal patent to appear less destabilizing. To explore this possibility, we include a variable, *Predecessor patents cited*, that counts the number of citations made by the focal patent to U.S. utility patents.

In addition to prior inventions, U.S. patents must also disclose when they build on existing knowledge that is not subject to patent protection (Fleming and Sorenson 2004). Although these works (usually technical manuals or scientific papers) are not incorporated in our indexes, we include a count of *Nonpatent predecessors cited* (log) in our models, because these may influence the nature and extent of a patent's uses. For example, inventions that cite scientific papers may be closer to the frontiers of knowledge and therefore more likely to open new technological domains.

Prior research also indicates that a patent's scope and distinctiveness are good indicators of its importance (Hall and Trajtenberg 2004, Lanjouw and Schankerman 2004). Some patents describe improvements within a narrow area whereas others make broader assertions. To capture these differences in scope, we followed earlier research and included in our models a count of the number of *Claims* made by each focal patent. We also used prior work to guide our measure of distinctiveness, which attempts to capture how different an invention is from earlier ones by determining whether it proposes novel combinations. Following this logic, we assign patents a *Distinctiveness* value of 1 if they are classified with a previously uncombined set of USPTO subclasses and 0 otherwise (Fleming 2001, Funk 2014).

The context of discovery also influences a new technology's importance. Although many contextual factors matter, contemporary discussions often focus on the effects of sponsorship. We therefore include a dummy variable that captures whether a focal patent declares a *Government interest*, meaning that the research leading to the patent was supported by federal grants. Grant support may indicate one of several things that could bear on the CD_5 or mCD_5 indexes. First, because federal R&D funding is competitive, grant support may simply be an indicator for high-quality research. That in itself may bear on a patent's eventual impact but does not suggest a clear implication for its destabilization. However, if the grant-funded research is higher quality and oriented to more fundamental objectives than privately funded R&D, we might expect government interest patents to be more destabilizing.

Finally, to evaluate the effect of changes in citation patterns over time and across different kinds of inventions, we included indicator variables for the grant year and NBER category of each focal patent (Mehta et al. 2010): *Computers*, *Drugs*, *Electrical*, *Mechanical*, or *Others* (with *Chemical* omitted).

Assignee Covariates. Researchers have shown that assignee characteristics may also influence the importance of new technologies. Universities, government laboratories, and private firms differ in terms of their research missions and may generate different kinds of inventions (Dasgupta and David 1994, Rosenberg and Nelson 1994, Stephan 2012). To examine potential differences attributable to organizational form, we included indicators for whether each focal patent listed an assignee that was a *Government* entity (including foreign and domestic), *Firm*, or *University*. Some patents have multiple assignees of different forms, in which case we assigned them a value of 1 on each of the relevant indicators. The USPTO does not keep systematic records on assignees' organizational forms and, therefore, to obtain our indicators, we relied on features of assignee names. We began by manually coding a small subsample, which we then used to train a naïve Bayes classifier to label the more than 300,000 unique assignee names in the USPTO database.

Experience may also influence technological importance. For instance, as an organization develops and patents more inventions, it may acquire a unique knowledge of particular components that when brought together form a destabilizing new technology. By contrast, there may also be an association between experience and the production of more consolidating inventions, as organizations seek to bolster or expand a particular technological trajectory. Recall the very clear case of such a development strategy, apparent in Monsanto's soybean patent. To capture these possibilities, we control for the stock of eventually successful patent applications that assignees made before applying for the focal patent. When there was more than one assignee we used the median stock of patents. We also added a quadratic term in the models to account for diminishing returns to experience.

Team Covariates. Invention is a social activity (Wuchty et al. 2007) and the structure of the team that creates a new technology may influence that technology's importance. Prior research indicates, for instance, that despite advances in information technology, geographic proximity among inventors still matters (Funk 2014). To capture these differences, we included a measure of *Median team distance* (log). This variable records the median geographic distance among each focal patent's inventors, adjusted for Earth's curvature. It takes a value of 0 for patents with a single inventor. We also added *Median team experience* (log) and a quadratic term, which we measured as the median number of ultimately granted patents applied for by the inventors of the focal patent. To evaluate differences in team size, we included a count of the number of *Inventors* listed on the focal patent in each model.

USPTO Covariates. Our last set of covariates focused on the USPTO examination process. As with assignees and inventors, examiner experience may influence a technology's importance. Lemley and Sampat (2012) reported that examiners who have prosecuted more patent applications tended to cite fewer predecessor technologies and were also less likely to issue rejections that would require applicants to revise their claims. We therefore added *Examiner experience* (log) to our models, which we measured as the number of granted patents on which the examiner of the focal patent also served as an examiner, before the focal patent's application date. The time and energy an examiner has to devote to review may also influence citations of prior patents. To capture these differences, we added a covariate for *Examiner workload*. This variable counted the number of open patent applications assigned to the examiner at the same time as the focal patent by identifying granted patents with application dates before and grants dates after a focal patent that were evaluated by the same examiner. This measure likely underestimates the actual workload of examiners because we do not include applications that were eventually denied. We also controlled for *Grant lag*, which was the number of years between the grant year and application year of the focal patent (Mehta et al. 2010).[14]

Statistical Approach. We used ordinary least squares (OLS) regressions to model the CD_5 and mCD_5 indexes because both indexes are continuous and our data are cross-sectional. Models of impact (I_5) used a negative binomial specification because the variable takes on only nonnegative integer values and likelihood ratio tests of overdispersion suggested that a Poisson process did not generate the data. After excluding patents with undefined CD_5 and mCD_5 indexes we had 2,828,700 observations. In models of impact (I_5) and those that set undefined values of CD_5 and mCD_5 to 0, our sample size increased to 2,910,506. Correlations among the covariates were low and the variance inflation factors (VIFs) and tolerances did not indicate multicollinearity.

3.3.2. Patent-Level Results. Table 3 displays estimates from four negative binomial models of patent impact (I_5). Overall, the coefficients are consistent in sign and significance and are supportive of findings from earlier research. At the patent level, all four models show a positive association between *Predecessor patents cited*, *Nonpatent predecessors cited* (log), *Claims*, and *Distinctiveness*, which together suggest that higher-impact patents tend to be broader in scope and novelty, while also building on existing streams of technology and science. Impact also varies across technological domains. Relative to *Chemical* (the omitted NBER category), patents in the *Computers*, *Drugs*, *Electrical*, *Mechanical*, and *Others* categories receive—according to estimates in Model 4—between $e^{0.120\times 1} \approx 1.13$ and $e^{0.710\times 1} \approx 2.03$ times more citations within five years of being granted. Also noteworthy, Models 2 and 3 suggest a negative association between *Government interest* and impact, although that effect washes away in more fully specified models.

There are significant associations between assignee-level characteristics and impact, such that patents awarded to a *Firm* or *University* are more highly cited, whereas those with a *Government* assignee are less acknowledged by future inventors. Echoing some research on team science (Wuchty et al. 2007), patents with more *Inventors* and greater *Median team distance* (log) receive more citations, as do those that have longer *Grant lag* and those that are reviewed by examiners with higher *Examiner workload*. Finally, we find consistent evidence that experience matters for patent impact, but in different ways across levels. Increases in *Median assignee experience* (log) and *Median team experience* (log) are associated with higher impact. However, as *Median examiner experience* (log) increases, impact decreases, a finding that is consistent with work by Lemley and Sampat (2012).

OLS models of the CD_5 and mCD_5 indexes are shown in Tables 4 and 5, respectively. Although the coefficients in each table are internally consistent with respect to their sign and significance, the estimates and their interpretations differ from our impact models. Beginning with the patent level, estimates in Models 5–8 of Table 4 and Models 11–14 of Table 5 reveal positive relationships between reporting a *Government interest* and the CD_5 and mCD_5 indexes, respectively. This finding makes sense in light of the federal government's tendency to fund basic research that seeks to open new areas.

Models in Tables 4 and 5 also suggest that the relationship between technological importance and the use of existing knowledge is more complex than is apparent from models of impact. Although *Predecessor patents cited* and *Nonpatent predecessors cited* (log) both have a positive relationship with patent impact, the former has a negative association with the CD_5 and mCD_5 indexes, whereas the latter has a positive association. These relationships are open to several interpretations. First, they may indicate that patents that build on more patented inventions tend to consolidate the status quo, whereas those that build on more knowledge that is not subject to patent protection, including scientific papers, tend to destabilize it. Second, the positive association between *Nonpatent predecessors cited* (log) and our indexes may happen as flurries of new scientific discoveries create opportunities for technological advances that are destabilizing (Azoulay et al. 2007). Finally, the relationship may result from patents building on scientific and other knowledge that is old but has never been applied to a technological domain.

Coefficients on our variables for assignee type also raise the possibility that evaluating impact alone may conceal important nuances. For instance, Model 4 in Table 3 reports a positive association between assignment to a *Firm* or *University* and a patent's impact. Moreover, with respective increases in citations of $e^{0.092\times 1} \approx 1.10$ and $e^{0.036\times 1} \approx 1.04$, the magnitudes of the

Table 3. Negative Binomial Regression Models of Patent Impact (I_5)

	Model 1	Model 2	Model 3	Model 4
Patent				
Government interest	0.006	−0.081***	−0.090***	0.009
	(0.007)	(0.006)	(0.006)	(0.007)
Nonpatent predecessors cited (log)	0.049***	0.045***	0.052***	0.042***
	(0.001)	(0.001)	(0.001)	(0.001)
Predecessor patents cited	0.014***	0.013***	0.014***	0.013***
	(0.000)	(0.000)	(0.000)	(0.000)
Claims	0.014***	0.014***	0.015***	0.014***
	(0.000)	(0.000)	(0.000)	(0.000)
Distinctiveness	0.164***	0.167***	0.163***	0.161***
	(0.002)	(0.002)	(0.002)	(0.002)
NBER—Computers[a]	0.700***	0.753***	0.695***	0.710***
	(0.003)	(0.003)	(0.003)	(0.003)
NBER—Drugs[a]	0.277***	0.248***	0.218***	0.269***
	(0.004)	(0.004)	(0.004)	(0.004)
NBER—Electrical[a]	0.389***	0.425***	0.386***	0.400***
	(0.003)	(0.003)	(0.003)	(0.003)
NBER—Mechanical[a]	0.099***	0.116***	0.077***	0.120***
	(0.003)	(0.003)	(0.003)	(0.003)
NBER—Others[a]	0.108***	0.109***	0.045***	0.140***
	(0.003)	(0.003)	(0.003)	(0.003)
Grant year indicators	Yes	Yes	Yes	Yes
Assignee				
Government	−0.273***			−0.273***
	(0.007)			(0.007)
Firm	0.113***			0.092***
	(0.003)			(0.003)
University	0.037***			0.036***
	(0.008)			(0.008)
Median assignee experience (log)	0.019***			0.011***
	(0.000)			(0.000)
Median assignee experience^2 (log)	−0.000			0.000**
	(0.000)			(0.000)
Team				
Median team distance (log)		0.009***		0.007***
		(0.000)		(0.000)
Median team experience (log)		0.068***		0.051***
		(0.001)		(0.001)
Median team experience^2 (log)		−0.011***		−0.008***
		(0.001)		(0.001)
Inventors		0.039***		0.032***
		(0.001)		(0.001)
Examiner				
Examiner experience (log)			−0.013***	−0.011***
			(0.001)	(0.001)
Examiner experience^2 (log)			−0.000**	−0.000
			(0.000)	(0.000)
Examiner workload			0.000***	0.000***
			(0.000)	(0.000)
Grant lag			0.003**	0.005***
			(0.001)	(0.001)
Constant	−0.053***	−0.030***	−0.006	−0.118***
	(0.007)	(0.006)	(0.006)	(0.007)
N	2,910,506	2,910,506	2,910,506	2,910,506
Log-likelihood	−6,722,030.578	−6,721,725.011	−6,730,242.211	−6,715,399.148

Note. Robust standard errors are in parentheses.
[a]The omitted NBER technology category is *Chemical*.
** $p < 0.01$; *** $p < 0.001$.

Table 4. OLS Regression Models of Patent CD_5 Index

	Model 5	Model 6	Model 7	Model 8	Model 9 Undefined = 0	Model 10 Undefined = 0
Patent						
Government interest	0.005***	0.012***	0.012***	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Nonpatent predecessors cited (log)	0.013***	0.013***	0.014***	0.013***	0.011***	0.012***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Predecessor patents cited	−0.003***	−0.003***	−0.003***	−0.003***	−0.003***	−0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Claims	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Distinctiveness	0.013***	0.012***	0.013***	0.012***	0.013***	0.012***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NBER—Computers[a]	0.005***	0.007***	0.007***	0.008***	0.011***	0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NBER—Drugs[a]	0.018***	0.017***	0.017***	0.018***	0.015***	0.017***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
NBER—Electrical[a]	0.016***	0.018***	0.017***	0.019***	0.021***	0.018***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NBER—Mechanical[a]	−0.004***	−0.004***	−0.006***	−0.003***	−0.001†	−0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NBER—Others[a]	−0.015***	−0.016***	−0.019***	−0.014***	−0.012***	−0.014***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Grant year indicators	Yes	Yes	Yes	Yes	Yes	Yes
Assignee						
Government	−0.001			−0.004**	−0.005***	−0.004**
	(0.001)			(0.001)	(0.001)	(0.001)
Firm	−0.008***			−0.009***	−0.008***	−0.008***
	(0.001)			(0.001)	(0.001)	(0.001)
University	0.005***			0.004**	0.003*	0.004**
	(0.001)			(0.001)	(0.001)	(0.001)
Median assignee experience (log)	0.002***			0.002***	0.002***	0.002***
	(0.000)			(0.000)	(0.000)	(0.000)
Median assignee experience^2 (log)	−0.000***			−0.000***	−0.000***	−0.000***
	(0.000)			(0.000)	(0.000)	(0.000)
Team						
Median team distance (log)		−0.001***		−0.001***	−0.001***	−0.001***
		(0.000)		(0.000)	(0.000)	(0.000)
Median team experience (log)		−0.001***		−0.002***	−0.002***	−0.002***
		(0.000)		(0.000)	(0.000)	(0.000)
Median team experience^2 (log)		0.001***		0.001***	0.001***	0.001***
		(0.000)		(0.000)	(0.000)	(0.000)
Inventors		0.006***		0.005***	0.005***	0.005***
		(0.000)		(0.000)	(0.000)	(0.000)
Examiner						
Examiner experience (log)			0.001***	0.001***	0.001***	0.001***
			(0.000)	(0.000)	(0.000)	(0.000)
Examiner experience^2 (log)			0.000†	0.000*	0.000*	0.000*
			(0.000)	(0.000)	(0.000)	(0.000)
Examiner workload			−0.000***	−0.000***	−0.000***	−0.000***
			(0.000)	(0.000)	(0.000)	(0.000)
Grant lag			0.001***	0.001***	0.001***	0.001***
			(0.000)	(0.000)	(0.000)	(0.000)
Imputed						−0.105***
						(0.000)
Constant	0.130***	0.110***	0.122***	0.120***	0.109***	0.120***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
N	2,828,700	2,828,700	2,828,700	2,828,700	2,910,506	2,910,506
R^2	0.040	0.041	0.040	0.041	0.038	0.044

Note. Robust standard errors are in parentheses.
[a]The omitted NBER technology category is *Chemical*.
†$p < 0.1$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Table 5. OLS Regression Models of Patent mCD_5 Index

	Model 11	Model 12	Model 13	Model 14	Model 15 Undefined = 0	Model 16 Undefined = 0
Patent						
Government interest	0.031**	0.040***	0.035***	0.034***	0.032***	0.031**
	(0.010)	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)
Nonpatent predecessors cited (log)	0.070***	0.066***	0.072***	0.064***	0.058***	0.062***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Predecessor patents cited	−0.015***	−0.015***	−0.015***	−0.015***	−0.015***	−0.015***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Claims	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Distinctiveness	0.113***	0.113***	0.113***	0.111***	0.112***	0.107***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
NBER—Computers[a]	0.299***	0.331***	0.312***	0.311***	0.320***	0.309***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
NBER—Drugs[a]	0.023***	0.010*	0.002	0.020***	0.010*	0.015***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
NBER—Electrical[a]	0.195***	0.218***	0.202***	0.209***	0.216***	0.206***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
NBER—Mechanical[a]	0.003	0.012***	−0.008**	0.016***	0.023***	0.016***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
NBER—Others[a]	−0.043***	−0.041***	−0.069***	−0.030***	−0.021***	−0.029***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Grant year indicators	Yes	Yes	Yes	Yes	Yes	Yes
Assignee						
Government	−0.121***			−0.137***	−0.137***	−0.131***
	(0.008)			(0.008)	(0.008)	(0.008)
Firm	−0.038***			−0.051***	−0.046***	−0.049***
	(0.003)			(0.004)	(0.003)	(0.003)
University	0.019			0.011	0.006	0.008
	(0.012)			(0.012)	(0.011)	(0.011)
Median assignee experience (log)	0.016***			0.013***	0.013***	0.013***
	(0.000)			(0.000)	(0.000)	(0.000)
Median assignee experience^2 (log)	0.001***			0.001***	0.001***	0.001***
	(0.000)			(0.000)	(0.000)	(0.000)
Team						
Median team distance (log)		−0.002**		−0.002**	−0.002*	−0.002**
		(0.001)		(0.001)	(0.001)	(0.001)
Median team experience (log)		0.007***		−0.001	0.000	−0.000
		(0.001)		(0.001)	(0.001)	(0.001)
Median team experience^2 (log)		0.001		0.001	0.000	0.001
		(0.001)		(0.001)	(0.001)	(0.001)
Inventors		0.039***		0.036***	0.034***	0.035***
		(0.001)		(0.001)	(0.001)	(0.001)
Examiner						
Examiner experience (log)			−0.003***	−0.002**	−0.002**	−0.002*
			(0.001)	(0.001)	(0.001)	(0.001)
Examiner experience^2 (log)			0.000	0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)
Examiner workload			−0.000	−0.000	−0.000	−0.000
			(0.000)	(0.000)	(0.000)	(0.000)
Grant lag			0.005***	0.005***	0.005***	0.005***
			(0.001)	(0.001)	(0.001)	(0.001)
Imputed						−0.373***
						(0.002)
Constant	0.288***	0.178***	0.242***	0.220***	0.188***	0.226***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
N	2,828,700	2,828,700	2,828,700	2,828,700	2,910,506	2,910,506
R^2	0.023	0.023	0.022	0.024	0.023	0.025

Note. Robust standard errors are in parentheses.
[a]The omitted NBER technology category is *Chemical*.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

associations are nearly identical. This result is surprising in light of prior research on the differences between approaches to research and invention at firms and universities (Dasgupta and David 1994, Rosenberg and Nelson 1994). Estimates using our indexes are more consistent with these earlier arguments. The negative and significant coefficients on the *Firm* indicator in Model 8 of Table 4 (for the CD_5 index) and Model 14 of Table 5 (for the mCD_5 index) suggest that commercial entities produce patents that do more to consolidate the status quo than other assignees. By contrast, the coefficients for the *University* assignee indicator are positive, which suggests that academic organizations generate inventions that destabilize existing technology streams, although only the coefficient on the CD_5 index is significant. In other words, both universities and firms tend to produce higher-impact inventions than other types of organizations, but that similarity masks important differences in how the technologies enter and change existing technological trajectories.

Results reported in Tables 4 and 5 also suggest that the CD_5 and mCD_5 indexes may offer insights into distributed teams that are not apparent from impact alone. As noted above, Table 3 reports a positive association between *Median team distance* (log) and patent impact, but this finding is somewhat hard to interpret in light of earlier research. Although some studies find value in distributed collaboration (Owen-Smith and Powell 2004), others emphasize the challenges of working across distances (Funk 2014). The positive and significant coefficients on *Median team distance* (log) in Tables 4 (for the CD_5 index) and 5 (for the mCD_5 index) imply that geographically distributed teams may have a greater tendency to create inventions that consolidate the status quo.

Finally, several coefficients are noteworthy because they help to further establish the face validity of our indexes, although they do not contrast with the results of our impact models. Patents that bridge a previously uncombined set of USPTO subclasses, for instance, and therefore score a 1 on our measure of *Distinctiveness* also challenge the status quo, as indicated by the positive and significant coefficients in Tables 4 and 5. Moreover, consistent with the research on team structure and invention, we also find, again in Tables 4 (for the CD_5 index) and 5 (for the mCD_5 index), a positive and significant association with *Inventors*: larger teams produce more destabilizing inventions. Last, models of the CD_5 and mCD_5 indexes both show positive coefficients for *Grant lag*, which is consistent with the idea that examiners require more time to evaluate patents that depart from the status quo and therefore their prior experience.

Robustness Checks. We also examined the robustness of our models to alternative specifications. First, to determine whether our focus on patents granted between 1976 and 2006 influenced our findings, we reran our models on subsamples that began several years later and ended several years earlier. Our findings were similar to those presented here. Second, as noted before, the CD_5 and mCD_5 indexes are undefined when neither a focal patent nor its predecessors receive any citations after the focal patent's issue, and therefore we had to exclude these patents from our models. To gain some insight into whether these exclusions influenced our results, we estimated new models where we set the CD_5 and mCD_5 indexes to 0. The results appear in Models 9 and 10 (for the CD_5 index) and Models 15 and 16 (for the mCD_5 index). Models 10 and 16 are identical to Models 9 and 15, with the exception of an *Imputed* indicator variable that takes on a value of 1 for the newly added patents. Once again, the results are nearly identical to our preferred models.

3.3.3. Organization-Level Analyses. The preceding analyses examined the relationships between impact and the CD_t and mCD_t indexes and factors that are known to have associations with the importance of individual patents. In this section, we move to a higher level of analysis to evaluate the ability of the CD_t and mCD_t indexes to offer insight into patenting by organizations. Aggregate adaptations of the CD_t and mCD_t indexes may be useful in research considering the sources and consequences of technological change for organizations and industries.

Our analyses focus on U.S. utility patents issued to the 110 most research-intensive American universities. The data set covers a broad set of high- and low-impact inventions and therefore serves as a useful setting in which to examine the value of our approach for analyzing portfolios of patents. Research on the organizational sources of important academic patents has yielded mixed results. We believe that the ambiguity in this line of work may stem from its reliance on impact measures of technological importance. Below, we demonstrate that, when analyzing portfolio-level variation, the CD_5 and mCD_5 indexes offer insights into the dynamics of academic patenting that are less apparent in examinations of patent impact.

We consider four variations of the CD_t and mCD_t indexes that we have adapted for use with patent portfolios. We chose these four adaptations for their diversity and conceptual appeal, not because they exhausted the list of possible approaches. The first measure, CD_5^{mean}, is the average CD_5 index among patents applied for by each university during year $t+1$. This is a simple approach to evaluating the consolidation or destabilization of multiple patents. Our second measure, mCD_5^{scale}, is a more complex adaptation of the mCD_5 index that attempts to capture the overall direction and magnitude of the effects of each university's patent portfolio on existing technology streams. We compute the mCD_5^{scale} measure as the product of the

CD_5^{mean} and the total impact (I_5^{total}) of patents applied for during year $t+1$. The third and fourth adaptations, CD_5^{total-} and CD_5^{total+}, are complementary measures that attempt to separately capture the effects of universities' consolidating and destabilizing patents by counting citations of patents with positive and negative values on the CD_5 index, respectively. Both the CD_5^{total-} and CD_5^{total+} indexes are computed based on patents applied for during year $t+1$.

In what follows we briefly survey literature that seeks to explain the scale and impact of academic patenting. We then present our models of organization-level patent importance. Although the findings suggest interesting new directions for research on academic patenting and the economic value of university R&D, we pay particular attention to the comparison of effects across dependent variables in order to highlight multiple possibilities for analyses using aggregated versions of the CD_t and mCD_t indexes.

3.3.4. Research on Academic Patenting. In 1980, Congress passed the Bayh–Dole Act, a law that allows organizations that perform federally funded research to file for patents and issue licenses on intellectual property they develop. The act accelerated a trend toward research commercialization on campus. Over the last 30 years, academic patenting has increased dramatically. Some inventions have been highly lucrative for the institutions that own them by generating new products, companies, and even industries.

Proponents of Bayh–Dole call it "prescient" (Cole 1993) and herald the act's importance in turning university science into an engine of economic development (Powell et al. 2007). In 2002, *The Economist* (2002, p. 3) called the act "possibly the most inspired piece of legislation enacted in America over the past half century" and went on to attribute to it an important role in "reversing America's precipitous slide into industrial irrelevance." By the same token, critics of Bayh–Dole and commercialization bemoan the "selling" of the university (Greenberg 2007), link the act to the "corporate corruption" of academia (Washburn 2005), and argue that proprietary research diminishes universities' scientific and public mission (Krimsky 2004).

Hyperbole aside, both the economic benefits and the dangers of academic commercialization are often attributed to the type of inventions that universities produce. For those with rosier views, it is the university's capability to generate unexpected, market-creating inventions outside the channels of corporate R&D that make academic inventions valuable. In the terms we use here, the economic benefits of Bayh–Dole rely in part on academic scientists' propensity to generate destabilizing inventions. Although critics approach Bayh–Dole from a range of philosophical starting points, one thread running through most negative appraisals is concern that attention to the commercial value of academic ideas leads to capture by corporate interests, and with it to university science closely wedded to industry priorities. Put differently, one significant concern about Bayh–Dole suggests that, as research commercialization becomes more widespread, both published and patented science will tend to consolidate the status quo.

This tension has led many academic analysts to assess the costs and benefits of university research commercialization (Trajtenberg et al. 1997, Henderson et al. 1998, Mowery et al. 2002). Two key themes in this line of work emphasize the value of academic inventions and the relationship between increases in the use of proprietary science and the vitality of more fundamental research and training.

Researchers pursuing the former question express concern over the relationship between the sources and types of R&D funding that support academic research and the impact of patented science on campus. Although the results of some studies conflict, most find evidence that increases in the quantity of academic patenting do not decrease its impact at the campus level (Mowery et al. 2002). These studies also suggest that connections with industry help academic institutions to learn to patent up to a point. Owen-Smith and Powell (2003) find a curvilinear (inverted U-shaped) relationship between ties to biotechnology firms and the impact of a university's patent portfolio. They attribute diminishing returns to the likelihood of corporate capture of technology transfer priorities.

The relationship between academic (papers) and proprietary (patents) research outputs has also been much examined. Owen-Smith (2003) demonstrates that patent flows are deeply intertwined with traditionally academic inputs and outputs such as federal grants and publications. Sine et al. (2003) find that academic visibility in the form of article citations increases the likelihood that patents will be licensed by industry. For a set of life science patents issued to 89 university campuses, Owen-Smith and Powell (2003) find a positive relationship between the citation impact of life science papers and the overall impact of a university's patent portfolio.

Sample. To determine whether the CD_t and mCD_t indexes can offer any new insights into debates over academic patenting, we collected data on a sample of universities that mirror those studied in previous research. We focus on the 110 most research-intensive U.S. universities (Owen-Smith and Powell 2003) and the 55,322 utility patents awarded to these institutions between 1976 and 2010. Our sample includes every institution that has ever ranked among the top 100 nationally by federal obligations for science and engineering research. After defining our sample, we created a university × year panel with annually updated variables for each institution.

Portfolio Importance. We considered six measures of portfolio importance. The first two measures, volume (V^{total}) and impact (I_5^{total}), capture the number of patents applied for by (and ultimately granted to) each university during year $t+1$ and the total number of citations received by those patents, respectively. Variants of these two measures have been widely used in previous work on university patenting (Mowery and Ziedonis 2002, Owen-Smith and Powell 2003). The last of our six measures are the four portfolio variations on the CD_t and mCD_t indexes discussed above: CD_5^{mean}, mCD_5^{scale}, CD_5^{total-}, and CD_5^{total+}. As in our earlier analyses, all measures are computed using citations received by patents in the first five years after being granted.

We frame the analyses we present here in terms of groups of right-hand side variables that operationalize key concepts from the literature. In particular, we attend to measures related to individual university levels of experience with patenting, the sources of funding and support for their research, and their scientific capacity.

Technology Transfer Experience Covariates. Prior work reports mixed results about the effects of experience with patenting. On the one hand, more experience in the form of increasing patenting may help a university to better identify potentially commercially valuable inventions and thus higher impact patents. On the other hand, experience may also be associated with declines in impact, because universities looking to develop strong patent portfolios pursue more incremental inventions (Henderson et al. 1998). We measure each university's experience with technology transfer as the volume of *Patents* applied for during year t. We also include a separate measure for *Life sciences* that captures the proportion of recent patents applied for by each university that fall within the NBER's *Drugs* category.

Industry Ties Covariates. Owen-Smith and Powell's (2003) observation that greater corporate engagement leads to the capture of university technology transfer efforts suggests that science supported by industrial partners is likely to generate inventions that increase the use of existing technologies. We thus propose that industry support of university R&D will lead universities to pursue more consolidating discoveries. *Industry-sponsored R&D* (log) measures the dollar value, in millions, of grants and contracts from corporations to researchers on campus. This variable comes from National Science Foundation (NSF) surveys of campus-level R&D efforts available from the online WebCASPAR database.[15] Our second measure, *Industry R&D ties*, captures formal R&D relationships with firms in technology-intensive industries. The information on R&D connections used to create this variable was content coded from Securities and Exchange Commission filings made by a sample of 634 publicly traded firms in high-technology sectors (see Buhr and Owen-Smith 2010, Owen-Smith et al. 2015).

Government Ties Covariates. Levels of support from the National Science Foundation (NSF), the National Institutes of Health (NIH), and the Department of Defense (DoD), the nation's premier funders of basic science, should yield research that is less connected to existing industrial needs. Thus, more federal grants and more patents derived from them should be associated with destabilizing inventions. We track the level of support (in millions of dollars) that flows to campuses from federal science agencies with three variables, *NSF grants* (log), *NIH grants* (log), and *DoD grants* (log). Federal grant measures were extracted from the NSF's WebCASPAR database.

Broadly speaking, if the process by which federal science agencies apportion R&D support is more likely to fund research focused on academic concerns divorced from the needs of industry, then campuses that perform more federally funded research and those whose patents emerge from federally funded projects should produce more destabilizing patents. Likewise, because corporate R&D funding is presumably linked to sponsors' proximate, market-driven goals, we expect campuses that pursue more industrially funded R&D to produce patents that consolidate the use of existing technologies. Although any source of external support seems likely to yield higher-impact patents, we anticipate that industrial connections will be associated with consolidating inventions, while public sector funding will lead to more destabilizing ones.

Scientific Capacity Covariates. Although existing measures of publication impact suffer from many of the same limitations as the patent citation indexes we critique above, we use them to provide some sense of the relationship between high-impact public and important proprietary science. We follow two lines of reasoning. Noting first with Sine and colleagues (2003) that articles confer a "halo effect" on associated academic patents while advertising their value to potential licensees, we expect both the volume and impact of academic science to be associated with higher-impact patent portfolios. To the extent that highly-cited papers generate scientific attention because they report novel, basic-science discoveries that are far removed from the current concerns of industry, we would expect higher-impact publications to be associated with more destabilizing inventions.

We use the count of *Scientific articles* published in the preceding year to index the volume of academic research on campus. In addition, we include a measure of the citation *Impact factor* of those articles as a proxy of the visibility and quality of a campus's published research. Both measures are drawn from the Institute for Scientific Information's (ISI) University Indicators Database.

Statistical Approach. Four of our measures of patent importance—V^{total}, I_5^{total}, CD_5^{total-}, and CD_5^{total+}—are counts that take on only nonnegative integer values. To capture time-invariant heterogeneity among universities, account for overdispersion, and match the approach taken in earlier research (Owen-Smith and Powell 2003), we model I_5^{total}, CD_5^{total-}, and CD_5^{total+} using a conditional fixed-effects negative binomial specification (Hausman et al. 1984). Our model of V^{total} also uses a negative binomial specification, but because it includes a lagged dependent variable, we use random instead of fixed effects.[16] Finally, to model CD_5^{mean} and mCD_5^{scale}, we use a fixed-effects OLS specification. All models include indicator variables for calendar year.

3.3.5. Organization-Level Results. Table 6 presents descriptive statistics and correlations for all variables used in these analyses. Table 7 reports results from a fully specified model for each one of our dependent variables. Nested specifications are available from the authors.

Consider the first two columns of Table 7 (Models 17 and 18), which present estimates for patent volume (V^{total}) and impact (I_5^{total}). The results of these models are broadly consistent with prior findings. Universities that have greater prior experience with patenting (*Patents*) produce more and higher impact patents. A greater focus on *Life sciences* patenting, however, is associated with diminished patent impact. This may be the case because, unlike physical science and engineering technologies, the most sought-after life science patents are those that offer exclusive protection for potential drug candidates. Such patents are typically licensed exclusively and do not rely on suites of complementary intellectual property for their application.

Perhaps unsurprisingly, universities that produce more *Scientific articles* and higher-impact (*Impact factor*) research publications also develop more and higher-impact patents. Connections to corporate partners in the form of *Industry-sponsored R&D* (log) and research-based university–industry alliances (*Industry R&D ties*) suggest more interesting associations. Increased industrial funding is modestly associated with more and higher-impact patenting, but campuses with more corporate alliances patent less, and this type of corporate connection has no significant relationship with patent impact.

By the same token, increases in research funding from key public sources (*NSF grants* (log), *NIH grants* (log), and *DoD grants* (log)) demonstrate largely positive relationships with patent volume and impact. The cross agency funding differences in these models warrant further scrutiny, but we expect that they have much to do with the relative proportion of each funding source in a university's portfolio of research support and the distinctive fields in which different agencies concentrate their grant making.

Model 19 regresses these same variables on the average CD_5 index (CD_5^{mean}) for a given university. Just one variable, the impact factor of published scientific articles, offers any explanatory purchase on this dependent variable, and that effect is marginal. Although the suggestion that higher-visibility scientific portfolios are associated with more destabilizing patents is in accord with some of the patent-level findings we present in the prior session, the lack of robust relationships in Model 19 implies that an average CD_5 index might not be the best aggregate measure for analyzing the kinds of diverse, decentralized patent portfolios that are commonplace on university campuses.

Table 6. Descriptive Statistics and Correlations

Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. *Patents/volume* (V^{total})	28.85	27.76	1.00													
2. *Impact* (I_5^{total})	107.93	164.16	0.74	1.00												
3. CD_5^{mean}	0.10	0.12	−0.06	0.02	1.00											
4. mCD_5^{scale}	10.94	19.34	0.56	0.81	0.30	1.00										
5. CD_5^{total+}	59.39	99.31	0.69	0.95	0.07	0.83	1.00									
6. CD_5^{total-}	43.30	70.18	0.68	0.90	−0.04	0.66	0.74	1.00								
7. *Life sciences*	0.48	0.21	−0.05	−0.17	0.15	−0.04	−0.20	−0.11	1.00							
8. *Industry sponsored R&D* (log)	2.30	0.89	0.44	0.30	−0.10	0.20	0.27	0.29	0.02	1.00						
9. *Industry R&D ties*	0.34	0.75	0.38	0.26	0.02	0.24	0.24	0.23	0.15	0.19	1.00					
10. *NSF grants* (log)	0.65	1.27	0.42	0.32	−0.10	0.22	0.32	0.27	−0.41	0.29	0.16	1.00				
11. *NIH grants* (log)	0.67	1.32	0.44	0.20	0.04	0.23	0.18	0.20	0.49	0.38	0.35	0.11	1.00			
12. *DoD grants* (log)	0.63	1.42	0.43	0.34	−0.09	0.25	0.33	0.30	−0.28	0.44	0.22	0.63	0.22	1.00		
13. *Scientific articles*	1,919.69	1,179.77	0.62	0.38	−0.01	0.37	0.36	0.35	0.10	0.52	0.48	0.51	0.65	0.47	1.00	
14. *Impact factor*	21.87	10.12	0.15	0.33	0.30	0.47	0.33	0.27	0.30	−0.11	0.17	−0.27	0.25	−0.16	0.10	1.00

Table 7. Regression Models of University Patenting

	Model 17 V^{total}	Model 18 I_5^{total}	Model 19 CD_5^{mean}	Model 20 mCD_5^{scale}	Model 21 CD_5^{total+}	Model 22 CD_5^{total-}
Technology transfer experience						
Patents	0.007***	0.007***	−0.000	−0.219**	0.007***	0.010***
	(0.001)	(0.001)	(0.000)	(0.065)	(0.001)	(0.002)
Life sciences	−0.177	−0.543*	0.015	−8.831*	−0.490*	−0.777**
	(0.127)	(0.214)	(0.068)	(4.364)	(0.242)	(0.274)
Industry ties						
Industry-sponsored R&D (log)	0.051†	0.118*	0.019	−3.540*	0.166**	0.090
	(0.029)	(0.050)	(0.012)	(1.520)	(0.053)	(0.063)
Industry R&D ties	−0.032**	−0.005	0.001	−2.051*	0.006	−0.027
	(0.012)	(0.023)	(0.005)	(0.904)	(0.028)	(0.035)
Government ties						
NSF grants (log)$_{(centered)}$	0.061*	−0.024	0.006	3.163†	0.035	−0.057
	(0.026)	(0.043)	(0.011)	(1.710)	(0.048)	(0.054)
NIH grants (log)$_{(centered)}$	0.167***	0.131*	0.016	4.351†	0.212**	0.103
	(0.039)	(0.061)	(0.025)	(2.376)	(0.067)	(0.071)
DoD grants (log)$_{(centered)}$	0.019	0.093**	0.002	2.642**	0.047	0.100*
	(0.016)	(0.033)	(0.007)	(0.786)	(0.034)	(0.043)
Scientific capacity						
Scientific articles	0.000***	0.000†	−0.000	−0.021***	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.006)	(0.000)	(0.000)
Impact factor	0.018***	0.028***	0.002†	0.902**	0.028***	0.009
	(0.003)	(0.006)	(0.001)	(0.274)	(0.006)	(0.007)
University fixed effects	No	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.714***	−19.452	0.029	39.160*	−18.873	−20.341
	(0.142)	(558.273)	(0.070)	(15.651)	(427.032)	(909.797)
N	1,270	1,265	1,006	1,006	1,265	1,265
R^2			0.136	0.384		
Universities	109	108	108	108	108	108
Log-likelihood	−4,309.140	−4,239.365	870.336	−3,876.887	−3,707.129	−3,465.603

Note. Standard errors are in parentheses.
$^{\dagger}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

In contrast, Model 20 offers what we believe to be the clearest and most compelling example of an aggregate version of our measures. mCD_5^{scale} weights a standard forward citation measure of impact for a group of patents by the CD_5^{mean} index. Comparing these results with those in Model 18 is thus illustrative of the benefits to be gained by incorporating the kinds of structural measures we propose into the analysis of portfolios of patents. Note first that, although high volume patenting (*Patents*) and publishing (*Scientific articles*) are both associated with increases in patent impact (Model 18), the same measures are associated with higher-impact patents that consolidate the status quo of their technology streams (Model 20). Universities that produce higher-impact portfolios of articles (*Impact factor*), however, also develop higher-impact patents that do more to destabilize the status quo.

Perhaps most tellingly, however, both measures of engagement with corporate partners (*Industry-sponsored R&D* (log) and *Industry R&D ties*) are strongly associated with patenting that consolidates existing technology trajectories. In contrast, increases in funding from all three sources of public research support (*NSF grants* (log), *NIH grants* (log), and *DoD grants* (log)) are linked to more destabilizing patent portfolios. This analysis holds potential lessons for both defenders of and detractors from Bayh–Dole. For the former, the implications are clear: the post–Bayh–Dole wave of university inventions depends on the foundation of academically important, publicly funded science. Thus, to preserve their economic contributions, the academic character of university science should be encouraged. For the latter, it appears that tighter industrial connections yield patents that reinforce existing technical arrangements, a finding that should deepen concerns about the long-term effects of commercialization on universities, their research, and ultimately their economic contributions.

Finally, turn your attention to Models 21 and 22, which examine variables that take a different approach to aggregation. Here we use the patent-level CD_5 index to differentiate between patents that destabilize or consolidate the use of existing technologies. We then calculate the forward citation impact for those patents. Both models offer less clear signal than Model 20, but some interesting features are apparent. Most notably, the coefficients for variables that capture scientific capacity (*Scientific articles* and *Impact factor*) in these two models are consistent with the findings we reported for our mCD_5^{scale} index. A higher volume of scientific papers is associated with higher-impact consolidating inventions (Model 22, CD_5^{total-}). In contrast, a higher-impact portfolio of scientific publications is associated with a more broadly used portfolio of patents that destabilize the use of the technologies on which they build (Model 21, CD_5^{total+}).

When considered holistically, these models suggest that there is value in pursuing more aggregate forms of our measures, but more research is needed. To our eyes, the admittedly schematic findings presented in Table 7 imply that, for organizations like universities that pursue research across many fields with multiple goals and partners, an integrated measure such as mCD_5^{scale} offers significant purchase. We suspect that the kinds of measures we created for Models 21 and 22 may be more adapted to studying the effects of changes in technology management and R&D practices for organizations, such as smaller firms, that pursue more explicitly destabilizing or consolidating invention goals in a more homogeneous range of fields. Regardless, the additional analytic flexibility that comes with our network-based measurement approach may yield dividends when applied to more specific examinations of technology strategy and its effects.

4. Discussion

We began this article with a quote from Schumpeter. That insight served as a stepping stone for two generations of research that views creative destruction as a motor for economic and social transformation. Although Schumpeter and others observe that what makes a technology important is the nature and extent of its use, quantitative evaluations of how, precisely, the use of new technologies strengthens or challenges the status quo have remained elusive. The purpose of this article has been to propose and evaluate measures—the CD_t and mCD_t indexes—that capture the effects that new inventions have on the use of their predecessors. Our approach differs from prior efforts by operationalizing the distinction between technologies that are valuable because they break from current standards and those whose value derives from reinforcing the trajectories from which they spring.

The CD_t index has several attractive features that may make it useful for future research. By treating new technologies as additions to evolving networks, the measure makes use of theoretically important structural information on second-order forms of impact that are overlooked by existing approaches. These network underpinnings also make the CD_t index naturally suited to dynamic analyses over the course of a particular technology's existence. Our method also offers a continuous and valenced characterization of an invention's impact, which allows for clear, qualitative distinctions while also recognizing that the consolidating or destabilizing character of technologies is often a matter of degree. Moreover, because the value of the CD_t index can vary over time for a single patent, the measure allows for the possibility that some important proportion of the effect that a new invention has is determined ex post in the context of its use rather than ex ante in the context of its discovery. Finally, by incorporating an impact weight into the CD_t index, it is possible to obtain an indicator (the mCD_t index) that characterizes both technologies that are major departures from the status quo and those that reinforce but offer substantial improvements over existing technologies. Together, these indexes capture the positive and negative dimensions of technological change.

In addition to their methodological benefits, the CD_t and mCD_t indexes may also help to facilitate theoretical development in some areas by clarifying conflicting empirical findings. For more than three decades, scholars have engaged in heated debates over the implications of increasing commercial engagement for the nature and quality of university science. Although patents are a potentially valuable source of data for adjudicating among competing views, empirical investigations using forward-citation-based measures of impact have been inconclusive. Using the CD_t and mCD_t indexes, we found consistent evidence that while increases in federal support for academic research appear to push universities to create technologies that destabilize the status quo, increases in commercial ties are associated with university research that consolidates existing technology streams.

The indexes we propose are not without limitations and more remains to be done. Most broadly, our approach rests on the assumption that relevant nodes (patents) and ties (citations) can be meaningfully identified, and that the network under investigation evolves in some way. Many settings in which invention occurs meet these criteria. However, in certain cases (for instance, where change is largely propelled by exogenous influences), the value of the approach will be limited. Our indexes are also limited because they are undefined when a focal invention and its predecessors are never cited by subsequent technologies. In the context of U.S. patents, we found that these kind of inventions are rare, occurring in 3% of cases when the CD_t and mCD_t indexes are measured five years after the focal patent's issue year. Nevertheless, inventions of this sort may still influence technological change (for instance, by leading inventors to believe a particular field has been saturated) and therefore diverting attention from components that were in existence before its introduction. A related limitation is that, even when our indexes are defined, they may be biased for inventions that offer improvements over some existing technologies but use entirely new methods and therefore do not build on those technologies, perhaps by using methods from a different domain. Clarifying these effects, both conceptually and with respect to measurement, is an exciting opportunity for future research.

Our analyses did not explore the possibility that some inventions might simultaneously consolidate and destabilize the use of predecessors in different technology streams. This phenomenon could occur if a particular invention made its antecedents more valuable for one community of users, but less so for others. Such patterns of alternating consolidation and destabilization may prove useful in identifying instances where a technology fails to cite the predecessors it most strongly destabilizes. When a new technology is based on a totally different set of mechanisms, for instance, we might not see destabilization on our measure for several patent generations. Our example of the Axel patent, which cited no examples of the chemistry-based drug discovery methods it eventually supplanted, offers a case in point. The same effect might also be present in cases where usage patterns change over the course of a technology's life cycle.

Finally, our empirical analyses suffer from some limitations common to all research that relies on archival data like patents. For instance, many important inventions are never filed with the USPTO, although, as critics suggest, many mediocre new technologies pass through the examination process and are awarded patent protection. Business and legal strategies may create additional noise or bias in the data through the intentional omission of legitimate citations or the inclusion of irrelevant references (Alcácer et al. 2009).

Although not without limitations, we believe that the CD_t and mCD_t indexes may help to expand research in multiple areas. Below, we address some implications of our approach where it is likely to be most useful.

4.1. Social Networks

The indexes we propose may help to generate new insights in research on social networks and invention (Burt 2004, Obstfeld 2005). A persistent challenge in this area has been to distinguish between the effects of more open, unconstrained social network configurations and more closed or cohesive structures. Some current findings suggest that the former are more effective for generating novel ideas whereas the latter are more suited for mobilizing collaborators around the often difficult work of development, but other research points to the importance of more complex, hybrid network arrangements (Fleming et al. 2007, de Vaan et al. 2015). Rather than reflecting differences in the effects of particular social network structures and the need to consider more complex configurations, however, the conflicting findings in this area may stem from noisy outcome indexes that mask fundamental differences between network positions that facilitate destabilizing ideas and those that support inventions that are more consolidating in nature. Closed groups of inventors with many overlapping, cohesive relationships, for instance, may collectively have deeper knowledge of a technological domain and therefore be especially suited for developing ideas that consolidate a trajectory. Alternatively, inventors who search through networks of otherwise disconnected contacts may leverage their vision advantage to pursue more fundamental insights that destabilize existing technological arrangements.

4.2. Industries and Firms

The CD_t and mCD_t indexes may also be useful for understanding industry evolution and its implications for firms (Nelson and Winter 1982; Tushman and Anderson 1986; Benner 2007; Sosa 2009, 2011). For instance, recall our brief discussion of two related technologies identified in Table 2: the scanning tunneling microscope (STM) and the atomic force microscope (AFM). The STM was highly destabilizing because of its major break with the technological standards in place at the time of its introduction. By contrast, the AFM was only moderately destabilizing because it built on and expanded the technological base created by the STM. Yet the AFM has proven to be more important to the development of nanotechnology. Abstracting from this dynamic, one may hypothesize and use our indexes in tandem with qualitative and historical case data to examine the possibility that, in emerging sectors like nanoscale materials or tissue engineering, early inventions will be the most likely to challenge the incumbents' capabilities, whereas later discoveries may enhance them as the technologies (and related organizations, networks, and markets) mature.

The ability to distinguish between inventions that consolidate and those that destabilize the use of existing technologies may also be valuable for examining a range of questions of relevance to technology strategy. For instance, consider debates over the effect of market power on incentives to develop new technologies. Much like research on social networks, this literature has produced conflicting theoretical arguments and empirical findings (Gilbert 2006, Ahuja et al. 2008). Although some contend that incumbents should pursue inventions in order to maintain their positions, others argue the opposite and claim that incentives are depressed due to lack of competition. Ahuja and colleagues (2008, p. 8) note that empirical efforts to resolve this debate have been challenging, "since the main effects are countervailing." To the extent that incumbents may differ with respect to the aims of their R&D efforts in relation to existing technology streams, the measures we propose could help to disentangle some of these countervailing effects.

4.3. Science Policy

In recent years, efforts to develop evidence-based science policy measures have triggered extensive work in what has come to be called the "science of science policy" (Lane 2010, Fealing et al. 2011, Powell et al. 2012). Among other concerns in this burgeoning field is the question of how to support, identify, and evaluate transformative research. We submit that variants of the CD_t and mCD_t indexes might help to document the transformative effects of different collaborative or funding models by, for instance, associating differing levels of interdisciplinarity or scientific team structure with the production of more or fewer findings that enhance or replace existing knowledge bases. Our findings about the differing implication of higher-impact university and corporate patents for established technological arrangements and the tendency of federally funded grants to generate more destabilizing inventions offer cases in point. Funders and performers of such research are under increasing political pressure to explain and justify their work in terms of its economic impact. However, findings like those we explore here suggest the importance of more fundamental, academic research as a means to open new technological trajectories. As such, the CD_t and mCD_t indexes may offer a more effective means to evaluate the technological significance of scientific discoveries in a fashion that justifies novel funding approaches at the federal and state levels. The findings we present in regard to the disparate effects that industrial and public R&D findings may have for different types of academic patenting, and the suggestion that support from different agencies is associated with different types of research outcomes, offer cases in point.

4.4. Geography and Space

The method we propose could also be of use in ongoing work on the causes and consequences of regional industrial agglomeration. Competition is stiffer within established clusters than outside them (Stuart and Sorenson 2003, Whittington et al. 2009). Work has documented the different roles that physical proximity to universities and other firms and geographically local versus distant ties play in the inventive performance of biotechnology companies (Owen-Smith and Powell 2004, Whittington et al. 2009). Both lines of work have suggested that location in vibrant regions forces firms to compete more vigorously to succeed, but research in this area has not attempted to distinguish among the types of inventions made by geographically clustered and geographically remote organizations. Adapting insights on social isolation and creativity (Taylor and Greve 2006, Singh and Fleming 2010), one may predict that firms located in "second-tier" regions (Mayer 2011) or outside established clusters entirely are better positioned to generate inventions that destabilize existing streams of technology, whereas those in closer proximity to industry peers are well suited to work that consolidates and reinforces them. The ability to characterize regions along these dimensions may be valuable for managers and urban planners, in addition to researchers (Bettencourt et al. 2007).

At a more microlevel, our finding of a greater tendency for distributed teams of inventors to create inventions that consolidate the status quo suggests that geographic diversity may help collaborators to perform better in some respects while also challenging their ability to create truly destabilizing new technologies. Existing studies of team-based research suggest that this could be the case, but pure impact measures lack the ability to distinguish among such claims. If, as some research on scientific and technical teams suggests, distance increases coordination challenges (Cummings and Kiesler 2005), then it may be that dispersed teams are more effective in pursuing additions to existing technological trajectories. In contrast, if serendipity is an important contributing factor for destabilizing discoveries and face-to-face interactions are a key mechanism for its recognition, then dispersed teams may be at a substantial disadvantage when it comes to making more destabilizing inventions (Kabo et al. 2014).

4.5. Beyond Technological Change

Finally, consider some possible uses of our dynamic network approach far afield from technological change. The CD_t and mCD_t indexes might be adapted to studies of the evolving link structure of the World Wide Web, where new pages will cite and be cited by others. Similarly the evolving structure of citations among judicial decisions that comprise an important aspect of U.S. law might be examined in these terms. Rather than measuring the effects of new technologies, this family of indexes might offer new insight into more political and cultural questions involving the dynamics of political polarization in the blogosphere, the evolution of management fads and fashions, the visibility of music artists and genres, the commercial and critical impact of films, and the larger legal implications of new court decisions. Evolving network data on relationships of deference among entrants and incumbents in different substantive domains are becoming more available and are potentially valuable for research questions in multiple fields.

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Endnotes

[1] Nevertheless, patent data have limitations. For example, inventors may not seek patent protection for their ideas. Moreover, the patent examination process has been criticized by observers who argue that the USPTO grants many patents that fail to meet the legal requirements of novelty and nonobviousness (Jaffe and Lerner 2004, Lemley and Sampat 2008). Firms may have strategic reasons for omitting citations, and examiners may fail to add these during their reviews (Alcácer et al. 2009).

[2] Although we do not include them in these diagrams, we also recognize and integrate into our measure the likelihood that later inventions will cite the focal patent's predecessors without citing the focal patent itself.

[3] Code for calculating the CD_t and mCD_t indexes along with values for U.S. patents are available at http://www.cdindex.info.

[4] More nuanced approaches could, for example, determine the values of $\mathbf{W}$ according to the issue date of i such that older citations have greater or lesser influence over the measure, or by differentially weighting citations made by examiners and patent applicants.

[5] Our focus on types of nodes and binary relations among them discards some structural data. We address these issues more in Online Appendix A, where we introduce variations on the CD_t and mCD_t indexes that allow for multiple focal patents.

[6] We identified government interest patents by extracting and coding information contained in the `GOVT`, `GOVINT`, and related fields of full-text patent documents, available from the USPTO.

[7] In unreported comparisons, we found few substantial differences in the distribution of the CD_5 index across broad (NBER) technology categories. Computers patents (including software), however, appear to have less influence in terms of either consolidating or destabilizing the status quo than other classes have.

[8] By convention, we refer to these patents using the last names of their authors. The inventors' full names are, respectively, Stanley N. Cohen and Herbert W. Boyer, Richard Axel (with Michael H. Wigler and Saul J. Silverstein), and Kary B. Mullis. Each of these patents covers what was to become a fundamental method for research in many fields of biology and the biotechnology industry. Cohen and Boyer established the fundamental technique of gene splicing. Axel and colleagues developed a method to insert genes into cells in order to turn them into protein "factories." Mullis invented an efficient method to produce large amounts of DNA from very small samples.

[9] The alternative version of the CD_t index presented in Online Appendix A may prove useful for estimating the effects that patent families have on their technological predecessors.

[10] This calculation does not account for possible right truncation due to delays between patent application and grant years and may also be inflated because of increases in the frequency of patenting and citation over time. In Online Appendix B, we present exploratory models that attempt to adjust for these and other factors. The results are similar.

[11] Patent 5,084,082 is owned by DuPont.

[12] The PageRank patent also differs from Monsanto in that its backward citations come from a more diverse base of organizations, as would be anticipated for a more destabilizing invention. The seven predecessors cited by the patent are owned by a total of four different corporations and one university, none of which are Stanford or Google.

[13] One important question is whether or not the Axel patent's high CD_5 index of 0.95 could stem from the fact that it only cited two pieces of predecessor patents. There is a modest negative correlation ($r = -0.17$, $p < 0.001$) between the number of citations of predecessors and a patent's CD_5 index. However, some association between the number of predecessors cited and the CD_5 index is anticipated as novel inventions should have fewer predecessors available on which to build.

[14] We thank Bhaven Sampat for sharing the data on USPTO examiners that made these analyses possible.

[15] http://ncsesdata.nsf.gov/webcaspar/.

[16] The results are similar if we drop the lagged term (*Patents*) and estimate the model using conditional fixed effects.

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