RECOGNIZING INNOVATION: HOW INSTITUTIONS AND COGNITION COMBINED TO FOSTER THE RISE OF NANOTECHNOLOGY

Yu-Chieh Lo

University of California, Los Angeles

Mark Thomas Kennedy

University of Southern California

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ABSTRACT

Social theory generally views structure as a constraint to departures from the familiar, but it also acknowledges moderators of this basic tendency. In this research, we explore the role that cognition and institutions play in recognizing nanotechnology, a field that emerged from inventions built on a diverse array of established areas of expertise. While combining elements of recognized specialties in new ways can produce novel inventions, the longer the list of combined specialties, the harder it is for experts in various fields to evaluate such inventions. To cope with these burdens, we argue that people will impose structure on these lists, especially by recognizing recurring combinations as patterns to be named—that is, by categorizing them. In the patenting context, the willingness to make new categories is supported by standards that frown on imitation and, with nanotechnology, the emergence of norms favoring interdisciplinary research (IDR). Thus, we expect the cognitive impetus for categorization to combine with a pro-IDR institutional logic to explain growing recognition of nanotechnology. Empirically, we test this argument using patents. Results show that pending time is longer and forward citations smaller for patents that build on a larger number of patent classes, but the emergence of a pro-IDR logic and typicality with the emerging nanotech category moderate these effects. These findings contribute to theory and explain how innovation is recognized by linking the value of conformity to cognitive limits and a logic of evaluation that prizes novelty.

(196 words)

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If it were easy to recognize innovations at the moment of invention, there would be no such thing as what Schumpeter (1934) called creative destruction—the catastrophic losses suffered by makers of established goods and services when they are displaced by innovations. It might seem that such shifts could be explained by studying the predictors of the diffusion of innovations, but Rogers (1983: 124) notes that diffusion is not determined by technical factors such as the "degree of advantage over the idea it is replacing", but "whether the individual perceives" it. Similarly, Wade (1995) argues that the success of a new product depends not just on "efficiency or technological superiority", but also on the level of organizational support it attracts. Institutional theory links both diffusion and related perceptions and adoption decisions to the collective view of whether a possible innovation is legitimate (Tolbert and Zucker 1983). Because such a legitimacy-focused approach tends to reward conformity with established structures and practices (DiMaggio and Powell 1983), however, individuals and organizations alike tend to overlook, dismiss and discount potential innovations when they are not yet seen as fitting categories that are established, or institutionalized (Hsu 2006; Zuckerman 1999). Thus, recognizing innovations—especially the ones that bring profound change—is a challenge for both researchers and practitioners.

The aim of pioneering new fields or markets is a risky one for would-be innovators and a vexing theoretical problem for scholars seeking to understand the dynamics of the categories used to define them. Following theory that links diffusion and widespread adoption to legitimacy, the not-yet-legitimate should be unlikely to diffuse through widespread adoption. This creates an important question that is the focus of this research: how do category-defying inventions get recognized as innovation? We see individual and social dimensions to this question. Specifically, how do context-independent features of human cognition and the logic of institutions that govern particular settings combine to affect the dynamics of categories?

Existing theory and research offers partial answers to these questions. Powell (1991), for example, argues that recombining elements of established institutions in new ways can be a catalyst for changing existing institutions or creating new ones. This becomes more likely when such recombinations are highlighted in widely circulated stories, as in the news media (Lounsbury and Glynn 2001). In the mutual fund industry, for example, Lounsbury and Rao (2004) relate recognition of new types of funds to media coverage of repeated mixing and matching of elements of already familiar types of funds. In the automotive world, Rosa et al. (1999) relate the emergence and growth of the market for minivans to "market stories" about products with car- and truck-like features. In theory, this is because public discourse that observes similarities between makers of similar but unfamiliar products effectively embeds them in a shared cognitive schema for understanding what they do—that is, in a category (Porac and Rosa 1996). This parallels organizational ecology that links the dynamics of different kinds organizational populations to the language of identities used to classify them. In studies that observe the ecological principle of allocation (Freeman and Hannan 1983), findings show that organizations suffer for attempting to fit several different contexts because it makes it inherently harder to fit any of them well (Hannan and Freeman 1989). While these studies generally view such situations as relatively unappealing category "straddles" (Hsu 2006a), such straddles are nonetheless theorized as patterns of partial membership in multiple categories that may change over time as a result (Hannan, Pòlos and Carroll 2007). Thus, a growing population of category straddlers can become an attractive identity (Rao, Monin and Durand 2003) or a category on its own (Negro, Hannan and Rao 2010).

This raises unanswered questions about how repeated blends of existing fields—as categorizations of types of expertise—sometimes become appealing categories or identities in their own right, which calls to mind White's (1981, 2002) argument idea that market categories emerge from social comparisons among producers. As they highlight similarities that reveal patterns in the linkages among instances and attributes of a nascent category, such comparisons embed category members in shared cognitive maps of both the structure and meaning of related categories (Mohr 1998; Mohr and Duquenne 1997). In the literature taking a relational approach to culturally shared classification systems (Mische 2011), however, scholars have yet to explain why and under what conditions such linkages are not only observed rather than overlooked (Hsu 2006b; Zuckerman 1999), but then recognized and celebrated as innovation.

In this research, we fill this gap by relating recognition of novel recombinations of the familiar to both cognitive limits and the logic of institutions that dictate standards of value. As we will argue, cognitive limits create pressures to categorize a recurring but previously unconventional combination of existing areas of knowledge, and institutions whose logic rejects replication while prizing novelty create incentives to try new things. While rare combinations of elements of the familiar are unlikely to be recognized or accepted (Ruef and Patterson 2009), repetition allows recognition of a new entity (Campbell 1958), in part by attracting sensemaking effort that makes it seem more plausible (Weick 1995). As a previously uncategorized approach to organizing proliferates, for example, it is more likely to be recognized as a new type or form of organization (Carroll and Hannan 1989). Similarly, seeing links among makers of unfamiliar products makes them recognizable as a new product market seen as increasingly "for real" (Kennedy 2008). In addition, recognizing the similar but unfamiliar as a new category is easier when novelty is promoted by the logic of governing institutions (Friedland and Alford 1991; March and Olsen 1989) and related standards of worth (Boltanski and Thévenot 1991). Although, as mentioned, studies have shown that audiences generally take a negative view of straddling or blending multiple categories (Hsu 2006b; Negro et al. 2010; Zuckerman 1999), such negative reactions are likely to ease or even reverse in settings with institutional logics that prize novelty and reject replication.

Thus, while blending multiple categories risks penalties that come with failing to fit one established category, blends that occur often enough stand to be recognized as a new category, and this is more likely still in contexts where institutional logics favor novelty. Building on the idea that category conformity pressures are the results of partial membership in multiple categories (Hannan et al. 2007), we argue that repeated partial membership patterns sometimes become new categories—and new standards of appropriateness. As this happens, category blends are less apt to be seen as ungainly hybrids and more likely to be accepted—and institutionalized—as new realities in the natural order of things (Berger and Luckmann 1966).

We develop and test this argument in the context of patents in nanotechnology, a field of research and development (R&D) that emerged as a growing body of R&D and related patents that combined prior art from multiple scientific and engineering disciplines in similar ways. This context is an excellent site for our investigation because each patent lists the "classes" of prior art it builds on and extends. According to the *Patent Examiner Handbook* of the United States Patent and Trademark Office (USPTO), the first patent classes were defined so that they "closely paralleled economic groupings", but with new developments, the USPTO periodically revamps its classification system to sync it with current "theories of classification." These data allow us to analyze nanotech patent recognition as a function of the number of classes a patent builds on and its interaction with the institutionalization of logic that increasingly rewards interdisciplinary research (IDR)—that is, research that builds on insights from multiple disciplines. Following Schumpeter's distinction between technological and social aspects of innovation (1939: 85) but focusing on the social, our approach also allows us to complement more technologically-oriented literatures of innovation and technology that have a long tradition of using patent data (for example, Fleming 2001; Jaffe 1986).

CONTEXT: NANOTECHNOLOGY AND INTERDISCIPLINARY RESEARCH

As implied by the use of the nano prefix (10^{-9}), the field of nanotechnology emerged from a vision for manipulating matter at a very small scale. This vision arguably harks back to a 1959 keynote speech Caltech physicist Richard P. Feynman gave to the American Physical Society. Entitled "There's Plenty of Room at the Bottom", Feynman dreamed up nanotech at a time when computers occupied entire rooms. Although Feynman was correct in predicting breakthroughs for "manipulating and controlling things on a small scale", much work would need to be done to achieve this vision. Consequently, Feynman's idea went nameless until Tokyo University of Science Professor Norio Taniguchi coined the term "nanotechnology" in a 1974 conference proceedings paper.

The realization of Feynman's vision would take more than physics and a catchy name. Small-scale research languished until the confluence of several developments led to the development of powerful "enabling inventions" (Darby & Zucker 2006). In 1981, researchers at IBM produced a "scanning tunneling microscope" that enabled scientists to see atomic-scale images for the first time (Darby & Zucker, 2006). A few years later, the "atomic force microscope" (AFM) broadened the range of materials viewable at nano-scale and enhanced capabilities for manipulating individual atoms and molecules.

In this same time period, nanotech got a lift from the writing and organizing efforts of Eric Drexler, an MIT student who became the nascent field's *de facto* prophet. As a follow-up to a serious scientific article that described the interdisciplinary breakthroughs what would enable nanotech, Drexler popularized the vision for nanotech in *Engines of Creation: The coming Era of Nanotechnology* (Drexler and Whitaker 1986). In addition to his writings, Drexler was a gifted mobilizer. With Chris Peterson, he co-founded the Foresight Institute, a futurist think-tank that proselytized nanotech by forging ties across diverse communities of researchers, investors and policy makers in universities, industry and government (Grodal 2008; Thurs 2007). With these books and Foresight's organizing efforts, awareness of nanotech spread from elite researchers to the broader scientific community and general public (McCray 2005).

As engineering developments continued to lower the cost and boost the expected payoffs of nano-scale research (Darby and Zucker 2006), a growing cadre of career scientists came to see nanotechnology as having real potential, and their efforts began to link far-flung communities in research and government to promote a more realistic nano-scale research program as a national priority. Building on an early program that investigated the synthesis of nano-sized particles, the National Science Foundation (NSF) inaugurated a full-fledged inter-agency program to formulate and fund a national strategy for nanotechnology (McCray 2005). This program featured a think-tank consisting of academics, industrialists and scientists from various US laboratories (Edwards, 2006).

By the late 1990s, these efforts had borne clear fruit. With US President Bill Clinton's personal announcement of the National Nanotechnology Initiative, the field was formally defined to include developments that fit one of three criteria: working at a scale of 1–100 nanometers; creating structures or devices whose size gives them novel properties or applications; and / or manipulating matter on an atomic scale (NNI, 2001; McCray, 2005). More broadly, nanotech is applied science or technology focused on manipulating matter at "nano-scale"—100 nm or less. As a further indication of nanotech's arrival as a field, the USPTO announced a new classification for nanotechnology patents in 2005—patent class 977. Class 977 now serves as a cross-reference to help examiners and investors search the prior art. Before Class 977, examiners relied on patent class combinations and keyword searches to find relevant patents.

These developments are echoed in U.S. government investment in nanotechnology; Figure 1 shows these investments from 1997 onward. Funding rose rapidly in the late 1990s and surged after 2000. Figure 2 shows the longer history of growth in nano-related patents.

[INSERT FIGURES 1 AND 2 ABOUT HERE]

The Emergence of a pro-IDR Logic

An equally important but less often heralded reason for nanotech's emergence was the shift toward greater acceptance of and even enthusiasm for interdisciplinary research—that is, research that pursues breakthroughs at the intersection of science and industry by drawing on multiple academic disciplines rather than cleanly fitting into one. An important enabler of this shift was the Bayh-Dole Act of 1980 (Gibbons et al. 1994; Powell and Owen-Smith 1998). This important legislation created new incentives for paying greater attention to the commercialization of inventions and research tools by granting universities full rights to royalties from commercialization of federally funded research. These incentives were further enhanced by additional legislation that further relaxed prior restrictions on university participation in commercialization of their faculty's research or inventions (Powell and Owen-Smith 1998). While the balance of basic versus applied research pursued by university professors appears not to have shifted as a result of this legislation (Mowery et al. 2004; Thursby and Thursby 2003), it is clear that universities and their faculties have become much more active in claiming and attempting to license rights to their research (Azoulay, Ding and Stuart 2007; Mowery, Sampat and Ziedonis 2002).

As commercialization gained greater currency in universities, interdisciplinary research (IDR) has become more common while also receiving more funding and greater recognition. Emboldened by these changes, IDR's most enthusiastic champions critique discipline-focused research as irrelevant and out-of-touch. In the IDR literature, the authors of one article put it this way: "current shortcomings of traditional scientific research and professional practice are … above all, the logical outcome of the narrow vision of so-called experts who do not address fundamental issues but only topics isolated from their societal context" (Lawrenece and Despres 2004). In a world where scientific careers can still be made by breakthroughs in basic research, this rhetoric is extreme, to be sure, but it does capture a new sensibility toward research—the more engaged it is with real world problems, the better. Thus, as more attention is given to potential commercialization of university research, fashions in funding have given considerable energy to research programs at the intersection of conventional academic disciplines, especially in the life sciences and engineering (Powell and Owen-Smith 1998; Powell et al. 2005). For example, in 2008, the US National Institutes of Health (NIH) formalized support of interdisciplinary research values by establishing the Exploratory Centers for Interdisciplinary Research. These centers are designed to stimulate "fresh and unexpected insights" by removing "roadblocks to potential collaboration" between and across multiple disciplines.

Theoretically, this explains why the R&D world may be kinder than other social worlds to new ideas that are hybrids of existing disciplines in the sense that they combine elements of multiple distinctly categorized knowledge domains. When reviewing applications for patent protection of new ideas, the USPTO review process not only prizes novelty, it rejects conformity. That is, being too similar to the prior art is one of the main reasons patent examiners reject patent applications. Unlike other environments where blending or straddling multiple categories is often viewed negatively, blending multiple fields of prior art is often seen as a recipe for originality—one of the keys to success when seeking intellectual property rights. As universities have become more comfortable claiming rights to the commercialization of R&D, norms favoring interdisciplinary have gained legitimacy. It stands to reason that the logic of evaluation emerging from these developments should moderate the generally negative effects of combining multiple categories or fields. We turn now to elaborating this theoretical argument and translating it into hypotheses.

RECOGNIZING INNOVATION

In collective sensemaking efforts (Weick 1995) about developments around which new fields might form, categories provide the "building blocks" for recognizing both what is real already (Berger and Luckmann 1966) and whether new ideas and inventions will be seen as real enough to be recognized as innovation. Thus, the structure of classification systems reflects not only the path dependent history of what has previously been recognized as innovation (Arthur 1989, 1990; David 1985), but also the limitations of human cognition. This is why we argue that explaining how inventions get recognized as innovation requires understanding both cognition and institutions.

Inventions that defy existing categories by building on a number of different fields are risky. Because influential third-party critics such as market analysts use categories to allocate their attention, not fitting established demand categories risks being overlooked and, therefore, undervalued (Zuckerman, 1999). In securities markets, organizations whose corporate portfolios span apparently unrelated market categories earn an "illegitimacy discount", a penalty for not fitting already legitimate categories of demand. Similarly, in the world of film, movies that combine several genres receive lower critical evaluations than those more readily associated with a familiar genre (Hsu 2006). When eBay sellers auction items in multiple categories, they are less likely to complete transactions than more focused sellers. In addition to the risk of being perceived as illegitimate, lacking peers or rivals undermines the sense that a potential development counts as a social reality that merits attention (Kennedy 2008).

When category-defying inventions are collectively recognized as deserving their own categories, however, such recognition eases the dismissals and discounts that plague would-be innovators. In the patenting context, the process of recognizing inventions that blend multiple categories as a new type of innovation is supported by (1) categorization as a mechanism for coping cognitive limits taxed by inventions that blend multiple categories repeatedly in similar ways, (2) the prospect of reaching a wider audience, and (3) the institutional logic that governs evaluation. The following sections explain the effect of these factors and the interaction of cognitive and institutional factors.

Cognitive Limits

Initially, inventions that build on a larger number of established categories are harder to evaluate because understanding how each included category goes with all the others creates a set of pairwise analyses that increases exponentially. Given human cognitive limitations (Miller 1956; Simon 1947, 1974), this quickly taxes the cognitive capacity of various kinds of evaluators. All else equal, therefore, incorporating elements from more disparate fields makes it harder to evaluate a new invention.

The relationship between category blending and evaluation time is not a simple linear one, however, because humans cope with increasingly heavy cognitive burdens by switching from procedural handling of data to the use of heuristics and intuitions (Chaiken and Trope 1999). This second mode makes provisional assessments in ambiguous situations by matching elements of the situation to patterns learned in prior applicable experiences (Kruglanski, Thomson and Spiegel 1999). Thus, experience permits surprisingly good decisions even in situations where task complexity increases or when decision makers are pressed for time. Such decisions require recognizing “chunks” of situations that are similar to patterns learned through prior relevant experience (Chase and Simon 1973; Gobet, Voogt and Retschitzki 2004). Thus, while blending elements of a larger number of categories makes it harder to evaluate whether and how all the pieces fit together, that job is also eased when expert evaluators use patterns they have seen before in heuristics for analyzing fit among the various elements of new inventions.

In nanotechnology, for example, distinct patent class combinations underlie subfields for nano-bio (classes 424, 435, 530 and 636) and manipulation (classes 222, 365, and 366). The nano-bio subfield combines (1) Drug, bio-affecting and body treating compositions; (2) Chemistry: molecular biology and microbiology; (3) Chemistry: natural resins or derivatives, peptides or proteins, lignins or reaction products thereof; and (4) Organic compounds. The manipulation subfield combines classes for (1) Dispensing, (2) Static information storage and retrieval, and (3) Agitating. The nano-bio classes co-occur frequently with each other but infrequently with the manipulation classes, and vice versa. When such combinations recur as distinct patterns, implicit belief about regularity make it likely that they will be seen not as random sets of unrelated elements, but as a case of something —this is what Peirce calls “abduction”, or “hypothesis” (Peirce 1992: 188). Such inferences streamline the search for prior art by making them more cognitively available to evaluators (Tversky and Kahneman 1973). While co-citing a large number of patent classes guarantees neither the recurrence nor recognition that they are a case worth naming, but longer lists do stimulate the search for such patterns.[1]

This argument suggests a relationship to evaluation or "pending" time, which is our first hypothesis:

H1: Pending time increases with the number of primary classes a patent builds on, but at a diminishing rate.

Casting the Net Wide

While one might expect an invention that builds on multiple knowledge domains to receive less recognition by subsequent inventors in their citations of relevant prior art (Hsu 2006b; Zuckerman 1999), social movement research provides an alternative perspective. As activists strategically frame their causes to "bridge" multiple potential framings of the key issues and, in so doing, expand their potential audience (Benford and Snow 2000; McAdam, McCarthy and Zald 1996; Snow et al. 1986), they stand to gain a wider audience and have a larger impact (Trajtenberg, Henderson and Jaffe 1997). In effect, inventions that blend elements of a diverse collection of prior art effectively spread the task of analyzing them out over a wider, more diverse audience. That is, inventions that cite disparate classes of prior art effectively ask a broader community of subsequent inventors to consider their possible relevance as prior art, and this distributes the task of understanding the invention's value more widely.

To be clear, we are not suggesting inventors strategically cite multiple fields as a deliberate strategy for expanding what later inventors will consider when looking for prior art. In fact, the novelty required of successful patent applications creates mild incentives for inventors to do just the opposite—that is, to be sparing in references to prior art and related patent classes. At the same time, omitting references to relevant classes also limits the claims a patent can make and, therefore, only works as a strategy for maximizing perceived novelty if patent examiners fail to catch the omission of prior art that should have been cited. Examiners, however, are fully empowered to add classes as they see fit. Because the USPTO

[1] Prior research shows that roughly 40% of patent classes are, on average, added by examiners, not filers (Alcacer and Gittelman 2006). If the ambiguities of nascent fields make this ratio higher for nanotech patents, this would bias results in the direction of our prediction, at least until the meaning of the field is better understood.

examination process requires both comprehensive disclosure of relevant prior art and convincing demonstration of clear departures from the prior art, patent examination procedures limit inventors' opportunities to game the outcome by failing to cite relevant prior art and its associated classes.

Because the patent examination process governs examiner and inventor alike, the effects of citing classes of relevant prior art are analogous to frame bridging and expansion. When inventions do build on multiple classes of prior art, the process demands saying so. As mentioned above, this flags such inventions as potentially relevant to a wider audience of subsequent inventors, thus offsetting the fact that not fitting squarely into one class generally undermines value. As the number of combined classes increases, however, the growing complexity of analyzing the value of these connections bumps up against human cognitive limitations, as described above. Thus, the benefits of drawing on—and thus appealing to—multiple domains should eventually dissipate. These offsetting effects suggest the number of patent classes listed in a patent should have an inverted U-shaped effect on recognition by subsequent inventors:

> H2: Building on a low to moderate number of patent classes has a positive effect on the recognition patents receive from subsequent inventors, but building on a larger number of patent classes eventually has a negative effect on such recognition.

Institutional Logic

Since institutions tend to promote conformity with the established and legitimate (DiMaggio and Powell 1983), it might seem strange to argue that an institutional logic enables innovation. Indeed, as culturally and legally supported patterns of organization, practice, and thought, institutions do tend to reward conformity and sanction deviation. As shared ways of seeing what matters in the world (Berger 1972; Berger and Luckmann 1966), they both reflect and affect classification systems. When institutions establish certain categories as valid ways of making sense of the world, they can become taken for granted and persist even when they are no longer accurate descriptions of the activities they purport to classify (Meyer and Rowan 1977). Hence, categories are generally highly durable (Tilly 1998).

As mentioned above, however, institutional theory also suggests change occurs through "recombination" of elements from familiar but distinct fields or areas of expertise (Powell 1991: 199).

Opportunities for recombination are heightened when new developments highlight contradictions within or between elements of established institutions (Friedland and Alford 1991). By opening room for socially savvy actors to question institutions, contradictions enable savvy actors affect change by rearranging elements of institutions seen as clashing—a practice often referred to as *bricolage* (Clemens 1997; Clemens and Cook 1999). In markets, recombining elements of different product classes is a mechanism for producing new product categories and, ultimately, transforming the classification system itself (Lounsbury and Rao 2004). The mere presence of contradiction is not enough to prompt change, however. Although observing intra-individual inconsistencies can motivate action to resolve them (Festinger 1957), macro-social inconsistencies are catalysts for institutional change, not guarantors of it (Clemens 1997; Powell 1991).

Beyond contradiction, therefore, we argue that change to prevailing classification systems also depends on principles for judging legitimacy—the institutional logic—written into particular contexts or environments (Friedland and Alford 1991), and such logics are particularly important to recognizing new fields like nanotechnology. As elaborated by Thornton and Ocasio (1999), an institutional logic is a set of patterns that order reality and provide meaning to actions. Institutional environments both define and are defined by these distinctive principles for determining legitimacy. While institutional logics are evident in discourse, they are fundamentally rooted in recognizable practices, behaviors, decisions and recurring social forms (Alford and Friedland 1985).

When analyzing the similarities and differences between the logics of different institutional environments, zooming out to society as a whole highlights spheres of society—the market, government, education, family, and religion—that harbor serious contradictions about what is valued and why. Boltanski and Thévenot (1991) elaborate this point in their thoroughgoing exploration of the divergent standards of evaluation found in distinct spheres of society—what they call social “worlds”—featuring incommensurate standards for judging and justifying value. In the world of inspiration (art, music, etc.), originality and creativity are paramount. In the domestic world (the family and similar traditional hierarchies), tradition trumps efficiency, but in the world of the market, it’s the opposite. In the world of civic affairs (where people have a voice in shaping policy and selecting leadership), collective consensus is the ultimate standard. Because each world's standards of worth are generally incommensurable, the value of a thing can vary greatly from world to world. In the world of the university, for example, worth is settled neither by vote nor money, but by experts who weigh debates according to standards set by fields in which they are acknowledged masters. Outside the ivory tower, however, the authority of such masters often fails to translate into influence in the worlds of, say, the market or the family.

Combining the Friedland and Alford (1991) idea of institutional logic with the Boltanski and Thévenot (1991) concept of standards of worth, we suggest the logics and standards for evaluating worth ought to affect recognition of attempts to innovate that blend multiple categories rather than fitting into one. More specifically, where an institutional logic sets up standards of worth that prize novelty, the negative effects of combining multiple categories ought to be lessened—especially when, as argued above, blends are repeated often enough to become recognizable as entities unto themselves.

The Rise of Norms Favoring Interdisciplinary Research

In the world of patenting, therefore, the fates of new inventions reflect not only the logic of evaluation written into the USPTO's examination process, but also changing tastes for various kinds of novelty. One such taste important to nanotechnology's rise is the emergence of norms that enhance the status of interdisciplinary research relative to work that more clearly fits established disciplines in R&D. As mentioned earlier, the movement to embrace interdisciplinary research (IDR) favored R&D efforts that build on elements of multiple previously distinct fields. Over the last several decades, this movement has seen a rise in university- and government-based funding for IDR, and these programs have gradually embodied and institutionalized a logic of evaluation that is conducive to the sort of R&D needed to make nanotechnology visions real. We call this a pro-IDR logic.

Thus, we expect the logic of the USPTO examination process to combine with pro-IDR logic to affect both pending time, which is the time it takes patent examiners to rule on applications, and patent citations, which measure the extent to which subsequent inventors recognize a patent as relevant to their work. Although the patent process imposes a common logic of evaluation on examiners and inventors alike, the differences between these two roles are sufficiently different to be worth separate explanations.

Effects on Patent Examiners

When searching for the prior art potentially relevant to a patent application's claims, the examiner's first step is to implicitly categorize the invention. That is, looking up the relevant prior art requires selecting the classes of prior art to be considered. The more difficult it is to determine which classes to search, the longer the patent examination process will take, even if the examiner attempts to speed things up things by chunking classes as described above. This is because the prior would not have been filed under the new categories recognized later. As the movement to embrace a pro-IDR logic for funding and evaluating R&D gained momentum in universities and federal agencies that fund research, however, examiners are likely to become aware of the increasing rewards that came with pursuing projects that blended multiple fields and the related classes of prior art. Examiners' increasing awareness of this new fashion would prompt them to be more attuned to notice patent classes co-occurring together more often. Moreover, when patent examiners conduct their own prior art search, they look beyond application materials to scientific and technical journal literature (Sampat 2004), which suggests that the growth of interdisciplinary research funding and the rise of a related pro-IDR logic of evaluation would incline examiners to be more attuned to searching for "hybrid" inventions. As examiners see more applications with longer class lists, they should gradually stop viewing each long list as anomalous and start looking for chunks in these lists that could be the basis of meaningful new categories of R&D.

Besides the effects on individual examiners, a pro-IDR logic should also exert influences on organizational routines. As the growing number of boundary-crossing inventions both reflected and fostered awareness of nanotechnology as a nascent field, it also eventually led the USPTO to create the 977 class for nanotechnology in 2005. Significantly, this eased searching for patents with citations to not only 977, but also the multiple patent classes on which 977 builds. In recognition of what many individual examiners were already doing, this amounts to an organizational level change in routines. That the

USPTO struggles to recruit and retain examiners in new technological areas (Popp, Juhl and Johnson 2004; Thomas 2001), however, suggests informal collective recognition of new patterns is an important impetus for establishing new classes and related organizational routines. This leads to a third hypothesis:

H3: As pro-IDR norms are institutionalized, they should dampen the negative effect that building on a large number of classes otherwise has on a patent's pending time.

Effects on Subsequent Inventors

A similar mechanism applies to subsequent inventors' search for prior art they should be citing. In our second hypothesis, we suggested that building on a larger number of patent classes makes it harder for inventors to find and cite a patent, but the emergence of a pro-IDR logic should affect this. Specifically, it should incline inventors to think not only about making interdisciplinary connections in their own work, but also to find and cite prior work that legitimates that style by having done the same thing. That is, pro-IDR norms should have similar effects on both the search for new ideas and the search for relevant prior art. Hence, the rise of a pro-IDR logic should encourage inventors to recognize inventions that combine elements of fields whose frontiers were previously pushed more independently. Thus, we hypothesize:

H4: As pro-IDR norms are institutionalized, they should dampen the negative effects that building on a large number of classes has on a patent's forward citations.

Pattern Recognition and Typicality

The more that new inventions build on a particular set of categories, as in the above examples of the nano-bio and manipulation subfields of nanotechnology, the more likely it becomes that the elements of that set of categories will be recognized a new category unto itself (Rosch 1983). As members of a repeatedly combined set of categories become their own category, they become features of the new category's prototype (Rosch, Simpson and Miller 1976)—standards against which category fit is judged.

Categories thus reflect cognitive limitations in two ways. First, they ease the workload of dealing with sense data that contain an infinitude of fine gradations that could be explored. Categories are therefore both guides to experience (Zerubvael 1993) and filters that obscure what they do not capture

(Zuckerman 1999). Second, classification systems are not closed loop systems because they reflect the ongoing work of using categories to make sense of reality. When category-defying patterns become frequent, classification systems fail to economize the cognitive workload of sensemaking. Consequently, revising classification systems to reflect new patterns widely seen as common is a response to cognitive limits. The more closely an erstwhile hybrid matches an emerging template for a nascent category, the easier it is to evaluate, and the more likely it is to be subsequently recognized (Rosch 2002). This echoes Fleming's (2001) finding that the use of familiar combinations reduces the technological uncertainty of an innovation. Thus, for inventions that build on multiple categories of prior art, the effects of building on a larger set of patent classes should be moderated by similarities between that set and others that emerge as new category prototypes.

This leads to two final hypotheses:

H5: Pending time will be lower for patents that combine multiple categories of prior art in ways that mostly match, or are typical of, an emerging category.

H6: Forward citations will be higher for patents that combine multiple categories of prior art in ways that mostly match, or are typical of, an emerging category.

We can now summarize our theoretical argument: inventions that blend multiple categories of prior art benefit from fitness with standards that emerge from repetition and standards of worth that favor novelty.

DATA AND METHODS

We test our theoretical argument with empirical analyses of patents in the field of nanotechnology, or "nanotech" as it is often called. Building on the context section above, this section describes our data, variables and study design.

Nanotechnology Patent Data

Our data comes from NanoBank (Zucker and Darby 2007), a comprehensive collection of over 187,000 nanotechnology-related patents issued by the USPTO between 1976 and 2005. These patents are identified as nanotechnology-related by two methods. First, NanoBank research staff analyzed patent application text for relevant key words. Second, NanoBank also includes patents that belong to patent class 977, the nanotechnology patent class defined by the USPTO in 2005, as described earlier.

There are several reasons NanoBank patents provide and excellent site for testing our argument about how innovation gets recognized. First, the USPTO requires patent applicants to cite the prior art that inventions build on using the US Patent Classification (USPC) system. Comprised of numeric codes used to denote relevant the industry, product market category, function, or structure of an invention, USPC codes help researchers, inventors, and patent examiners, and intellectual property attorneys to find and indicate the relevant prior art. While examiners assign each patent to a single "original class" based on its most significant claim, a patent is assigned to more than one primary class when it builds on and extends prior art in multiple classes. According to USPTO's Manual of Patent Examining Procedure (MPEP), a patent class "has a title descriptive of its subject matter, is identified by a class number, and is subdivided into a number of subclasses" (§902.01). Per the MPEP, examiners weigh each claim carefully, checking it against the prior art they deem relevant. When the USPTO issues a patent, the number of patent classes it lists incorporates inputs from inventors and examiners.

Thus, we used the number of primary patent classes listed on granted nanotech patents as a measure of the extent to which a patent fits into a single distinctly categorized area of prior art versus building on and extending multiple areas of prior art. Even in nanotech patents, the mean number of primary classes was just less than 2 with a standard deviation of around 1, but the maximum was 16.

Variables

We used patents in the Nanobank dataset to construct the variables for our analyses.

Dependent Variables

Our hypotheses call for two dependent variables: pending time and forward citations.

Pending Time. Since the USPTO strives to assign patent applications to examiners based on matches between the patent claims and examiners' areas of expertise, the time it takes to review a patent provides a measure of how recognizable a patent application is to USPTO examiners. The USPTO measures pending time as the elapsed calendar time between submission and decision. Following this, we define our pending time variable as the natural log of the number of months elapsed between the filing date of a patent and the date it gets approved.

While pending time generally reflects the difficulty of evaluating a patent's claims, it could be affected by several factors such as year-to-year differences staffing relative to the overall volume of patent applications, or the adoption of technologies assist examiners in their work. While we control for several such factors, as described below, overall staffing shortages—a problem the USPTO did report having at several points in our analysis window—should bias results against our predictions by extending patent time even after nanotechnology becomes widely recognized.

Forward Citations. Because each patent application must cite the relevant prior art in the development of its claims to novelty, subsequent filers' citations to a patent reflect recognition of an invention's significance. All else equal, the number of citations a focal patent receives measures how widely the patent is recognized as being important to subsequent inventions. In the literature of technology and innovation, it is conventional to use patent citations as proxy for perceived values and/ or technological importance of a patent (Hall, Jaffe and Trajtenberg 2005; Jaffe 1986; Jaffe, Trajtenberg and Henderson 1993). We measure the recognition of a patent using the cumulative number of citations to a patent receives in its first three years.

Independent Variables

Number of Classes. We measure the number of categories an invention builds on by noting the number of primary patent classes it cites as prior art. While patents list both primary and secondary classes from the USPC, we only count primary classes. We also tried measures based on alternative classification systems, including the International Patent Classes (IPC) and the corresponding technology fields (instead of patent classes) defined by the World Intellectual Property Organization (WIPO). As detailed in "Robustness checks" (below), results were very similar.

Institutionalization of a pro-IDR Logic. Hypotheses 3 and 4 suggest the institutionalization of norms favoring IDR should reverse the negative effects of category blending. To measure the institutionalization of a pro-IDR logic for evaluating research, we interviewed 12 experts involved with NSF or NIH efforts to measure or promote IDR growth. From these interviews, we learned that the NSF and NIH—like the universities they fund—have struggled to define a clear standard for research that should be counted as interdisciplinary. While there is not yet a single approach that satisfies all stakeholders, our interviewees suggested we use their current best measure, which is the growth of government grants awarded to proposals with multiple principal investigators (PIs). In practice, reviewers find proposals from multiple PIs typically come from researchers with different disciplinary backgrounds. This measure is supported by the NSF's internal documentation and a National Academy of Sciences publication titled *Facilitating Interdisciplinary Research* (National Academy of Sciences 2004). The NSF itself uses annual statistics on single- versus multiple PI grants to demonstrate the trend of increasing NSF support for interdisciplinary research in a number of reports, including the *Impact of Proposal and Award Management Mechanisms (IPAMM) Final Report* (National Science Foundation 2007) and *Report to Congress on Interdisciplinary Research (National Science Foundation 2008).*

Thus, we measure the increasing institutionalization of pro-IDR norms using the percentage of multi-PI NSF grants for each year (%Multi-PI Awards). In pending time analyses, we use this measure for the year in which patent applications are filed (application year). In forward citation analysis, we use the percentage of multi-PI awards in the year a patent application is approved (grant year). Figure 3 shows the general pattern of multi-PI versus single-PI proposals funded by NSF over years. The overall trend shows steady growth in %multi-PI variable throughout our study period. Not surprisingly, therefore, When we used time as a proxy for the increasing institutionalization of norms favoring interdisciplinary research, results of our analyses were very similar, as we explain further below.

[INSERT FIGURE 3 ABOUT HERE]

Typicality. For hypotheses 5 and 6, we constructed a variable that measures how similar a patent's cited primary classes are to those in other nanotech patents. This is done in two steps. First, we compute a proximity index for each pair of classes in the dataset based on the number of times classes *i* and *j* appear together in the same patent. The proximity index P_{ij} for two classes *i* and *j* is the average of two proportions, and is calculated by dividing the number of times the classes are co-mentioned by the total number of times the first and second are mentioned, respectively. It cab written as follows:

$$P_{ij} = \frac{1}{2}\left(\frac{C_{ij}}{C_i} + \frac{C_{ij}}{C_j}\right) \tag{1}$$

where C_{ij} is the number of times classes *i* and *j* appear together in a patent (except for the focal patent) over the five years prior to the focal patent year, and C_i and C_j are the total number of times that class *i* and *j* appear in that time window, respectively. Second, to measure how typical a patent is with respect to others in the Nanobank data, we average the proximity indices for every unordered pair of patent classes it lists. Larger scores mean that a patent's listed classes occur together more frequently; conversely, smaller scores mean a patent's listed classes represent a more unusual or atypical blend of prior art areas. We calculate typicality as follows:

$$T = \frac{\Sigma P_{ij}}{\left[L(L-1)\right]/2} \tag{2}$$

where T is patent typicality, P_{ij} are the proximity indices for each unordered pair of classes listed by the patent, and L is the length of the patent's primary class list.

Control Variables

For yearly field-level controls, we use total NSF funding (in dollars), the number of nano-related patents granted, and the number of NSF-funded proposals. Our patent-level control variables include the year a patent is applied for (for pending time analyses) or granted (for forward citation analyses), number of inventors, number of assignees, assignee's patenting capability measured as the average number of patents previously granted by a patent's primary assignee, the primary assignee's institutional affiliation (university, firm or research institution), the number of claims a patent makes, and whether the USPTO was selected by NanoBank-specific content analysis procedures but has not (yet) been assigned to class 977 by the USPTO. Also, to control for situations where a patent's typicality score could be affected by a pair of classes that co-occur rarely even though other pairs are common, we also compute the standard deviation of the proximity indices for each patent.

As described briefly above, we also control for several organizational factors at USPTO that could affect evaluation time. Specifically, we control for staffing level, total number of pending patents, averaging pending time, and two measures that capture the pressure examiners faced, workload and backlog. Examiner workload is computed as total pending patents divided by total staffing, i.e., the average number of patents that an examiner is currently processing, and the backlog ratio is computed as the number of total pending patents divided by total filed applications. Moreover, to control for the effect personal computers and text-based search techniques had on examiner routines and productivity, we also include two era dummies: the PC era (1987-1999) and Internet era (2000 onwards). If our independent variables are significant when controlling for these new tools, that would suggest (a) class list length pushes examiners toward chunking over and above pressures related to workload, and that this holds (b) even as technology enables them to handle larger loads.

Models and Estimation

Since the dependent variable for our pending time analyses is the number of months before a patent is approved, we use survival analyses to assess the effects of covariates on the hazard rate of patent approval. We chose to fit our data with piecewise exponential models because the rate at which patent submissions of increasing age (pending time) are approved is not constant. Rather, it increases in the first few months and then decreases, yet it should be steady in any given period. Piece-wise exponential estimation is thus a reasonable technique. As described in the robustness section below, we also tried other functional forms for the hazard rate, but tests suggested that piecewise models had the best model fit.

For the forward citation analyses, the dependent variable is a count with overdispersion, so we use negative binomial regression with robust standard errors (Miles and Cameron 1982); results of Poisson regressions with robust standard were essentially the same.

To avoid multicollinearity problems from including quadratic and interaction terms, and also to make our results more interpretable, the independent variables were centered before creating the interaction variables. Also, to ensure our results are robust to different model specifications and choices of measures, we performed a series of robustness checks. For example, in evaluation time analyses, we also tried a different set of modeling technique and dependent variables: we first took the natural log of the number of months between a patent's submission date and approval date, and we then ran OLS regressions with this log-transformed dependent variable. The results were consistent with those of piecewise exponential analyses, showing solid support for our hypotheses. In OLS regressions, we also added year dummies to account for the possibility that examiners in different periods may have taken different approaches to evaluating applications. Although the pattern of results was unchanged, R-squared values were higher as expected when adding year dummies. Since many patents did not receive any citations during the observation window, we also tried zero-inflated count models for forward citation analyses to account for potential problems due to excess zeros. We discuss these alternative estimation methods and measures in greater detail below, and are happy the supply the results upon request.

RESULTS

Table 1 shows the correlations among variables used in our analyses. While correlations were high between our variable for the institutionalization of IDR and year-level controls, computing VIF scores after our regressions showed numbers well below the suggested thresholds (Greene 2000), and we found no signs of multi-collinearity. This is perhaps due to large number of observations in our analyses (over 187,000). That the percentage of multi-PI awards was highly correlated with year variables is consistent with the qualitative evidence suggesting that the emergence of a pro-IDR institutional logic precedes and aids the institutionalization of nanotechnology as a single new class of R&D.

[INSERT TABLE 1 ABOUT HERE]

Analyses of Pending Time

Table 2 shows results for analyses of evaluation time and tests of Hypotheses 1, 3 and 5; coefficients are unstandardized. Model 1 is a baseline with controls only. The negative signs of number of inventors and assignees suggest that patents with more inventors and assignees take longer to approve, and pending time is be longer for university patents than for firm patents. The positive sign of assignee patenting experience suggests that it accelerates the approval processes, hence reducing pending time. Lastly, the number of claims reduces the hazard rate, implying that complexity and scope of patents tend to prolong the evaluation time.

[INSERT TABLE 2 ABOUT HERE]

Model 2 shows results for Hypothesis 1, our prediction that pending time increases with the number of primary classes cited, but at a decreasing rate. Results support this prediction. The number of primary classes listed in each patent and its square are negatively and positively related to approval rate (both $p < .01$). This suggests that, all else equal, citing a larger number of primary classes makes patents harder to evaluate, and yet this eventually pushes evaluators to use chunking strategies to treat multiple classes as single items.

Model 3 shows results for Hypothesis 3, our prediction that emergence of a pro-IDR institutional logic should flip the hypothesized relationship between a patent's pending time and the number of classes it cites. The signs of the linear and quadratic versions of the primary class variable are the same as those in Model 3: the first and second order simple effects of class list length are negative and positive, respectively, for the full sample when the pro-IDR measure is at the average value (since we mean-centered both predicting variables). However, the first- and second-order interaction terms are significantly negative and positive, respectively (both $p < .01$), and the coefficient of the first-order class list length effect decreases dramatically in face of the interaction terms, indicating that the effect of class list length is moderated by a pro-IDR logic. But to better interpret our results, it is necessary to plot the predicted relative hazard of approval at different values of class list length and of pro-IDR logic.

[INSERT FIGURE 4.1 ABOUT HERE]

In Figure 4.1, we use the equation from Model 3 to graph the relationship between a patent's predicted pending time and the number of primary classes it cites. As we used actual data to generate the graph instead of holding everything covariates at their mean level, all values are within our data range and no hypothetical value is imposed when producing the charts. In Figure 4.1, the X-axis is the number of primary classes listed in each patent, and the Y-axis is the relative approval hazard (relative to the baseline hazard), and we plotted the relationship against the backdrop of three different levels of IDR, corresponding to different time periods. When the pro-IDR logic was weak, the data show a clear decreasing relationship between the number of primary classes patents cited and relative approval hazard, but the right tail of the line goes down at a slower rate as the number of classes goes up. This is consistent with our prediction that the number of primary classes a patent builds on increasing pending time, but at a diminishing rate, and that an increasing number of primary classes eventually pushes examiners to simplify lists by "chunking" multiple items together as a single one. As the pro-IDR logic catches on, however, the relative approval hazard initially decreases with the number of primary classes, but increases gradually again beginning at between 5 and 6. This suggests initial increases in the number of cited classes prolong pending time, but this effect eventually reverses. With further institutionalization of the pro-IDR logic, this pattern is even clearer, and the turnaround happens earlier, at about 4 primary classes.

To make the interpretation more intuitive and more consistent with our hypotheses, we also plotted the results from a parallel set of OLS analyses using the natural log of actual calendar time as the dependent variable[2], so the Y-axis is now "months to approval" instead of hazard ratio, as shown in Figure 4.2. The pattern presented in Figure 4.2 is very similar to what we saw from Figure 4.1 and supports our hypotheses. When the pro-IDR logic is still weak, the data show an increasing relationship between pending time and the number of primary class a patent cites, but the OLS results do not show the predicted diminishing relationship. As a pro-IDR logic grows and gets institutionalized, however, pending time initially increases with the number of primary classes yet declines gradually, supporting our argument that evaluators cope with the complexity of evaluating inventions that build on multiple classes by identifying recurring patterns and treating those class combinations as "chunks" that make it easier to relate such patents to relevant prior art.

Models 4 and 5 show results for Hypothesis 5, our prediction that building on multiple patent classes leads to lower pending time only when the classes cited together match those most typical of an emerging new field or category such as nanotech. To test this prediction, we split the Nanobank patents into low- and high-typicality subsamples based on the typicality score described above. Model 4 shows results for patents with typicality scores 1 S.D. or more below the mean, and Model 5 shows results for patents with typicality scores 1. S.D. or more above the mean. As predicted, our hypothesis that the penalties associated with blending multiple classes will reverse with the rise of a pro-IDR logic was supported only in the high-typicality sub-sample. In fact, the first- and second-order terms for the interaction between class list length and the pro-IDR logic are both significantly positive ($p < .01$), suggesting that the negative effect of building on multiple classes completely disappears for the high-typicality group. This pattern of results supports our argument that blending multiple patent classes—or categories of R&D—generally makes an invention less accessible and harder to evaluate unless multiple categories are repeatedly combined in an institutional environment where standards of worth prize novelty so that the blended categories are more likely to be recognized as a single new one.

[2] As mentioned before, we also ran OLS models with robust standard errors as alternative estimation. See the Appendix, Table A1, for results.

Analyses of Forward Citations

Table 3 shows the results of our analyses of forward citations and tests of Hypotheses 2, 4 and 6. Recall that we measure forward citations as the number of citations a patent receives in the first three years after its granting year. Model 1 is a baseline model with controls only. It shows that number of inventors, assignee's patenting experience, and number of claims listed in a patent all contribute to the number of citations nanotech patents receive from subsequent inventors. Patents with university and firm ownership tend to be cited more than patents assigned to other types of institutions.

[INSERT TABLE 3 AND FIGURE 5 ABOUT HERE]

Model 2 shows results for the test of Hypothesis 2, our prediction that forward citations have an inverted U-shaped relationship to the number of classes a patent builds on and extends. Model 2 shows strong significance ($p < .01$) for coefficients of both the linear and quadratic versions of the number of primary classes cited, but the signs suggest a convex curve, not the concave one we predicted. When the IDR interaction is added in Model 3, however, coefficients for both variables specifying the main effect of classes and its interaction with IRD are all significant ($p < .01$).

Again, it is necessary to interpret these results graphically to understand the interaction of the two quadratic functions, and doing so shows strong support for our dynamic predictions. Figure 5 uses the equation from Model 3 to show the predicted relationship between the number of primary classes a patent builds on the number of citations it receives in its first three years. The predicted values are graphed for each of 3 different levels of IDR: low (corresponds to years before 1988), moderate (roughly 1988-1998), and high (after 1998). While the main effect of primary classes shows different signs than what we predicted, this graph shows that this average effect over all periods breaks down by different levels of IDR just as we predicted. That is, the citations-to-classes relationship is concave at first, following an inverted-U shape. Later, however, the relationship is strictly increasing, and in later years when a pro-IDR logic is institutionalized, it flips to be convex, following a U-shaped relationship.

This is consistent with our argument that emergence of a pro-IDR institutional logic moderates negative reactions to category-blending innovations. As increased support for IDR institutionalized a pro-IDR logic for evaluating research, the relationship between forward citations and the number of primary patent classes it builds goes from convex to concave—that is, the inverted U-shaped relationship flips to a U-shaped relationship. As predicted in Hypothesis 6 and shown in Models 4 and 5, however, these effects occur only in the high typicality subsample. Patents with unusual class combinations do not seem to benefit from either the changing institutional logics or collective pattern recognition processes in the emerging nano community.

Robustness Checks

We performed a series of robustness checks to make sure that our findings are robust to alternative measures and model specifications. To eliminate the possibility our findings might be artifacts of the US Patent Classification (USPC) system, we also ran our analyses using measures based on both International Patent Classes (IPC) and the World Intellectual Property Organization (WIPO) proposed list of "technology fields" corresponding to the IPC system. Using information on how WIPO technology fields map into IPC codes (see *http://www.wipo.int/ipstats/en/statistics/patents*), we constructed measures for each of the two alternative systems and re-ran our analyses with them. In both case, results were consistent with the results reported in Tables 2 and 3, lending further support to our findings.

We also explored whether our findings are robust to different observation windows for forward citations. In addition to three-year window, we also tried windows of two years, four years, and five years. We also conducted time-series analyses to account for potential time effects. Based on these results, it appears our findings are not sensitive to reasonable changes in the forward citation window.

To assess whether results depend on patents with highly unusual characteristics, we re-ran the analyses after excluding outliers—cases such as a 10-year pending time or an extremely high number of citations. After removing such outliers from the analyses, however, results were unchanged. Thus, the results in Tables 2 and 3 include the entire Nanobank collection of nanotech patents.

To assess robustness with respect to estimation techniques, we tried several alternative model specifications. For the pending time analyses, we conducted Cox proportional hazards, log-normal, and OLS regressions with logged dependent variable. The patterns were consistent across models. To rule out effects of unobserved time-specific factors such as shortages or surpluses in examiner time, we included year dummies in the models; results were essentially the same with or without them. Since many patents receive no citations, we also tried zero-inflated Poisson and zero-inflated negative binomial regressions, but results were essentially unchanged.

Finally, we also conducted additional analyses to test the validity of our argument about typicality and cognitive load. Using the number of claims patents make as a proxy complexity, the number of claims should prolong pending time. As indicated in the controls section of Table 2, the number of claims does have a significant positive effect on pending time. Consistent with our argument that typicality reduces the cognitive demands of evaluation, there ought to be a significant interaction between typicality and the number of claims. With collective recognition of inventions that build on similar collections of categories of prior art, recognition of the emerging field should support a negative interaction between typicality and the number of claims. Consistent with this check, the typicality-claims interaction has a significant and negative effect on pending time after institutionalization, but not in the earlier periods.

DISCUSSION

Like all human institutions, classification systems can and do change, but not fitting into an established category risks being overlooked, dismissed or devalued (Zuckerman 1999). Existing categories fall into disuse when they fail to help people classify the world they encounter, and new ones emerge when people see things not easily stuffed into ready-at-hand boxes. When developments widely seen as useful fail to fit existing category systems, people fashion new categories for them by recombining elements of categories they already understand (Lounsbury and Rao 2004). Especially in cultural industries (Hirsch 1972), however, research in organization theory shows that audiences and critics often greet developments that blend elements of multiple existing categories with less than enthusiastic reviews (Hsu 2006b; Hsu, Hannan and Koçak 2009).

Things appear to be different in the worlds of academic research and technology R&D. In these institutional environments, prevailing standards of worth are kinder to category blends. Over the last generation, universities and government agencies have sponsored a growing number of initiatives to encourage researchers to combine ideas from distinctly categorized areas of expertise. As support for interdisciplinary research (IDR) have crystallized into a pro-IDR institutional logic, the idea of blending elements of multiple disciplines has become an increasingly standard recipe for advances likely to be recognized by academics as "contributions" or by industry leaders as "progress." In contrast, stakeholders in cultural industries are still more apt to view potential category-blending "innovations" as ungainly hybrids or even dangerous Frankenstein-like monstrosities (e.g., Ansell, Maxwell and Sicurelli 2006).

Asking how category hybrids get naturalized, we offer our own bit of blending by drawing on work in social psychology and organizational sociology to explain how cognition and context interact to produce change in classification systems. Cognition enters the picture because humans devise and use categories to cope with their cognitive limits, so categories are most meaningful when their definitions are widely understood without too much ambiguity. Since categories direct attention toward what people already understand, developing widespread understanding of a particular category blend is only likely if it shows up often enough that people start to see it as reasonable and useful to have a simpler "handle" for recognizing and talking about it. Institutions enter the picture because, as mentioned just above, the institutions of the R&D world support a logic for evaluating new ideas that favors new contributions. While it is probably stretching things to say this logic rejects conformity, it does de-value as "marginal" proposed contributions when they are too much like what is already known.

Contributions

Our study's main contribution is thus that cognitive limits and institutional logic combine to ease, but not eliminate, the categorical imperative (Zuckerman 1999)—the idea that the sanctions that come from combining elements of multiple categories rather than fitting one cleanly. In this, our study joins others that are finding situations when actors can break the bonds of categories (Phillips and Zuckerman 2001; Reagans and Zuckerman 2008). Ironically, however, we suggest that the price of this freedom from existing categories is to become similarly embedded in new ones. From that fate, there seems no escape.

While the emergence of a field like nanotechnology might appear to suggest categories and categorization are less important to the emergence of macro-social structures such as fields and markets than suggested by current theory (e.g., Hsu, Koçak and Negro 2010), we do not think so. Rather, we argue that repetition of the new and unfamiliar creates cognitive burdens that combine with institutions that prize novelty combine to change classification systems so that such things are recognized as innovation. As our findings show, nanotech inventions based on multiple patent classes were recognized faster and more widely as they grew in number and, in addition, with the emergence and institutionalization of a pro-IDR logic for evaluating research. This finding echoes theorists concerned with collective cultural recognition of patterns as enduring and real rather than ephemeral or purely subjective. For example, Durkheim ([1912] 1995) argues that collective agreement naturalizes beliefs about what is real versus, say, synthetic or inauthentic. Extending Durkheim, Berger and Luckmann (1966) argue that categories—and institutions—play a central role in naturalizing particular ways of seeing and structuring the world. In *Durable Inequality*, Tilly (1998) further expands on the importance of categories by showing how they support the naturalization of inequitable distributions of resources and opportunities—even for those who may be oppressed by the social arrangements they've taken for granted.

While prior research tends to view cognitive limits as a constant in generally negative responses to category blends, our findings show institutional logics moderate responses to developments that tax cognitive capacity. Building on institutional theory that links legitimacy to cognition (DiMaggio 1997; DiMaggio and Powell 1983; Friedland and Alford 1991; Scott 1995), we find that patents are recognized faster and more widely as norms favoring interdisciplinary research emerge and become institutionalized. Developments that blend multiple categories in similar ways generally attract attention as they grow in number, but our results suggest institutional logics can accelerate that response—or perhaps dampen it.

This finding holds implications for the diverse and growing literature exploring cross-level linkages between the micro-foundations and macro-social effects of attention, cognition and categorization (Breiger and Mohr 2004; Hsu et al. 2009). Within this broadly defined research program on categories, organizational ecologists have re-conceptualized the notions of organizational environment and form around categories, codes and identities (Hannan et al. 2007). A central feature of this program of research is the proposition that conformity pressures can arise from patterns of partial membership in multiple categories, not just the degree of membership in a single category (Hannan et al. 2007). Consistent with this idea, we show that the repetition of particular patterns of partial membership coincided with the recognition of nanotechnology as a theme uniting a diverse collection of category-blending inventions. In contexts where the logic of evaluation is less friendly to departures from the familiar, we do not expect such a finding will always occur, but our analysis suggests unorthodox inventions are more likely to be recognized as innovation when similar patterns of category blending recur in a context that discourages imitation while rewarding creativity.

Also, as a complement to literatures that emphasize the underlying quality of technologies and patents as determinants of field evolution (for a good overview, see Shane 2008), our study highlights factors relevant to the social process of determining which technologies most deserve recognition as innovation—that is, patents, patent citations, licenses, or, of course, sales, adoption and market growth. We say our study complements these literatures because we believe these outcomes are closely related to widespread perceptions of which technologies are superior in various ways.

Limitations and Directions for Further Research

Because the USPTO provides data on granted patents but not applications for years prior to 2001, our analysis includes only granted patents. Because rejected patents are not cited in patent applications, this limitation has no effect on the forward citation analysis. For the pending time analysis, however, results could be affected by unobserved heterogeneity that might be explained by including applications that are ultimately rejected. For example, some rejected patents that cite many primary classes could take less time to evaluate if they build on multiple classes in ways that suggest a lack of knowledge. If this is so, a two-stage analysis might show that the number of classes cited has different relationships to pending time for accepted and reject patents. In any case, our pending time analysis only speaks to the effects of class list size for approved patents.

To address this limitation, we used controls variables that could affect both approval and pending time. Specifically, we used application year to control for slow-downs to the increasing workload of patent examiners (Patent Office Professional Association 2007), number of claims as a proxy for complexity, and applications with more claims tend to take longer to review and suffer higher likelihood to be rejected; number of assignee's past patents, a proxy for assignees' patenting experience, and the assumption here is that patents filed by more experienced actors are more likely to be approved in a shorter amount of time. To a limited extent, these controls account for possible approval-related unobserved heterogeneity. Since data on patent applications is available for recent years, further research could explore these issues, albeit with a more limited smaller analysis period.

We also lacked data about how patents were assigned to divisions and examiners, and whether they were reassigned, but these factors could affect pending time. As Simon (1982) observed, organizations help humans cope with the wealth of information that creates a poverty of attention. Just as accumulated change periodic restructuring of the USPC to align it with current theories of classification, the USPTO also periodically restructures its divisions to take into account shifting demand for examiners' time. Ideally, our pending time analyses would control for these factors. Not having this data, however, we rely on comparing the analyses of two complementary dependent variables. In the forward citation analyses, coefficients for the number of primary classes and its square were highly significant, but not in the direction we predicted. Even as this finding suggests our pending time results are not spurious, it also suggests the possibility that unobserved structural features of examiner assignment could account for the difference in these results. Future research should explore how organizational structures result in better or worse fit for examiner assignment and how this affects the link between primary classes and pending time.

Given the growing importance of interdisciplinary research, measuring the extent of interdisciplinary research is a challenging problem that deserves of further investigation. As noted earlier, this is a question of considerable interest to policy makers and university leadership, so it is matter of both theoretical and practical significance. Drawing on current practice and recent publications on this matter (National Academy of Sciences 2004; National Science Foundation 2007, 2008), we used the percentage of multi-PI proposals as a measure of interdisciplinary research because, as we learned, collaborative activities are more likely to involve more than one discipline. Still, there are two alternative approaches that could also be used. First, we could count projects sponsored by NSF organizations that support so-called "cross-cutting" research, especially as defined by NSF's Office of Integrative Activities. Second, we could count proposals that are supported by multiple divisions at a funding agency. The first approach is easiest in terms of data gathering, but also probably the least precise since these initiatives include the pooling of divisional resources to fund large-scale investments in research equipment shared among projects that may or may not be truly interdisciplinary. The second measure may provide better data, but counting the actual number of interdisciplinary proposals is difficult. As the NSF's *2008 Report to Congress* suggests, "The proportion of co-funded awards is certainly lower than the proportion of awards supporting interdisciplinary research as this does not include, for example, the many programs that explicitly call for interdisciplinary proposals but are funded out of a single division."

While institutional context is important to easing negative reactions to hybrids, future research should critically examine this argument by studying change in social worlds that are more oriented to preserving the status quo. The world of R&D offers unique support and encouragement for launching into the spaces between disciplines in academics and engineering, and we intentionally chose such a world for this study. Studies of changes in the practices or beliefs held by families or members of religious communities would be excellent counterpoints to our research.

Speaking of context, using formally controlled patent classes to explore the effects of category blending raises several questions. Do classification systems such as USPC or SIC codes work in the same way as categories that are not formally maintained by government agencies? What effect does such support have for the stability of classification systems? How susceptible are such systems to influence attempts from actors affected by them? By replacing patent classes with technology fields in our supplemental analyses (see “Robustness Checks”, above), we found evidence that suggests our findings are not artifacts of the USPC. Still, these checks do not even scratch the surface of what could be gained from future research that could explore differences between classification systems like the USPC and categories that are less managed. If the former is less arbitrary than the latter, one might expect a system like the USPC to be less susceptible to change brought about by category blending. By this logic, our study is a somewhat conservative test. Further research should explore these issues more fully.

Finally, the Thornton and Ocasio (1999) study of shifting logics in higher education publishing suggests future research should consider a critical appraisal of the potential consequences of norms favoring interdisciplinary research. Among higher education publishers, Thornton and Ocasio found that hiring CEOs for business- rather than subject matter-expertise instituted a more market-oriented logic. This new logic tended to equate a title’s merits with its profits, not just the academic status of its authors, and that shifted power into the hands of business-oriented executives. As we noted earlier, some question whether the shift to logic favoring research that is more interdisciplinary—and more commercial—is doing the same thing to universities. As universities are increasingly active in licensing to control use of intellectual property developed by their faculty members (Mowery et al. 2002; Mowery et al. 2004), more academics are becoming entrepreneurs (Stuart and Ding 2006). In the extreme, this could lead universities away from open science (Colyvas and Powell 2006; Owen-Smith and Powell 2001).

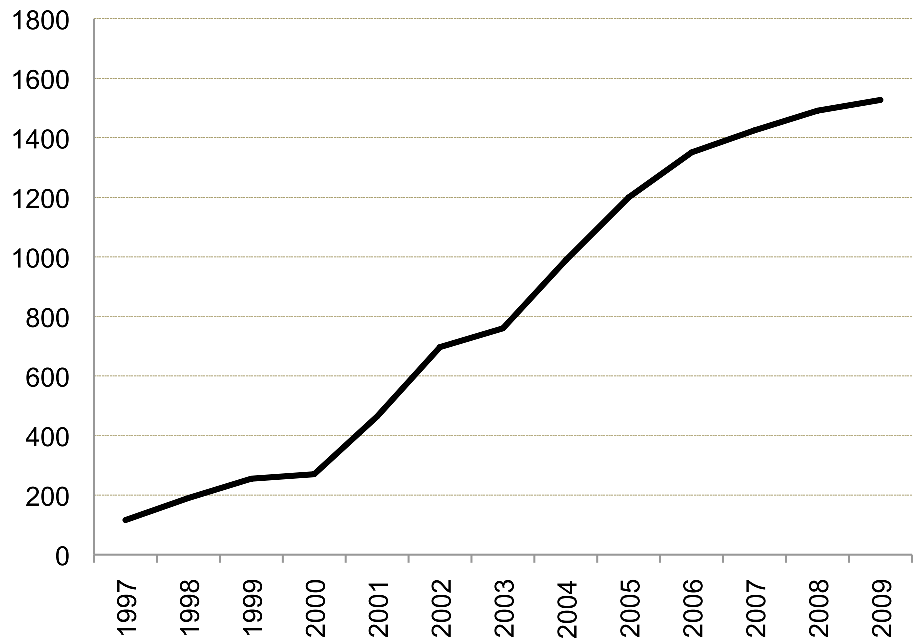
Our finding that institutional logic moderates negative reactions to category blends suggests future research should further explore how pro-IDR logic affects universities. In no way do we mean to argue that the conservative standards of certain cultural industries are either more or less appropriate than the more “progressive” standards found in certain academic institutions. What we do argue, however, is that amending a classification system to recognize new innovations depends on these standards, and the system-level ramifications of such recognition may not be immediately apparent.

CONCLUSION

Our society's high regard for innovation creates the impression that a similar regard applies to all sorts of efforts that involve "thinking outside the box", to use the vernacular. Using a less positive framing of much the same idea, persuasive research shows that "coloring outside the lines" draws predominantly negative reviews (Hsu 2006a, b; Hsu et al. 2009; Zuckerman 1999). Even if many category-blenders are dismissed as crackpots who lack the sense to see that their apparent disregard for field boundaries signals ignorance or poor taste, patenting is one context in which some nonetheless get recognized as innovators who pioneer new fields by blending elements of established ones in new ways. Obviously, getting recognized as a field pioneer depends on hitting upon ideas or technologies others find more profitably useful than prior alternatives, if any even exist. As Schumpeter acknowledged (1939: 85), however, reaching consensus about which technologies are best for a task is a social process that is distinct from the technological determinants of innovation. To that, we add that the social process of recognizing innovations that usher in new fields depends on both context-independent features of human categorization and cognition and on context-specific logics of evaluation institutionalized by organizational routines and socially shared norms. More specifically, recognizing innovation depends on cognitive limits that demand categorization of that which is new and unfamiliar yet seen repeatedly, and on institutions that encourage the supply of new ideas by rewarding novelty.

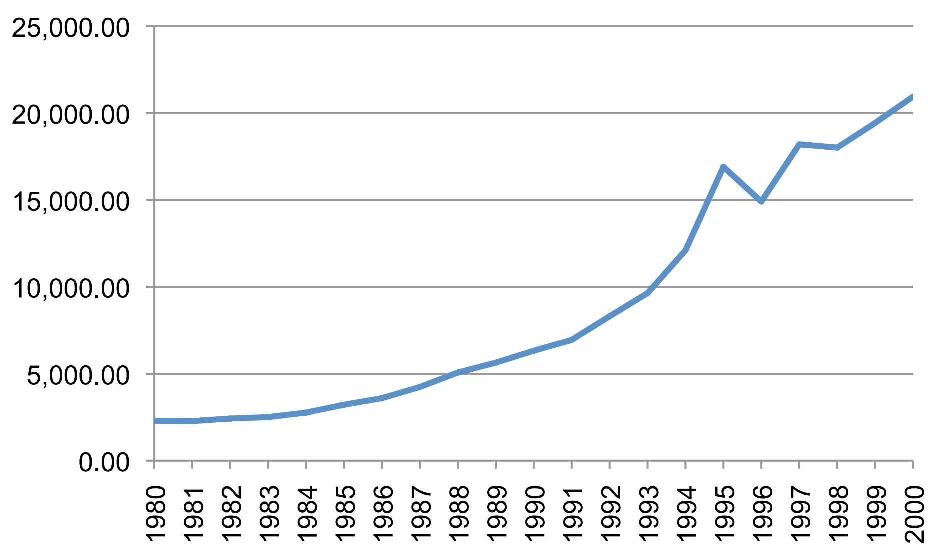
FIGURES AND TABLES

Figure 1: U.S. Government Nanotechnology R&D Expenditures, 1997-2009 ($ Millions)*



* Source: National Nanotechnology Initiative: http://www.nano.gov/html/about/funding.html
NSF Report: http://www.nsf.gov/crssprgm/nano/reports/mcr_05-0526_intpersp_nano.pdf

Figure 2: Nano Patents, 1980-2000*



**Note:* The numbers shown here are based on patents granted by USPTO and are drawn from NanoBank, a database that includes information on *granted* patents, but not applications as well.

Figure 3: Percentage of Multi-PI Proposals Funded by NSF among All NSF Awards, 1982-2006

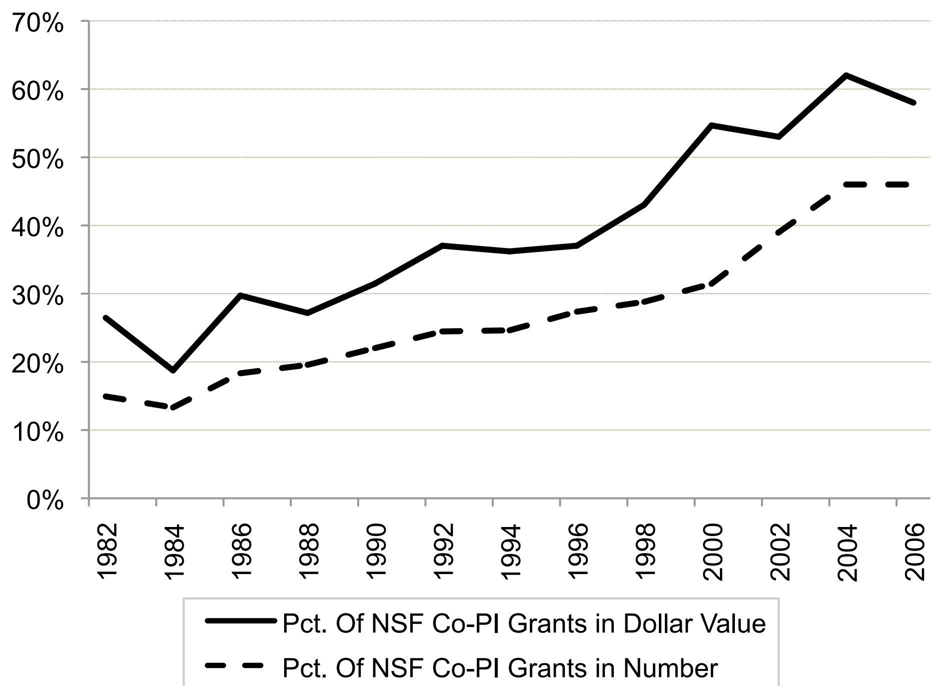


Figure 4.1: How pro-IDR norms affected the relationship between relative approval hazard and the number of classes a nanotech patent builds on (Hazard Rate estimates)

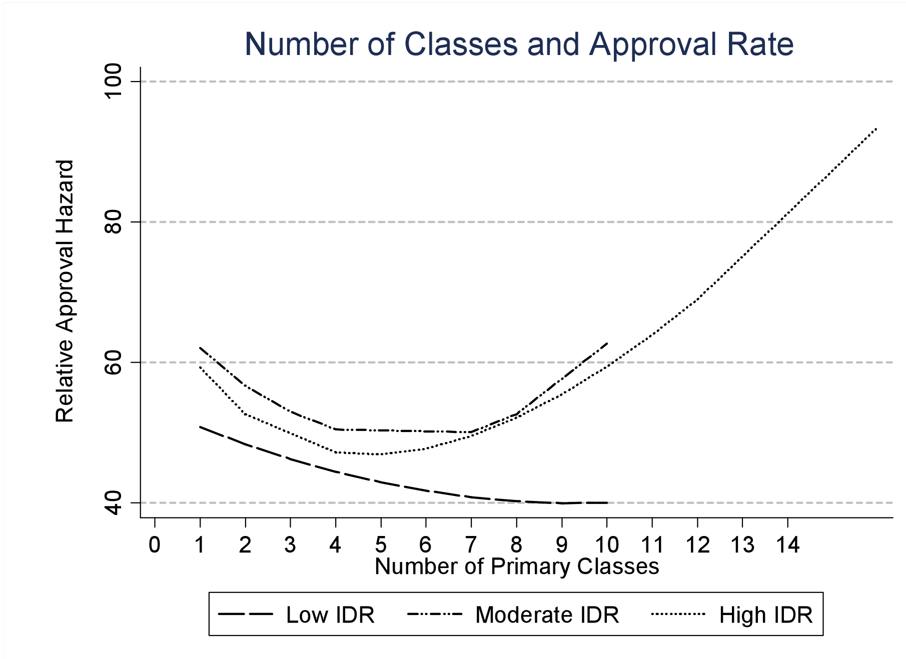


Figure 4.2: How pro-IDR norms affected the relationship between pending time and the number of classes a nanotech patent builds on (OLS estimates)

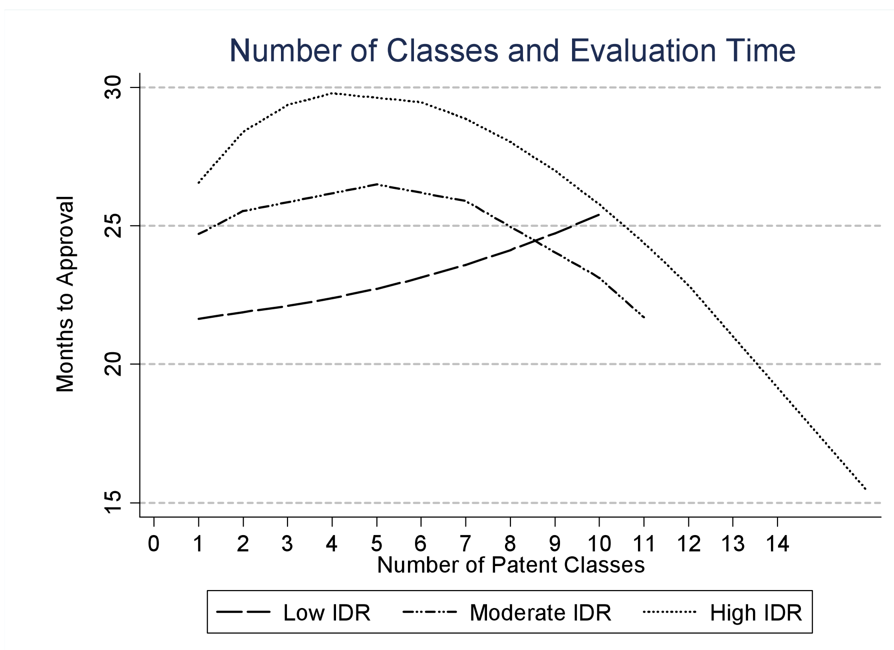


Figure 5: How pro-IDR Norms affected the relationship between forward citations and number of classes a nanotech patent builds on

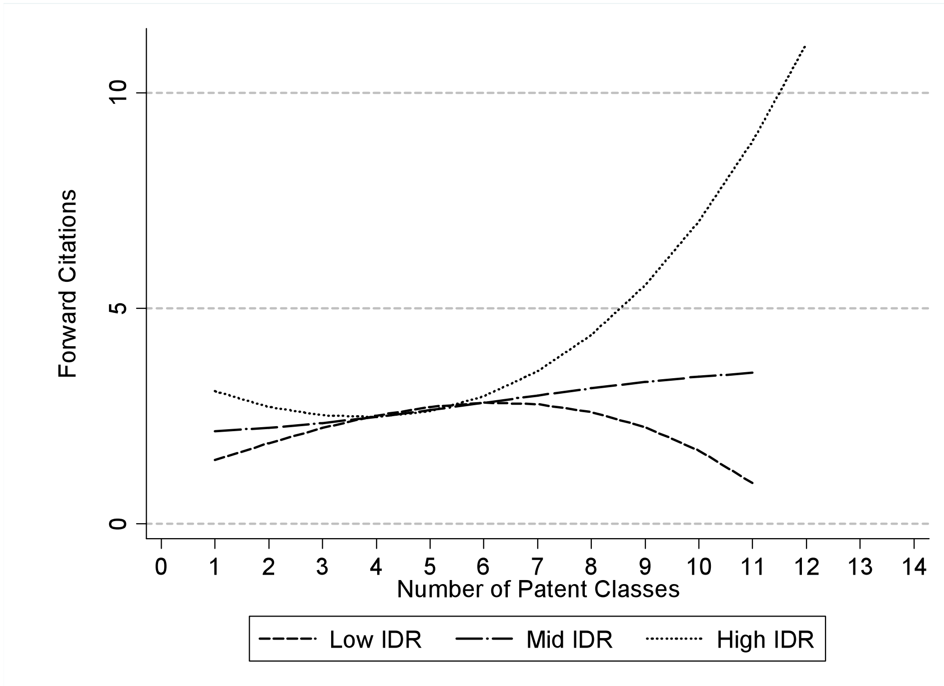


Table 1: Descriptive Statistics and Correlations

Variables	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. Forward Citations, 3 Yr	2.15	3.66																		
2. Months to Approval	27.62	13.74	–.05																	
3. Grant Yr (1946=0)	48.56	6.94	–.04	.20																
4. Application Yr (1946=0)	50.86	6.80	–.04	.04	.98															
5. Same Yr Patents	13.44	6.67	–.02	.20	.89	.87														
6. NSF Funding in App. Yr ($B)	1.49	0.48	–.08	.07	.82	.85	.79													
7. NSF Awards in App. Yr / 1000	5.75	0.46	–.06	.05	.73	.76	.68	.90												
8. NSF Funding in Grant Yr ($B)	1.52	0.50	.08	.18	.86	.83	.89	.79	.57											
9. NSF Awards in Grant Yr / 1000	5.78	0.46	.07	.16	.77	.74	.78	.64	.46	.90										
10. Number of Inventors	2.86	1.91	.03	.07	.15	.14	.13	.08	.07	.10	.09									
11. Number of Assignees	1.09	0.46	–.01	.03	.01	.01	.01	.00	.00	.01	.01	.16								
12. Assignee Exp. / 1000	0.81	1.14	.06	–.06	.01	.02	.00	–.02	–.01	–.02	–.01	.12	–.08							
13. Firm Dummy	0.79	0.41	.06	–.08	–.01	.00	–.01	.01	.01	–.02	–.02	.09	–.20	.22						
14. University Dummy	0.07	0.26	–.02	.08	.06	.05	.05	.02	.02	.04	.04	–.02	–.01	–.09	–.54					
15. Research Inst. Dummy	0.02	0.15	–.03	.02	.02	.02	.02	.01	.00	.01	.01	.03	.02	–.08	–.29	–.04				
16. Number of Claims / 10	2.07	1.79	.12	.08	.10	.09	.10	.09	.07	.07	.06	.05	.00	–.06	.00	.02	–.02			
17. Classes	1.91	1.07	.00	.05	–.11	–.12	–.10	–.07	–.06	–.06	–.06	.02	.02	–.10	–.05	.06	.01	.04		
18. % Multi-PI Awards in App. Yr	0.28	0.06	–.13	–.02	.90	.94	.73	.84	.75	.80	.70	.08	.00	.00	.02	.01	.01	.08	–.09	
19. % Multi-PI Awards in Grant Yr	0.32	0.09	–.15	.21	.93	.90	.82	.88	.75	.85	.77	.10	.01	–.01	.01	.03	.01	.10	–.07	.88

Table 2: Pending Time Analyses of Approval Rate for Patents in Nanotechnology, 1976−2005 †

Model Factors	(Model 1) Controls	(Model 2) H1	(Model 3) H3	(Model 4) Low Typ.	(Model 5) High Typ.
Classes		-3.421*** (0.185)	-0.063*** (0.005)	-0.015 (0.034)	-0.414*** (0.017)
Classes2		0.011*** (0.001)	0.012*** (0.001)	0.007 (0.009)	0.031*** (0.011)
Classes*%Multi-PI			-0.244*** (0.059)	0.057 (0.563)	0.646*** (0.213)
Classes2*%Multi-PI			0.066*** (0.023)	-0.075 (0.169)	0.821*** (0.300)
% Multi-PI Awards	2.994*** (0.578)	3.010*** (0.578)	2.959*** (0.579)	6.415*** (2.329)	2.562*** (0.874)
Total NSF Funding ($B)	0.261*** (0.095)	0.271*** (0.095)	0.273*** (0.095)	0.549 (0.381)	0.313** (0.131)
Total NSF Awards/1000	-0.075** (0.030)	-0.078*** (0.030)	-0.078*** (0.030)	-0.095 (0.118)	-0.112*** (0.042)
Examiner Staffing/1000	-0.179 (0.000)	-0.169 (0.000)	-0.169 (0.000)	-0.347 (0.000)	-0.120 (0.000)
# Pending Patents/1000	-0.001** (0.000)	-0.001** (0.000)	-0.001** (0.000)	0.000 (0.000)	-0.001 (0.000)
Ave. Pending Time	0.024*** (0.002)	0.023*** (0.002)	0.023*** (0.002)	0.023*** (0.007)	0.024*** (0.002)
Workload	-0.003** (0.001)	-0.003** (0.001)	-0.003** (0.001)	-0.008 (0.005)	-0.003* (0.002)
Backlog Ratio	0.573*** (0.039)	0.572*** (0.039)	0.572*** (0.039)	0.779*** (0.152)	0.563*** (0.056)
PC Era (1987-1999)	0.154*** (0.020)	0.155*** (0.020)	0.156*** (0.020)	0.177** (0.076)	0.182*** (0.030)
Internet Era (2000-)	-0.012 (0.058)	-0.017 (0.058)	-0.018 (0.058)	-0.275 (0.234)	-0.008 (0.081)
Nano Patents Entry/1000	-0.110*** (0.001)	-0.110*** (0.001)	-0.110*** (0.001)	-0.110*** (0.003)	-0.105*** (0.001)
App. Year	0.085*** (0.008)	0.084*** (0.008)	0.084*** (0.008)	0.049 (0.032)	0.072*** (0.011)
Number of Inventors	-0.035*** (0.001)	-0.034*** (0.001)	-0.034*** (0.001)	-0.021*** (0.005)	-0.033*** (0.002)
Number of Assignees	-0.030*** (0.006)	-0.030*** (0.006)	-0.029*** (0.006)	-0.040* (0.021)	-0.017** (0.008)
University Dummy	-0.197*** (0.011)	-0.194*** (0.011)	-0.194*** (0.011)	-0.135*** (0.042)	-0.132*** (0.015)
Firm Dummy	0.087*** (0.007)	0.087*** (0.007)	0.087*** (0.007)	0.042 (0.027)	0.071*** (0.010)
Research Inst. Dummy	-0.027* (0.016)	-0.024 (0.016)	-0.024 (0.016)	0.022 (0.069)	-0.017 (0.023)
Assignee Exp./1000	0.037*** (0.002)	0.036*** (0.002)	0.036*** (0.002)	0.008 (0.008)	0.024*** (0.003)
Number of Claims	-0.032*** (0.001)	-0.032*** (0.001)	-0.032*** (0.001)	-0.045*** (0.005)	-0.034*** (0.002)
Observations	927555	927555	927555	57160	483133
Log Likelihood	-117402.7	-117343.0	-117334.5	-6899.9	-61142.9

Model Imp. (lrtest. Chi2)	119.3***	136.4***

† Piecewise Exponential Hazard Rate Models; coefficients are exponentiated.

Table 3: Analyses of Forward Citations for Patents in Nanotechnology, 1976−2005 †

Model Factors	(Model 1) Controls	(Model 2) H1	(Model 3) H3	(Model 4) Low Typ.	(Model 5) High Typ.
Classes		-0.019***	0.348***	0.200	0.735***
		(0.004)	(0.015)	(0.144)	(0.031)
Classes2		0.016***	-0.039***	-0.045	-0.161***
		(0.001)	(0.006)	(0.042)	(0.020)
Classes* % Multi_PI			-1.306***	-0.191	-3.714***
			(0.053)	(0.494)	(0.120)
Classes2* % Multi_PI			0.185***	0.104	0.929***
			(0.021)	(0.148)	(0.120)
% Multi-PI Awards	4.870***	4.823***	4.101***	4.039	2.981***
	(0.915)	(0.915)	(0.914)	(3.574)	(1.311)
Total NSF Funding ($B)	0.809***	0.798***	0.810***	0.501	1.059***
	(0.099)	(0.099)	(0.099)	(0.412)	(0.141)
Total NSF Awards/1000	-0.179***	-0.174***	-0.176***	-0.012	-0.269***
	(0.042)	(0.042)	(0.042)	(0.174)	(0.061)
Examiner Staffing/1000	-0.132	-0.135	-0.196	-1.095**	0.274
	(0.129)	(0.129)	(0.129)	(0.504)	(0.192)
# Pending Patents/1000	-0.005***	-0.005***	-0.005***	0.001	-0.009***
	(0.001)	(0.001)	(0.001)	(0.004)	(0.001)
Ave. Pending Time	-0.019***	-0.019***	-0.020***	-0.015	-0.035***
	(0.003)	(0.003)	(0.003)	(0.013)	(0.005)
Workload	0.003*	0.003*	0.002	-0.009	0.007***
	(0.001)	(0.001)	(0.001)	(0.006)	(0.002)
Backlog Ratio	0.762***	0.759***	0.759***	0.381	0.968***
	(0.066)	(0.066)	(0.066)	(0.252)	(0.095)
PC Era (1987-1999)	-0.065**	-0.067**	-0.055**	-0.301***	-0.087**
	(0.027)	(0.027)	(0.027)	(0.102)	(0.041)
Internet Era (2000-)	-0.088*	-0.091**	-0.070	-0.371**	-0.127*
	(0.046)	(0.046)	(0.046)	(0.177)	(0.065)
Same Year Patents/1000	0.001	0.001	0.003	0.005	0.013***
	(0.002)	(0.002)	(0.002)	(0.010)	(0.003)
Grant Year (1940=0)	0.040***	0.041***	0.051***	0.055***	0.060***
	(0.002)	(0.002)	(0.002)	(0.010)	(0.002)
Pending Time	-0.002	-0.003	-0.010	-0.015	-0.014
	(0.010)	(0.010)	(0.010)	(0.039)	(0.014)
Number of Inventors	0.013***	0.013***	0.014***	0.028***	0.016***
	(0.002)	(0.002)	(0.002)	(0.007)	(0.002)
Number of Assignees	-0.006	-0.006	-0.004	0.023	-0.019**
	(0.007)	(0.007)	(0.007)	(0.030)	(0.010)
University Dummy	0.069***	0.068***	0.071***	0.231***	0.054***
	(0.015)	(0.015)	(0.014)	(0.056)	(0.021)
Firm Dummy	0.226***	0.227***	0.227***	0.274***	0.238***
	(0.010)	(0.010)	(0.010)	(0.036)	(0.014)
Research Inst. Dummy	-0.104***	-0.102***	-0.108***	-0.104	-0.041
	(0.023)	(0.023)	(0.023)	(0.096)	(0.032)
Assignee Exp./1000	0.074***	0.074***	0.071***	0.036***	0.067***
	(0.003)	(0.003)	(0.003)	(0.011)	(0.004)
Number of Claims	0.123***	0.122***	0.122***	0.125***	0.126***
	(0.002)	(0.002)	(0.002)	(0.007)	(0.003)
Constant	-1.584***	-1.633***	-1.659***	-0.840***	-1.124***
	(0.228)	(0.228)	(0.228)	(1.415)	(0.315)
Observations	183375	183375	183375	11222	96310
Log Likelihood	-390292.2	-390218.2	-382831.6	-24075.0	-197458.0
Model Imp. (LL test. Chi2)		132.1***	838.1***		

† ML Estimates of Negative Binomial Regressions

APPENDIX

Table A1: Alternative Analyses of Pending Time for Patents in Nanotechnology, 1976−2005 †

Model Factors	(Model 1) Controls	(Model 2) H1	(Model 3) H2	(Model 4) Low Typ.	(Model 5) High Typ.
Classes		0.024**	0.025**	0.011	0.101**
		(0.001)	(0.001)	(0.009)	(0.003)
Classes2		-0.005**	-0.005**	-0.001	-0.019**
		(0.000)	(0.001)	(0.003)	(0.005)
Classes*%Multi-PI			0.134**	0.071	-0.012
			(0.025)	(0.204)	(0.128)
Classes*%Multi-PI			-0.048**	-0.008	-0.208
			(0.010)	(0.056)	(0.184)
% Multi-PI Awards	-2.034**	-1.991**	-1.947**	-3.079**	-1.945**
	(0.219)	(0.219)	(0.220)	(0.845)	(0.336)
Total NSF Funding ($B)	-0.010	-0.020	-0.021	0.008	-0.046
	(0.038)	(0.038)	(0.038)	(0.145)	(0.052)
Total NSF Awards / 1000	0.066**	0.069**	0.069**	0.031	0.083**
	(0.011)	(0.011)	(0.011)	(0.043)	(0.016)
Examiner Staffing	-0.000**	-0.000**	-0.000**	0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total # Pending Patents	0.000**	0.000**	0.000**	0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average Pending Time	-0.034**	-0.033**	-0.033**	-0.035**	-0.033**
	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)
Workload	-0.002**	-0.002**	-0.002**	0.002	-0.001+
	(0.000)	(0.001)	(0.000)	(0.002)	(0.001)
Backlog Ratio	-0.300**	-0.295**	-0.295**	-0.411**	-0.304**
	(0.013)	(0.013)	(0.013)	(0.050)	(0.019)
PC Era (1987-1999)	-0.061**	-0.060**	-0.061**	-0.095**	-0.061**
	(0.007)	(0.007)	(0.007)	(0.027)	(0.011)
Internet Era (2000-)	-0.113**	-0.105**	-0.105**	-0.121	-0.090**
	(0.022)	(0.022)	(0.022)	(0.084)	(0.031)
Same Year Patents / 1000	0.102**	0.101**	0.101**	0.097**	0.098**
	(0.001)	(0.001)	(0.001)	(0.004)	(0.001)
App. Year	-0.088**	-0.087**	-0.087**	-0.081**	-0.081**
	(0.003)	(0.003)	(0.003)	(0.012)	(0.004)
Number of Inventors	0.013**	0.013**	0.013**	0.009**	0.013**
	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)
Number of Assignees	0.013**	0.012**	0.012**	0.017+	0.007**
	(0.002)	(0.002)	(0.002)	(0.008)	(0.003)
Assignee Exp. / 1000	-0.014**	-0.012**	-0.012**	-0.001	-0.009**
	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)
Number of Claims	0.015**	0.014**	0.014**	0.019**	0.016**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Constant	7.825**	7.770**	7.230**	6.771**	6.933**
	(0.140)	(0.140)	(0.167)	(0.659)	(0.240)
Observations	201672	201639	201639	12594	104950
Adjusted R^2	0.284	0.285	0.286	0.249	0.288
Model Imp. (F Test)	3130.61**	287.11**	23.47**		

†Robust OLS regression; standard errors in parentheses.
Significance Levels: + p<.10, * p<.05, ** p<.01

Control variables omitted for space: Dummies for University (sig.), Research Institute (N.S.) and

Firm (Sig. except model 4), Authority (Sig. except model 4) and Nanobank ID (Sig.)

REFERENCES

Alcacer, J., M. Gittelman. 2006. How do I know what you know? Patent examiners and the generation of citations. *Review of Economics and Statistics* **88**(4) 774-779.

Alford, R.R., R. Friedland. 1985. *Powers of Theory: Capitalism, the state, and democracy*. Cambridge University Press, New York: NY.

Ansell, C., R. Maxwell, D. Sicurelli. 2006. Protesting Food: NGOs and Political Mobilization in Europe. C. Ansell, D. Vogel, eds. *The Contested Governance of European Food Safety*. The MIT Press, Cambridge, MA.

Arthur, W.B. 1989. Competing Technologies, Increasing Returns, and Lock-In by Historical Events. *Economic Journal* **99**(394) 116-131.

Arthur, W.B. 1990. Positive Feedbacks in the Economy. *Scientific American* **262**.

Azoulay, P., W. Ding, T.E. Stuart. 2007. The Impact of Academic Patenting on the Rate, Quality, and Direction of (Public) Research Output. *Journal of Industrial Economics* **63** 599-623.

Benford, R.D., D.A. Snow. 2000. Framing Processes and Social Movements: An Overview and Assessment. *Annual Review of Sociology* **26** 611-639.

Berger, J. 1972. *Ways of seeing*. British Broadcasting Corporation (Penguin), London.

Berger, P.L., T. Luckmann. 1966. *The Social Construction of Reality: a treatise on the sociology of knowledge*. Anchor Books, NY.

Boltanski, L., L. Thévenot. 1991. *On Justification: Economies of Worth*. Princeton University Press, Princeton, NJ.

Breiger, R.L., J.W. Mohr. 2004. Institutional Logics from the Aggregation of Organizational Networks: Operational Procedures for the Analysis of Counted Data. *Computational & Mathematical Organization Theory* **10**(1) 17-43.

Campbell, D.T. 1958. Common fate, similiarity, and other indicies of the status of aggregrates of persons as social entities. *Behavioral Science* **3**(14-25).

Carroll, G.R., M.T. Hannan. 1989. Density Dependence in the Evolution of Populations of Newspaper Organizations. *American Sociological Review* **54**(4) 524-541.

Chaiken, S., Y. Trope. 1999. *Dual-process theories in social psychology*. Guilford Press, New York.

Chase, W.G., H.A. Simon. 1973. Perception in chess. *Cognitive psychology* **4**(1) 55-81.

Clemens, E.S. 1997. *The People's Lobby: Organizational Innovation and the Rise of Interest Group Politics in the United States, 1890-1925*. University of Chicago Press, Chicago.

Clemens, E.S., J.M. Cook. 1999. Politics and Institutionalism: Explaining Durability and Change. *ARS* **25** 26.

Colyvas, J., J.A. Powell. 2006. Roads to Insititutionalization: The Remaking of Boundaries Between Public and Private Science *Research in Organizational Behavior* **27** 305-353.

Darby, M., L. Zucker. 2006. Grilichesian Breakthroughs: Inventions of Methods of Inventing in Nanotechnology and Biotechnology. *Annales d□conomie et Statistique*.

David, P. 1985. Clio and the economics of QWERTY. *Economic History* **75** 227-332.

DiMaggio, P. 1997. Culture and Cognition. *Annual Review of Sociology* **23** 263-287.

DiMaggio, P., W.W. Powell. 1983. The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Fields. *ASR* **48** 147-160.

Drexler, K.E., R. Whitaker. 1986. *Engines of creation: the coming era of nanotechnology*. Doubleday/Anchor Press.

Durkheim, E. [1912] 1995. *The Elementary Forms of Religious Life*. Free Press, NY.

Festinger, L. 1957. *A Theory of Cognitive Dissonance*. Row, Peterson and Company, Evanston, IL.

Fleming, L. 2001. Recombinant uncertainty in technological search. *Management Science* **47**(1) 117-132.

Friedland, R., R.R. Alford. 1991. Bringing society back in: symbols, practices, and institutional contradictions. W.W. Powell, P.J. DiMaggio, eds. *The New Institutionalism in Organizational Analysis*. University of Chicago Press, Chicago, 232-263.

Gibbons, M., C. Limonges, H. Nowotny, S. Schwartzman, P. Scott, M. Trow. 1994. *The New Production of Knowledge: the dynamics of science and research in contemporary societies*. Sage Publictaions, Thousand Oaks, CA.

Gobet, F., A.d. Voogt, J. Retschitzki. 2004. *Moves in mind: The psychology of board games*. Psychology Press.

Greene, W.H. 2000. *Econometric Analysis*, Fourth ed. Prentice-Hall, Upper Saddle River, NJ.

Grodal, S. 2008. Categorizing a Field: The Use of the Nanotechnology Label Across Communities *Working Paper.* Boston University, Boston, MA.

Hall, B.H., A. Jaffe, M. Trajtenberg. 2005. Market value and patent citations. *Rand Journal of Economics* 16-38.

Hannan, M.T., J. Freeman. 1989. *Organizational Ecology*. Harvard University Press, Cambridge, MA.

Hannan, M.T., L. Pòlos, G.R. Carroll. 2007. *Logics of Organization Theory: Audiences, Codes, and Ecologies*. Princeton University Press, Princeton.

Hirsch, P.M. 1972. Processing fads and fashions: an organization-set analysis of cultural industry systems. *AJS* **77**(4) 639-659.

Hsu, G. 2006a. Evaluative schemas and the attention of critics in the film industry. *Industrial and Corporate Change* **15** 467-496.

Hsu, G. 2006b. Jacks of All Trades and Masters of None: Audiences' Reactions to Spanning Genres in Feature Film Production. *ASQ* **51** 420–450.

Hsu, G., M.T. Hannan, Ö. Koçak. 2009. Multiple category memberships in markets: A formal theory and two empirical tests. *ASR* **74**(1) 150-169.

Hsu, G., Ö. Koçak, G. Negro, eds. 2010. *Categories in Markets: Origins and Evolution*. Emerald.

Jaffe, A.B. 1986. Technological Opportunity and Spillovers from R&D: Evidence from Firms' Patents, Profits and Market Value. *American Economic Review* **76**(No. 5, December) 984-1001.

Jaffe, A.B., M. Trajtenberg, R. Henderson. 1993. Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations. *The Quarterly Journal of Economics* **108**(3) 577-598.

Kennedy, M.T. 2008. Getting Counted: Markets, Media, and Reality. *ASR* **73** 270-295.

Kruglanski, A., E. Thomson, S. Spiegel. 1999. Separate or equal? Bimodal notions of persuasion and a single process "unimodel". S. Chaiken, Y. Trope, eds. *Dual-Process Theories in Social Psychology* Guilford Press New York, 293-313.

Lawrenece, R.J., C. Despres. 2004. Futures of Transdisciplinarity. *Futures* **36**(4) 397-405.

Lounsbury, M., H. Rao. 2004. Sources of Durability and Change in Market Classifications: A Study of the Reconstitution of Product Categories in the American Mutual Fund Industry, 1944-1985. *SF* **82**(3) 969-999.

March, J.G., J.P. Olsen. 1989. *Rediscovering institutions : the organizational basis of politics*. Free Press, New York.

McAdam, D., J.D. McCarthy, M.N. Zald, eds. 1996. *Comparative Perspectives on Social Movements: Political Opportunities, Mobilizing Structures, and Cultural Framings*. Cambridge University Press, Cambridge.

McCray, P. 2005. Will small be beautiful? Making policies for our nanotech future. *History and Technology* **21**(2) 177-203.

Meyer, J.W., B. Rowan. 1977. Institutionalized Organizations: Formal Structure as Myth and Ceremony. *ASR* **83** 340-363.

Miles, R.H., K.S. Cameron. 1982. *Coffin nails and corporate strategies*. Prentice-Hall, Englewood Cliffs, N.J.

Miller, G.A. 1956. The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological Review* **63** 81-97.

Mische, A. 2011. Relational Sociology, Culture, and Agency. J. Scott, P. Carrington, eds. *Sage Handbook of Network Analysis*. Sage, New York.
Mowery, D.C., B.N. Sampat, A.A. Ziedonis. 2002. Learning to Patent: Institutional Experience, Learning, and the Characteristics of U. S. University Patents after the Bayh-Dole Act, 1981-1992. *Management Science* **48**(1) 73-89.
Mowery, D.C.M., Nelson, Richard R., B.N. Sampat, A.A. Ziedonis. 2004. *Ivory Tower and Industrial Innovation: University-Industry Technology Transfer before and after the Bayh-Dole Act*. Stanford University Press, Stanford, CA.
National Academy of Sciences. 2004. Facilitating Interdisciplinary Research. National Academies Press.
National Science Foundation. 2007. Impact of Proposal and Award Management Mechanisms (IPAMM) Final Report
National Science Foundation. 2008. Report to Congress on Interdisciplinary Research at the National Science Foundation.
Negro, G., M.T. Hannan, H. Rao. 2010. Categorical contrast and audience appeal: niche width and critical success in winemaking. *Industrial and Corporate Change* **19**(5) 1397-1425.
Owen-Smith, J., W.W. Powell. 2001. To Patent or Not: Faculty Decisions and Institutional Success at Technology Transfer. *Journal of Technology Transfer* **26** 99-114.
Patent Office Professional Association. 2007. Open Letter From a Coalition of Patent Examiner Representatives.
Peirce, C.S. 1992. Induction, Deduction and Hypothesis. N. Houser, C. Kloesel, eds. *The Essential Charles Peirce*. University of Indiana Press, Bloomington, 186-199.
Phillips, D.J., E.W. Zuckerman. 2001. Middle-Status Conformity: Theoretical Restatement and Empirical Demonstration in Two Markets. *AJS* **107**(2) 379-429.
Popp, D., T. Juhl, D. Johnson. 2004. Time in purgatory: Examining the grant lag for US patent applications. *Topics in Economic Analysis and Policy* **4**(1).
Powell, W.W. 1991. Expanding the scope of institutional analysis. W.W. Powell, P. DiMaggio, eds. *The New Institutionalism in Organizational Analysis*. University of Chicago Press, Chicago.
Powell, W.W., J. Owen-Smith. 1998. Universities and the Market for Intellectual Property in the Life Sciences. *Journal of Policy Analysis and Management* **17**(2) 253-277.
Powell, W.W., D.R. White, K.W. Koput, J. Owen-Smith. 2005. Network Dynamics and Field Evolution: The Growth of Interorganizational Collaboration in the Life Sciences. *AJS* **110**(4) 1132-1205.
Rao, H., P. Monin, R. Durand. 2003. Institutional Change in Tocque Ville: Nouvelle Cuisine as an Identity Movement in French Gastronomy. *AJS* **108**(4) 795-843.
Reagans, R.E., E.W. Zuckerman. 2008. All in the family: reply to Burt, Podolny, and van de Rijt, Ban and Sarkar. *Industrial and Corporate Change* **17**(5) 979-999.
Rosch, E. 1983. Prototype classification and logical classification: The two systems. E.F. Scholnick, ed. *New Trends in Conceptual Representation: Challenges to Piaget's Theory?* Erlbaum, Hillsdale, NJ.
Rosch, E. 2002. Principles of categorization. D.J. Levitin, ed. *Foundations of cognitive psychology: Core readings.* MIT Press, 251-270.
Rosch, E., C. Simpson, R.S. Miller. 1976. Structural Bases of Typicality Effects. *Journal of Experimental Psychology-Human Perception and Performance* **2** 491–502.
Ruef, M., K. Patterson. 2009. Credit and Classification: The IMpact of Industry Boundaries in Nineteenth-century America. *ASQ* **54** 486-520.
Sampat, B.N. 2004. Examining patent examination: an analysis of examiner and applicant generated prior art, University of Michigan.
Schumpeter, J.A. 1939. *Business Cycles*. McGraw-Hill Book Company, Inc., New York.
Scott, W.R. 1995. *Institutions and organizations*. Sage, Thousand Oaks.
Shane, S., ed. 2008. *The Handbook of Technology and Innovation Management*. Wiley-Blackwell, West Sussex, England.

Simon, H.A. 1947. *Administrative Behavior: A Study of Decision-Making Process in Administrative Organizations*. MacMillan, Chicago.

Simon, H.A. 1974. How big is a chunk? *Science* **183** 482-488.

Simon, H.A. 1982. *Designing organizations for an information-rich world*. MIT Press, Cambridge, MA.

Snow, D.A., B.E. Rochford, S.K. Worden, R.D. Benford. 1986. Frame Alignment Processes, Micromobilization, and Movement Participation. *American Sociological Review* **51**(4) 464-481.

Stuart, T.E., W. Ding. 2006. When Do Scientists Become Entrepreneurs? The Social Structural Antecedents of Commercial Activity in the Academic Life Sciences. *AJS* **112**(1) 97-144.

Thomas, J. 2001. Collusion and Collective Action in the Patent System: A Proposal for Patent Bounties, 2001 U. *Ill. L. Rev* 305-354.

Thornton, P.H., W. Ocasio. 1999. Institutional Logics and the Historical Contingency of Power in Organizations: Executive Succession in the Higher Education Publishing Industry, 1958-1990. *AJS* **105**(3) 43.

Thurs, D.P. 2007. Tiny Tech, Transcendent Tech: Nanotechnology, Science Fiction, and the Limits of Modern Science Talk. *Science Communication* **29**(1) 65-95.

Thursby, J.G., M.C. Thursby. 2003. University Licensing and the Bayh-Dole Act. *Science* **301**(5636) 1052.

Tilly, C. 1998. *Durable inequality*. University of California Press, Berkeley, Calif.

Trajtenberg, M., R. Henderson, A. Jaffe. 1997. University versus corporate patents: A window on the basicness of invention. *Economics of Innovation and New Technology* **5**(1) 19-50.

Tversky, A., D. Kahneman. 1973. Availability: A heuristic for judging frequency and probability **5**(2) 207.

Weick, K.E. 1995. *Sensemaking in Organizations*. Sage, Thousand Oaks.

White, H.C. 1981. Where Do Markets Come From? *AJS* **87** 517-547.

White, H.C. 2002. *Markets from Networks: Socioeconomic models of production*. Princeton University Press, Princeton.

Zerubvael, E. 1993. *The Fine Line: Making Distinctions in Everyday Life*. University of Chicago Press, Chicago, IL.

Zucker, L.G., M.R. Darby. 2007. Nanobank Data Description, Release 1.0 (beta-test). UCLA Center for International Science, Technology, and Cultural Policy and Nanobank.

Zuckerman, E.W. 1999. The categorical imperative: securities analysts and the illegitimacy discount. *AJS* **104**(5) 1398-1438.