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OBLITERATION, SYMBOLIC ADOPTION, AND OTHER FINICKY CHALLENGES IN TRACKING INNOVATION DIFFUSION

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INTRODUCTION

Diffusion is a central topic in strategic management and entrepreneurship. At their core, diffusion studies seek to explain “how things…get from here to there” (Katz, 1999: 145). In most cases, however, researchers cannot directly assess whether and when a “thing” actually has moved from “here” to “there” and must rely, therefore, on proxies such as keywords and index terms to identify patterns. Unfortunately, we have little evidence on the correspondence between these proxies and “actual” diffusion patterns. In this paper, we develop four mechanisms that can account for divergence between “actual” diffusion patterns and patterns derived from two oft-used measures, keywords and index terms. We then quantitatively examine the diffusion of “green chemistry” by comparing results obtained from keywords and index terms against assessments by domain experts. Our results point to considerable differences between measurement approaches, especially in the early years of the field. Specifically, we detail how different measures reflect different magnitudes of activity, publication outlets, organizational demography, and collaboration patterns. We then describe circumstances in which domain expert assessments may be especially valuable to researchers. We conclude that diffusion studies must be cautious to interpret their results in light of the particular measure used, and we make a case for strengthening diffusion studies by exploiting differences between measures.

MEASUREMENT OF INNOVATION DIFFUSION AND ASSOCIATED CHALLENGES

Researchers have employed a number of approaches to measure innovation diffusion. One of the most common methods is to examine citations by patents (e.g., Jaffe, 1989) and/or publications (e.g., Cockburn & Henderson, 1998). Citation-based analyses face a fundamental problem, however, in that many innovations do not have a clearly-defined originating patent or publication from which citations can be traced. This is especially true of innovative

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organizational practices, strategies, or orientations. Moreover, even if an initial record exists, subsequent adopters may not leave a trail of records to indicate the innovation's diffusion.

In light of these challenges, many researchers have employed other methods of measurement. Two of the most common alternatives are to search for keywords in a relevant set of documents (e.g., Davis & Greve, 1997; Fiss & Zajac, 2004; Fligstein, 1985; Westphal & Zajac, 1994) or to rely upon database or report index terms (e.g., Abrahamson & Fairchild, 1999; David & Strang, 2006; Greve, 1998; Jonsson, 2009). In each case, diffusion researchers can use keyword or index term "hits" to build a list of all adopters and then analyze the adoption patterns over time to assess diffusion. An outstanding question, of course, with any approach to diffusion measurement concerns the correspondence between the data obtained from a particular measurement approach and the "actual" diffusion pattern that a researcher hopes to investigate and explain. In turn, there are a number of mechanisms that may be at work, individually or collectively, that result in keywords or index terms not fully or accurately reflecting diffusion.

First, in some cases, a label for a practice might not yet exist, a phenomenon we call "pre-labeled emergence." For example, researchers studying "nanotechnology" trace the term to a 1986 publication by Eric Drexler, but they are quick to note that much research in the field took place prior to 1986 (Granqvist et al., 2012). Reliance upon existing labels to assess diffusion may result in false negatives, which we expect to be especially prevalent in early adoption stages.

Second, people or organizations may intentionally avoid a label, even if it accurately describes what they do – a practice that we call "strategic avoidance." (See also Okhuysen, 2009; Terlaak & Gong, 2008; Zuckerman, 1999.) A primary motivation for strategic avoidance lies in concerns over (il)legitimacy or negative perceptions by others. As Colyvas and Jonsson (2011) point out, diffusion and legitimacy are distinct concepts; thus, some things can diffuse widely without becoming legitimate. "Adult shops," for example, may be common in many cities, yet many of the people associated with such shops might obscure or disclaim their involvement with them. Thus, strategic avoidance also produces a measurement problem of false negatives.

On the other hand, "symbolic adoption" may result in false *positives*. As Fiss (2008) and others note, individuals and organizations can take "calculating, manipulative, or even deceptive actions" (Fiss, 2008: 397) to show apparent conformity even as the reality is non-conformity. For example, Carpenter and Feroz (2001) found that state governments claimed to adopt certain reforms to increase their legitimacy, but they limited implementation of these reforms. Symbolic adoption, therefore, suggests that keywords and index terms may result in false positives.

Finally, Merton (1968) argued that some knowledge becomes taken-for-granted over time and, therefore, no longer warrants a citation – a phenomenon that he labeled "obliteration by incorporation." As Lederberg summarized the phenomenon: "The work that *everybody* knows…is hardly cited at all!" (Lederberg, 1977). Obliteration by incorporation thus suggests that keywords and index terms may result in false negatives – especially in later periods.

Of course, it is possible for all four of these mechanisms to operate simultaneously, resulting in both false negatives and false positives and raising the possibility that results obtained from keywords and index terms may differ widely from actual diffusion. Unfortunately, we have very little evidence of the extent and direction of biases arising from reliance upon keywords and index terms. In this paper, we offer a starting point for discerning these effects by investigating whether and how patterns derived from keywords and index terms differ from those based upon assessments by "domain experts." We focus specifically on the magnitude and timing of diffusion, along with three primary variables in the diffusion literature: organizational demography, publication outlets, and collaboration patterns.

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SETTING, DATA AND METHODS

To conduct this investigation, we draw upon the field of "green chemistry." Green chemistry is an attempt "to make humanity's approach to chemicals…environmentally sustainable. The focus is on the prevention of problems before they occur by (re)designing chemicals and chemical production processes at a molecular level" (Woodhouse & Breyman, 2005: 200). Towards this goal, green chemistry embodies twelve principles that are straightforward to practice and that any knowledgeable chemist can easily identify (Anastas & Warner, 1998; Linthorst, 2010). Green chemistry is not, however, based upon a focal patent or publication and it cannot be traced through simple citation-based approaches.

We measured the diffusion of green chemistry using keyword search, database indexing, and the manual sorting of records by two practicing green chemists (hereafter, "domain expert assessment"). We constructed the keyword search dataset by searching for the phrase "green chemistry" in SciFinder Scholar. We constructed the database indexing dataset by capturing those articles that received a "green chemistry" index term from SciFinder Scholar's database managers. Finally, we constructed our "domain expert assessment" dataset by searching for a wide range of terms with potential relevance to green chemistry in SciFinder Scholar. Since this broad search resulted in a large number of irrelevant articles (in addition to articles of interest), practicing chemists with expertise in green chemistry then reviewed each article (n=10,231) to determine if it reported on experiments/findings that employed one or more of the twelve principles of green chemistry. (It is important to note that the twelve principles have little technical ambiguity.) As a check on our process and assessments, we consulted with a third practicing chemist, a tenured professor who also specializes in green chemistry.

We acknowledge that this lack of ambiguity and the existence of coherent, stable, and widely-acknowledged criteria may mark green chemistry as an unusual case and that the determination of "what" falls within a field is often subject to important political and sociological pressures. Our interest in this study, however, is less around the margins or boundaries of the field and more around the potentially different views of diffusion obtained via these three forms of measurement (keywords, index terms, and domain expert assessment).

Our full dataset (including articles captured via any of the three approaches) contained 6,394 articles spanning 1990 through 2008. With these records identified, we then coded each article for publication outlet; organizations represented; organization type (firm, university, government, or other); and collaborative patterns on an individual and organizational basis. We followed past studies on measurement of innovation (Hagedoorn & Cloodt, 2003; Nelson, 2009; Nelson, 2012) by comparing diffusion patterns over time and across these different dimensions.

RESULTS

Different approaches to the identification of green chemistry articles yielded very different results: keyword search yielded 5,799 articles; database indexing yielded 5,592 articles; and domain expert assessment yielded 4,763 articles. Notably, the three approaches identify different starting points for green chemistry, with domain expert assessment, keyword search, and database indexing placing the first publication in 1990, 1995, and 1999, respectively.

Through the year 2000, domain expert assessment yields more results in any given year than either of the other two approaches. The comparatively low number of keyword articles suggests that many authors were not labeling their articles as "green chemistry" even though the

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underlying science reflected green chemistry. Further, the lack of articles in the index term data set prior to 1999 reflects the fact that SciFinder did not create an index term for green chemistry until late in that year. In 2001, there is a shift as keywords and index terms identify more articles than does domain expert assessment. This result indicates that authors and indexers alike may have grown overzealous in their application of the label.

Of course, multiple pressures for under- and over-labeling may be active simultaneously and it is difficult to disentangle their effects on the basis of raw yearly counts alone. Thus, we compared each measurement approach on an article-by-article basis. As indicated in Figure 1, both keywords and index terms miss a substantial, but declining portion of the articles identified by domain experts (indicated by solid lines in Figure 1). Specifically, keyword and index searches miss the vast majority of expert-identified green chemistry articles published in the early years of the field, and miss about ten-percent of articles published in the most recent years.

Figure 1 about here

Figure 1 also indicates that keywords and index terms pick up a number of false positives (indicated by dashed lines in Figure 1). In other words, these articles are labeled with "green chemistry" even though our experts judged that the underlying science does not correspond to green chemistry. These differences decrease over time, though experts still judge about one-quarter of articles in the most recent years as "false positives."

As a first cut, these results indicate that keywords and index terms exhibit considerable differences from domain expert assessments and that these differences are especially severe in the first decade of diffusion. Next, we examine these differences across the dimensions of publication outlets, organizational demography, and collaboration.

Publication Outlets

The journal population data reflect these same general patterns. Green chemistry research appeared in a large number of journals: keyword searching indicates 864 unique journals, database indexing indicates 849 unique journals, and expert assessment indicates 682 unique journals. As with the assessment of overall publishing activity, the data are especially inconsistent through 2001 and keywords and index terms appear to miss many of the journals that were among the first publishers of green chemistry research. For example, *Chemical Engineering* published some of the earliest work (with two 1991 articles), but it is not included in the keyword and index datasets. *Chemistry for Sustainable Development* published a pair of 1993 articles, when there were less than 15 articles in the whole field, but keywords or index terms also miss this journal – perhaps because it published only three articles total. (The last one appeared in 1996.) Because keywords and index terms pick up later activity, they appear to miss publication outlets that were active early but that fizzled before field took off. More generally, these findings suggest that if keywords and index terms under-capture early activity in a field, they may miss entirely those individual, organizational, or other participants that also exit early.

On the other hand, about 35-percent of journals in the keyword and index term datasets do not appear in the domain expert dataset. For example, *Environmental Science and Technology* ranks as the sixth most frequent journal in the keyword dataset (and seventh in the index term dataset). Domain expert assessment, by contrast, ranked the journal 39th. (It is worth noting that

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this journal is an ACS publication.) Similarly, the *International Journal of Life Cycle Assessment* appears seventh in the keyword dataset and sixth in the index dataset. According to expert assessments, however, this journal does not actually publish green chemistry research.

Organizational Demography

The lists of the most active overall organizations according to each measure are relatively consistent: the top ten most active organizations according to expert assessment appear in the "top 11" in the index term dataset and the "top 12" in the keyword dataset. In terms of dates of first engagement, however, the discrepancies are much greater. For example, the domain expert data show the US EPA – an important early advocate of green chemistry according to qualitative histories of the field (Linthorst, 2010) – publishing as early as 1992, whereas the keyword and index data do not pick up the US EPA until 1998 and 1999 respectively. Aston University in the UK, one of the earliest organizations in the field according to the expert assessment data (1990), does not enter the keyword and index term datasets until 2002. Similarly, Union Carbide chemical company is one of the earliest organizations in the expert data (1991), but enters the keyword and index datasets only in 2003. In fact, other early organizations are missed entirely since their publishing activities were limited to the early years of the field.

These early differences also show up in the relative prevalence of organization types. In the first five years, especially, the measures show very different patterns of involved organizations. Specifically, the keyword dataset highlights a large percentage of unaffiliated authors and other types of organizations (55-percent in the keyword dataset, versus 5-percent in the index dataset and 9-percent in the domain expert dataset). By contrast, the index term dataset highlights a dominant role for universities (70-percent of organizations, versus 27-percent per keywords and 41-percent per domain experts), while the expert dataset shows a far greater role for firms (32-percent of organizations, versus 10-percent per index terms and 2-percent per keywords). Thus, the different measures lead to different conclusions about the role of the public and private sectors in green chemistry's emergence and diffusion.

Collaboration Patterns

Our final assessment concerned the collaborative patterns reflected in the articles. The measurement approaches yield similar results in the most recent years. The articles picked up by keywords and index terms in the first decade, however, are far less collaborative – on both an individual and organizational basis – than those picked up by expert assessment. In turn, the differences between measures suggest very different roles for collaborative work in the emergence of the field, with expert assessment portraying a much more collaborative field.

DISCUSSION AND CONCLUSION

This paper provides initial evidence that diffusion measurement is, indeed, a problem. It documents the timing, magnitude and direction of potential biases, and it presents potential solutions in the form of expert assessment and comparative measures. Our research also suggests that prior studies may have understated – to different extents – the degree of diffusion during the earliest time periods and that some activity captured may not, in fact, reflect actual practice – particularly in later time periods. Of course, the extent of these concerns depends a great deal on

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the particular research question and setting at hand. Our results suggest that concerns are most acute when studying emergence patterns, especially when researchers attempt to identify timing, participation, collaboration patterns, and relevant literature. The fact that false positives and false negatives vary over time and appear simultaneously, however, means that these issues probably demand consideration in most cases and cannot be subsumed under a simple error term.

Our study points to the value of incorporating domain expert assessment into measurements of diffusion. This approach answers calls for increased interdisciplinary research and grounded studies that draw upon participants embedded in phenomena of interest (e.g., Barley, 2001). However, we acknowledge the difficulty of finding and involving such experts and we propose that the nature of the research question and setting should inform the potential benefit of this approach, weighed against the cost in terms of research time and other factors.

More generally, and regardless of the incorporation of experts into a research design, our results encourage tighter linkages between the innovations investigated and the measures employed to study these innovations – along with a greater discussion of how any particular study's results may be tied to or influenced by a researcher's particular choice of measures. In turn, our results suggest that researchers may improve the measurement of their focal phenomena by drawing upon multiple sources and by comparing across them (e.g., Nelson, 2009). Thus, even if a study cannot obtain a "gold standard" measure, it can examine differences between measures to learn more about diffusion processes and mechanisms. For this reason, measurement differences are not something for researchers to minimize, but rather something to investigate as potentially informative about where and how actors interpret and contest diffusion.

Of course, our study is exploratory in nature and limited to a single field. Given the importance of innovation diffusion to a broad range of strategic management questions, further research into the accuracy and completeness of diffusion data is sure to bear much fruit.

REFERENCES AVAILABLE FROM THE AUTHORS

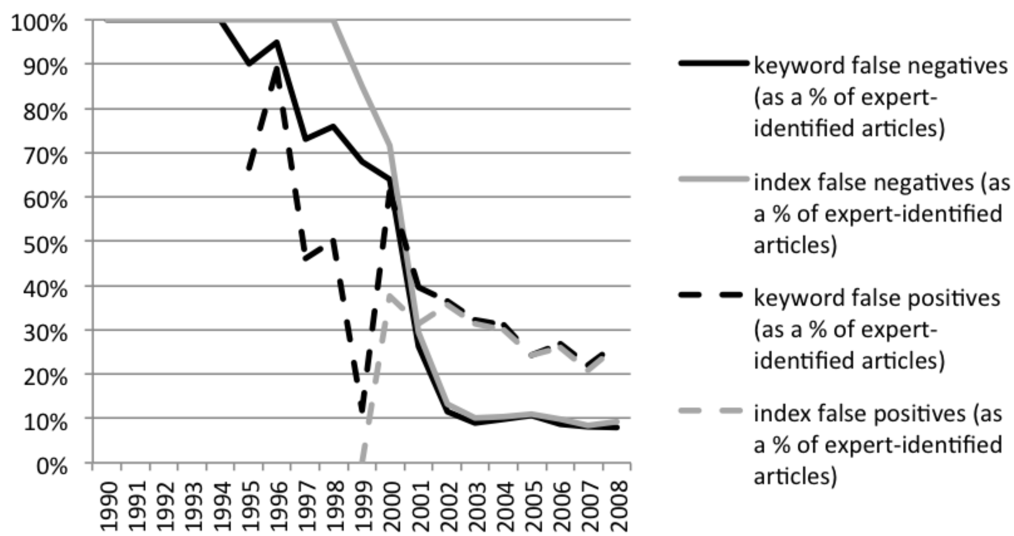

Figure 1: Differences between Keyword/Index-Term Datasets and Domain Expert Assessment (Articles)