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Do innovation measures actually measure innovation? Obliteration, symbolic adoption, and other finicky challenges in tracking innovation diffusion

Andrew Nelson[a,*], Andrew Earle[b], Jennifer Howard-Grenville[a], Julie Haack[c], Doug Young[d]

[a] Lundquist College of Business, University of Oregon, Eugene, OR 97403, United States
[b] Peter T. Paul College of Business and Economics, University of New Hampshire, Durham, NH 03824, United States
[c] Department of Chemistry, University of Oregon, Eugene, OR 97403, United States
[d] Department of Chemistry, Lane Community College, Eugene, OR 97403, United States

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ABSTRACT

Although innovation diffusion is a central topic in policy and strategy, its measurement remains difficult – particularly in cases where the innovation is a complex and possibly ambiguous practice. In this paper, we develop four theoretical mechanisms that may bias diffusion markers by leading to the understatement and/or overstatement of diffusion at different points in time. Employing the case of "green chemistry," we then compare three different diffusion markers – keywords, database index terms, and domain expert assessments – and we demonstrate how they lead to differing conclusions about the magnitude and timing of diffusion, organizational demography, publication outlets, and collaboration. We also provide suggestive evidence of extensive "greenwashing" by particular organization types and in particular countries. Building on these findings, we point to potential challenges with existing diffusion studies, and we make a case for the incorporation of practitioners in construct measurement and for the integration of comparative metrics in diffusion studies.

1. Introduction

Innovation diffusion is a central topic in public policy and strategic management (e.g., Abrahamson and Rosenkopf, 1993; David, 1986; Geroski, 2000; Rosenberg, 1986; Stoneman and Diederen, 1994). At their core, diffusion studies seek to explain "how things. . .get from here to there" (Katz, 1999: 145). Essential to such explanations are accurate data about whether and when a "thing" actually has moved from "here" to "there." Unfortunately, common measurement methods can both over- and under-state diffusion, and these errors can vary in prominence and magnitude over time.

Researchers occasionally benefit from good data on innovation diffusion, as when sales records, census data, or other markers exist to trace a given product or practice. In many cases, however, well-formed, reliable and complete diffusion records are not available. In particular, novel strategies, practices and other innovations that are not tied directly to an artifact can be especially difficult to measure. Moreover, such innovations may be more likely to be ambiguous in their labeling and are especially prone to adoption fads (e.g., David and Strang, 2006; Fiss and Zajac, 2004; Hendricks and Singhal, 1997; Wang and Bansal, 2012).

Measurement is further challenged by the fact that participants in diffusion processes can manipulate, intentionally or not, diffusion indicators. For example, organizations sometimes claim to adopt practices that they have not in fact adopted, believing that adoption confers legitimacy or other benefits (Carpenter and Feroz, 2001; Elsbach and Sutton, 1992; Fiss, 2008; Fiss and Zajac, 2006; Oliver, 1991; Westphal and Zajac, 1994). Alternatively, adopters sometimes fail to report their adoption because they fear that it might signal *illegitimacy* (Colyvas and Jonsson, 2011; Granqvist et al., 2013; Terlaak and Gong, 2008) or they presume that a practice is so widespread that it no longer warrants specific mention (Lederberg, 1977; Merton, 1968). For all of these reasons, scholars struggle to obtain reliable diffusion data. In turn, data limitations can hamper efforts to build theory around innovation diffusion itself.

In this paper, we contribute to a growing literature that addresses the correspondence between measures and the activities or phenomena that these measures are attempting to capture

* Corresponding author. Tel.: +1 541 346 1569.
E-mail address: ajnelson@uoregon.edu (A. Nelson).

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(e.g., Aguinis and Edwards, 2014; Boyd et al., 2013; Chatterji et al., 2009; Colyvas and Powell, 2009; Freeman and Soete, 2009). Specifically, we develop four mechanisms that can account for divergence between "actual" diffusion patterns and patterns derived from two commonly employed measures: keywords and index terms. We then quantitatively examine the diffusion of "green chemistry" by comparing results obtained from keywords and index terms against those obtained from careful 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 also show how certain organization types, countries, and author-team compositions may be particularly subject to measurement errors. To conclude, we describe circumstances when the use of domain expert assessments might be particularly valuable to researchers; we discuss why diffusion studies must be cautious to interpret their results in light of the particular measure used; we make the case for exploiting differences between measures; and we offer several policy implications and recommendations.

2. Measurement of innovation diffusion and associated challenges

Researchers have employed a number of approaches to measure innovation diffusion (see Rogers, 2003, for a useful summary). One of the most common methods is to examine patent and/or publication citations (e.g., Cockburn and Henderson, 1998; Jaffe, 1989; Nelson, 2009). 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. Moreover, even if an initial record exists, subsequent adopters may not leave a paper trail to indicate the innovation's diffusion. For example, Total Quality Management (TQM) is a highly influential and widespread management practice. Constructing a TQM paper trail is difficult, however, since many adopters may not cite the original developers of the practice (Westphal et al., 1997), others may differ in what they label TQM (Giroux, 2006; Zbaracki, 1998), and still others may not produce any public records of their adoption (David and Strang, 2006).

In light of these challenges, many researchers have employed other methods of measurement. Two of the most common alternatives are to search for traces of an innovation by its "label," using either keywords or index terms. In a keyword search, a researcher sorts through a set of documents to find instances of a label(s) associated with an innovation. Previous studies have conducted keyword searches of patent databases (e.g., Beaudry and Allaoui, 2012; Hu and Jaffe, 2003; Jamasb and Pollitt, 2011; Lee et al., 2011; Xie and Miyazaki, 2013), other databases (e.g., Gay and Dousset, 2005; Hendricks and Singhal, 1997; Mogoutov and Kahane, 2007), annual reports (e.g., Fiss and Zajac, 2004), websites (e.g., Wang and Bansal, 2012), and company directories (e.g., Zaheer and Mosakowski, 1997).

In an index-term search, a researcher relies on another party's identification of specific codes, as with JEL codes assigned to articles that appear in *Research Policy*. As with keyword searches, the researcher still consults a corpus of documents such as a publication database (e.g., Abrahamson and Fairchild, 1999) or an industry directory (e.g., David and Strang, 2006; Greve, 1995, 1996; Jonsson, 2009). In an index-term search, however, the search terms themselves are defined in advance rather than open-ended. Nevertheless, the search strategies underlying keywords and index-terms are very similar, with diffusion researchers using search "hits" on the label associated with an innovation in order to construct a list of adopters and to analyze adoption patterns.

Of course, an outstanding question 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, to distort the correspondence between actual patterns and those patterns derived from keywords or index terms.

First, in some cases, a label for an innovation might not yet exist. For example, researchers studying nanotechnology have traced the term "nanotechnology" to a 1986 publication by Eric Drexler, but they are quick to note that much research that qualifies as nanotechnology took place prior to 1986 (Granqvist et al., 2013). Scholars in the social construction of technology emphasize that actors contest boundaries and definitions around innovations, especially in the early years of emergence (Kaplan and Radin, 2011). In turn, reliance upon existing labels to assess diffusion, especially in an early period, may result in "false negatives" or missed data. We refer to this early lack of a coherent label as "pre-labeled emergence."

Second, actors may intentionally avoid using a label, even if it accurately describes their adoption – a practice that we call "strategic avoidance." One motivation for strategic avoidance lies in concerns over illegitimacy 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 providing legitimacy. "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. Granqvist et al. (2013) cite examples of executives at nanotechnology firms who did not use the term "nano" because they feared that it would signal a lack of commercially viable products (see also Hudson and Okhuysen, 2009; Zuckerman, 1999). For innovations that will eventually become legitimate, Terlaak and Gong (2008) propose that strategic avoidance (or "concealed adoption," as they label it) will be most prevalent in earlier diffusion stages when an innovation's value is unclear, as are external reactions to it.

Competitive concerns also can lead to strategic avoidance. In their study of patenting in the electricity sector, Jamasb and Pollitt (2011: 315) note, "Patentees might hence behave strategically and use [or avoid] particular words in the titles/abstracts in order to reduce the probability that others find their patents and reproduce their invention and market [it] in another country where the invention is not protected." Whatever the motivation, strategic avoidance produces a measurement problem of false negatives or missed data since searches for an innovation by its label will not identify all adopters.

On the other hand, "symbolic adoption," a third mechanism, may result in false positives, or the *overstating* of adoption. Symbolic adoption expands the classic notion of decoupling, developed most thoroughly by institutional theorists who note separation between formal structures and actual practice (e.g., Scott, 2000; Powell and DiMaggio, 1991; Bromley and Powell, 2012). Often, the motivation for symbolic adoption lies in an individual's or organization's desire to obtain legitimacy or some other benefit derived from conformity to a practice, without incurring the cost that may be incurred by actually engaging in the practice. Thus, as Elsbach and Sutton (1992), Oliver (1991), 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, Westphal and Zajac (1994) found that many firms adopted long-term incentive plans for management even though they never actually implemented these plans. Similarly, Carpenter and Feroz (2001) found that state