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How Innovative Are Innovations? A Multidimensional, Survey-Based Approach

Wesley M. Cohen, You-Na Lee, and John P. Walsh

4.1 Introduction

Policy makers, scholars and managers have a keen interest in tracking innovative activity. Measuring innovation has, however, proven difficult. For example, in the last couple of years, the Organisation for Economic Co-operation and Development (OECD) revised the Oslo Manual, the basic handbook for survey-based measures of innovation, reflected particularly in the Community Innovation Survey (CIS) administered across Europe. In the United States, the National Science Foundation (NSF) has sponsored two workshops on innovation indicators, and following earlier work in Europe

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and elsewhere, NSF has begun to track self-reported innovation in its Business R&D and Innovation Survey (BRDIS). One challenge with existing innovation surveys (e.g., BRDIS, CIS) is that it is not clear what respondents mean when they report that they have introduced to the market a product or process that is new or significantly improved. Underlying this question of interpretation is the concern about whether reported innovations are "important." For example, does a reported innovation reflect simply a new flavor of toothpaste, or is it the first 3D printer? In this chapter, we suggest that the question of what respondents mean by "innovation" and the related question of its importance are fundamental ones that should be addressed conceptually and that this conceptualization should precede and guide measurement.

We start with Schumpeter's distinction between invention and innovation (Schumpeter, 1934). *Invention* refers to a discovery or the creation of a novel tangible (or virtual) artifact. *Innovation* refers to the commercialization of an invention—that is, the introduction of an invention to the market—and all that entails. Accordingly, we accept the definition of an innovation as a good, service, or process that is new to the market.[1] We suggest, however, that simply defining an innovation as being "new or significantly improved" is insufficient. Without knowing more, we cannot assess how innovative or important the innovation is. In this chapter, we propose moving beyond a categorical judgment of an innovation that focuses exclusively on novelty (e.g., "first to market") to consider the question of what features of an innovation potentially affect social welfare or, indeed, the likelihood of the invention being discovered and commercialized to begin with. In this chapter, we first propose what the relevant features may be. We then empirically illustrate the usefulness of such a multidimensional characterization using recently collected survey data for the US manufacturing sector and selected service sector industries. Finally, we provide some suggestions for new attribute-based innovation measures and conclude the chapter.

Figure 4.1 helps clarify the distinctions we are trying to highlight. The figure shows the innovation process, from the inputs (such as R&D) and its various determinants (such as technical information and information on market needs), to ideas (some of which are observable through patent data), to innovation (the new or significantly improved good, process, or service), to the social welfare impacts. This figure is used to organize the conceptual discussion rather than being an attempt to impose a "linear model" on the innovation process. For simplicity, the many external influences and feedback loops are excluded. A key distinction in this schematic is between the

1. In this chapter, we are not analyzing organizational or marketing innovations, which have also begun to be incorporated into innovation surveys. In addition, while we are discussing innovations by firms, much of what we discuss would also apply to public or nonprofit sector innovations, where one might use the phrase "implementation of the invention" rather than "introduction to the market."

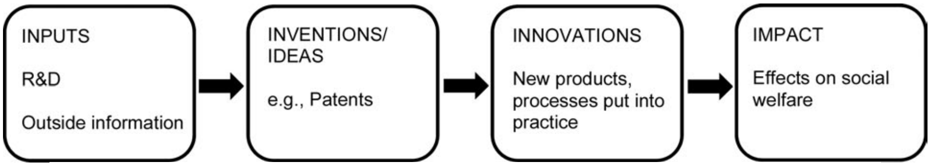

Fig. 4.1 The innovation process

characteristics of the innovation and its impact. We argue that it is important to measure how "innovative" an innovation is, separate from its impacts, in order to understand the relationships between inputs and innovations and between innovations and their impacts (Dahlin and Behrens 2005).

A fair question is, Why collect data on the characteristics of innovations per se? Why not just focus exclusively on their social welfare impacts, including their impacts on, say, productivity growth, lives affected, and so on? The reason is that, from both a managerial and policy perspective, it is useful to know, first, what kinds of innovations are worthy of private or public investment. Should they be innovations that are technologically significant in the sense that they represent a large inventive step? How about the prospective utility of the investment—reflecting the acuteness or the pervasiveness of a social need? At a first order, managers and policy makers make decisions that target specific features of an innovation, typically assuming some relationship between those features and an innovation's impact, either on profit, sales, and growth for managers or on social welfare for policy makers.

Correspondence between features of an innovation and their impact is not, however, straightforward. As a consequence, we need measures characterizing those features to better understand what features impact social welfare, including how and under what conditions, as well as to better understand the drivers of the different features of innovation. To illustrate, what we may call technological significance is not necessarily predictive of impact. For example, consider the discovery of high-temperature superconducting materials. This was a Nobel Prize–winning discovery that was expected to be transformative for the cost of electricity transmission and numerous other applications. That has not come to pass, at least not yet, largely due to the inability to manufacture such materials at commercial scale. Or consider the introduction of the Segway, a technically challenging achievement that was initially also thought to be transformative—at least by its inventor, Dean Kamen—for human-level transportation. Segways are indeed now commercialized and in use, but they are far from transformative. At the same time, there are numerous instances of innovations that are technologically incremental that have had enormous economic impacts. Consider, for example, the introduction of self-service grocery stores (and the follow-on innovation of the shopping cart) or the commercialization of containerized shipping. Neither of these innovations reflected large inventive steps technologically, but their impacts on productivity and economic growth have been substantial. Thus we suggest that it would be helpful for policy makers and managers to understand, for example, the circumstances under which more or less substantial technological leaps may pay off, particularly if those leaps come at considerable expense. Such understanding requires, however, measures of the relevant characteristics of an innovation—and that those characteristics be identifiable independent of their ultimate commercial or social impacts.

In this chapter, we are also arguing that we need surveys to collect data on critical features of innovations. But why? Why not rely exclusively on existing administrative patent data or R&D survey data to characterize innovations? Why go to the additional expense and effort of designing and administering surveys to characterize innovation? First, we would suggest it is not a question of using either administrative data or innovation surveys. Indeed, these approaches can complement one another, by allowing us both to use one modality to address questions that cannot be addressed by the other and also, where both approaches can be used, to compare findings to illuminate the virtues and limitations of each. For example, by comparing survey-based and patent-based measures of knowledge flows from public research institutions, Roach and Cohen (2013) showed that the patent citation data systematically underestimate the knowledge flows from public research to industrial R&D—by as much as 50 percent. At the same time, this comparative exercise suggested that as a measure of knowledge flows from public research, patent references to the nonpatent literature were a superior measure to using references only to other patents.

One possible advantage of innovation surveys over patent and existing R&D data is that large-scale innovation surveys offer a more flexible vehicle for collecting data than either the R&D or patent data, at least currently. With innovation survey data, at least when one is in a position to guide the formulation of questions, one is not restricted to the construction of measures from preexisting administrative data or from long-standing standardized surveys constructed for other purposes, including the R&D data collected through financial reporting systems or national statistical agencies. At the same time, survey data come with their own limitations, with pitfalls that may afflict sample construction as well as survey design and administration. Hence we begin below with a summary assessment of the advantages and limitations of R&D and patent data as measures of innovation. The purpose is to make an argument for supplementing these conventionally employed data sources with surveys that collect data on specific attributes of innovations that allow one to assess their importance.

In section 4.2 of the chapter, we briefly review several current approaches to measuring innovation, including R&D surveys, patent data, and innovation surveys. In section 4.3 we discuss the multiple dimensions of innovation that innovation surveys can be designed to capture. In section 4.4 we make an initial effort to empirically operationalize those dimensions. In section

4.5, we conduct a number of exploratory, empirical analyses to illustrate the utility of this multidimensional characterization. Section 4.6 suggests alternative measures of these dimensions of innovation. Section 4.7 presents our conclusions.

4.2 Current Approaches to the Measurement of Innovation

Social scientists, from different disciplines and often with different scholarly objectives, have used different data sources in their statistical studies of innovation. The three major data sources employed to study innovation are government data on R&D expenditures, patent-based measures, and survey-based measures.[2]

4.2.1 R&D Expenditures

R&D expenditures reflect an input into the innovative process, with research expenditures typically thought to be associated with invention and development associated with the prototyping and other activities designed to prepare an invention for market introduction. Innovation scholars, particularly economists, have typically used R&D data either as a dependent variable in studies of the factors driving firms' investments in innovative activities or as a factor of production—R&D or knowledge capital—in analyses of productivity growth. An advantage of R&D expenditure data is their availability, at least for public companies in the United States. Data on nonpublic companies are accessible via confidential NSF data, which also provide limited data on R&D composition across the categories of basic, applied, and development activity and, more recently, R&D dedicated to product versus process innovation.

It has been widely recognized since Mansfield (1968), however, that, while R&D is a key input into both invention and innovation, it is not the only one. Mansfield estimated that R&D expenditures reflect only about 50 percent of the investment required to bring an innovation to market, with additional investments in marketing, distribution, and manufacturing required for commercialization. We also know from a survey of the inventors of patented inventions that not all the patented inventions of firms originate from the firms' R&D operations, although most do (Lee and Walsh 2016). In addition, other sources of innovation within firms escape any recognition by either R&D or patenting activity, and these can be important, as shown by the literature on learning by doing (Thompson 2012; cf. Hollander 1965 for Dupont's rayon manufacturing processes).

There is perhaps an even more significant challenge to thinking that R&D expenditures are a reliable index of firms' innovative activities. On the basis

2. See section 2 of Cohen and Levin (1989) for an early critical discussion of R&D and patents as measures of innovation.

of the survey data used for the present study, Arora, Cohen, and Walsh (2016) indicate that for the US manufacturing sector, 49 percent of innovating firms report that the invention underlying their most important product innovation in the 2007–9 period was acquired from an outside source. Moreover, this percentage varies substantially across industries and across firms within industries. Hence for a significant (and varied) share of innovations, the R&D (or other inventive activity) that produced the underlying invention did not occur in the innovating firm, weakening the link between a firm's own R&D and its innovations.

There are other well-known concerns with R&D data. Griliches (1979) long ago argued that a proper measure of innovative input should reflect not the knowledge generated by R&D in any one period but the services of an accumulated stock of knowledge. Such an exercise, however, runs into challenges tied to the specification of lags, the determination of an appropriate depreciation rate, and the impact of spillovers from other firms (Cohen and Levin 1989).

4.2.2 Patent Measures

In addition to R&D data, patent data are also often used in studies of innovation. An important virtue of patents as a data source is that patent applications are vetted and curated by examiners. In addition, recent efforts by scholars such as Hall, Jaffe, and Trajtenberg (2001) and Li et al. (2014) have added value to these administrative data by cleaning the data, constructing useful measures based on the data, and making the data more accessible, creating an important data resource for innovation scholars. Another virtue of such data is that patents and linked documentation offer a wealth of information that lends itself to creative use and measure construction. Indeed, scholars have employed patent data to construct analogs to a number of the characteristics of innovations considered below, as well as other features, including, for example, measures of originality, generality, novelty, and economic value (Jaffe and De Rassenfosse 2017).

Notwithstanding these considerable virtues, patents reflect an intermediate outcome of the innovative process—invention—and thus do not constitute a measure of innovation (i.e., newly commercialized product/process) per se. Underscoring this limitation, only a fraction of patented inventions are ever commercialized (Griliches 1998; Svensson 2015; Walsh, Lee, and Jung 2016). Moreover, for those patents that are commercialized, the correspondence between patents and commercialized products varies substantially. In what are called discrete product industries, such as chemicals and pharmaceuticals, a new product may comprise relatively few patented elements. In contrast, in complex product industries such as computers, telecommunications equipment, and others, there may be hundreds of patents or more tied to a given product (Cohen, Nelson, and Walsh 2000; Nagaoka and Walsh 2009).

Even as a measure of invention, patents are also limited. First, not all inventions are patented, and patent propensity (measured as the percentage of innovations associated with at least one patent) varies considerably across industries. For example, according to Arora, Cohen, and Walsh (2016), patent propensities in the manufacturing sector range from 11 percent in the furniture industry to 72 percent in the medical equipment industry, with an average product patent propensity of about 50 percent.

4.2.3 Surveys

Numerous survey efforts have addressed innovation, and we will only briefly identify a handful here. Surveys dealing with innovation may be divided into three groups: (1) surveys focusing on R&D and its correlates, including the "Yale Survey" (Klevorick et al. 1995; Levin et al. 1987) and the "Carnegie Mellon Survey" (Cohen, Nelson, and Walsh 2000, 2002); (2) surveys of inventors of patented inventions (Giuri et al. 2007; Nagaoka and Walsh 2009); and (3) surveys tracking innovation itself. In this chapter, we are only concerned with the latter, the most prominent of which is the CIS, which was first administered in 1992 and is now administered widely in Europe, with equivalent surveys administered across the globe. While surveys also have a variety of limitations and concerns (as documented in the Oslo Manual), including cost, sampling issues, response biases, and difficulties with questionnaire design, here our main concern with innovation surveys as currently designed is the problem of interpretation. What do respondents mean when they report "new to the market" innovations, and are these reported innovations important? If so, in what sense? Is there an impact on sales, profits, growth, and so on? What about industry-wide impacts?

4.3 Toward a Multidimensional Perspective

In this chapter, we are proposing that some portion of innovation surveys employs the innovation as the unit of analysis and focuses on selected attributes of identified innovations as a basis for constructing measures of those attributes. By adopting this perspective, we are departing from the standard approach of the CIS and almost all innovation surveys in current use. Taking the firm as the exclusive unit of analysis, the CIS asks respondents to address questions regarding a firm's innovations considered collectively. For example, the CIS commonly asks what percentage of sales are accounted for by all products that are new to the market.[3] The approach described here, in

3. The CIS questions, following the harmonized July 2014 version of the CIS questionnaire, ask for the prior three years, 2012–14, whether the respondents introduced any "new or significantly improved goods" that were (1) "New to your market"; (2) "Only new to your enterprise"; or (3) "A 'first' in your country, Europe or the world?" The survey then asks what share of total turnover comes from each of these categories.

contrast, is most effectively implemented if questions are framed in terms of a specific innovation. The proposed approach, however, is not a substitute but a complement to current practice. While firm-level analyses can answer some questions about innovation, innovation-level analyses can answer others, and as a practical matter, both types of questions can be implemented in the same instrument. The impossibility of using surveys to collect data on the population of all innovations, however, requires careful attention to sampling strategies.

We begin with a basic definition of an innovation that is consistent with that employed in CIS surveys. We define an innovation as a new or significantly improved offering (i.e., a good, service, or process) that is "new" relative to the *status quo ex ante* in a given market. As argued above, however, we suggest that characterizing an offering as "new or significantly improved" is not very helpful if we ultimately want to understand how and to what degree a new offering impacts social welfare. Going beyond a categorical judgment of novelty, we suggest five features of an innovation to be *potentially* relevant for an assessment of its potential social welfare impact. We are not claiming that this is a definitive list but simply hope to initiate a dialogue around the idea that for the purpose of assessing the impacts of innovation, it is useful for innovation surveys to characterize different dimensions of innovation.

4.3.1 Features of Innovations

In this section, we identify features of an innovation that are potentially tied to its social welfare impact. These particular features are drawn from writings on innovation in a range of fields, including economics, history, organizational theory, and sociology.[4] These attributes do not characterize innovations in any absolute sense (e.g., the absolute gain in efficiency of an algorithm) but characterize innovations in relation to a context such as the state of technical knowledge, market acceptance, the capabilities of a firm to bring an innovation to market, or even the capacity of the broader market environment to support a new product's commercialization. Some of these attributes, such as technological significance, bear on the invention(s) underlying an innovation, while others, such as utility, characterize the commercialized product or process.

Technological Significance. The technological significance of an innovation may be characterized in terms of either its novelty or its impact on technical performance. Regarding novelty, one would want to know the extent to which the technical characteristics of an innovation differ from existing products or processes. *How* novel or technologically different is an identified innovation as compared to existing goods, processes, or services? To what

4. We do not claim that our focus on the features of identified innovations is novel. As noted above, scholars working with patent data have long been constructing measures of different features of inventions.

extent does an innovation reflect an advance in the underlying knowledge? This notion of technological novelty resembles what a patent examiner tries to assess by judging both an invention's absolute novelty against prior art and whether an invention is nonobvious (where nonobviousness may be more critical for our purposes). In Europe, examiners assess the "inventive step," which is closer to the concept of this dimension of technological significance. Several different patent-based measures have been constructed and employed in the past to evaluate degree of novelty.[5] The correspondence between degree of novelty and ultimate social impact is, however, not straightforward, as suggested by the observation that the preponderance of patents is never commercialized. However, without some independent metric of technological significance (i.e., one not based on impact), we are unable to answer the question of when or how technological novelty leads to greater or lesser impact and what aspects of the innovation process produce more or less novel technologies.

A second way to characterize the technological significance of an innovation is the degree to which an innovation improves the technical performance of a process or a product as compared to prior generations of similar processes or products. For example, we might track the degree of improvement in the clock speed of a microprocessor, the conversion rate of a solar cell, or the improvement in fuel efficiency of a new automobile engine. For a process innovation, technological performance improvement would be reflected in the cost savings per unit of output. For products and processes, one complication with this characterization is that the relevant performance dimensions of a new or improved product can be complex, and the assessment of performance improvements may also be challenging where such improvements are only realizable when a product is implemented with other technologies or in different organizational settings (see below). Moreover, there may well be improvements in performance unrelated to the technology of a product or process. Finally, an open question is the strength of the relationship between the first way of characterizing technological significance—that is, the novelty of an advance—and the degree to which the associated innovation affects the technological performance of a product or process.

Utility. Utility may be characterized in terms of the pervasiveness or acuteness of the need addressed by the innovation. Although firms and others have expectations regarding the utility of a new or improved product at the moment of introduction, it is difficult to assess utility without evidence

5. For example, Fleming (2001) and Strumsky and Lobo (2015) classify inventions as novel if the associated patent reflects "combinatorial novelty" either by being the first instance of a (new) technology (United States Patent and Trademark Office [USPTO] subclass) on a patent or if it is the first instance of a particular pairwise combination of existing technologies on patents. Shane (2001) assessed the novelty of an invention simply on the basis of the number of backward citations. Text-analysis methods have been used to check for the technological distance between new patents and existing patents (Yoon and Kim 2012).

of actual impact on use. Pragmatically assessing utility could entail gathering data on the sales of a new product over time, though such data are also limited as a measure of demand for an innovation, since they reflect the interaction of supply and demand and also reflect related decisions, such as those around marketing and distribution. Nonetheless, detailed data on price and volumes would be helpful. And more helpful still would be sales data on any prior generations of a new product, allowing one to begin to assess the incremental benefit.

One problem, however, with market-based measures of utility is the possibility that for some products and in some settings, there may be numerous individuals who could benefit from a new product but lack the means to pay for it. Consider, for example, the utility of a malaria vaccine in sub-Saharan Africa. The need for such a vaccine is obvious, suggesting a different, nonmarket-based measure of utility, such as lives saved or improved.

We might also examine utility of an invention or innovation in terms of its potential for increasing firms' abilities to achieve future innovations, possibly spawning a wide variety of subsequent technologies and applications. One may think of two ways in which an innovation may significantly contribute to subsequent innovation. First is the use of the technology as an input to the research process for other innovations (i.e., research tools). Some innovations in biotechnology might be of this sort. CRISPR is a recent example; recombinant DNA is an earlier example. Second are general-purpose technologies (GPTs) that can generate a wide variety of applications across numerous industries (Bresnahan and Trajtenberg 1995). The microprocessor, the computer, and the internet are prominent examples.

Distance or "Implementation Gap." The management literatures on corporate strategy and organizations (e.g., Adner 2006; Teece 1986) and the economics literature on diffusion (e.g., David 1990; Rosenberg 1976) highlight a third attribute of innovations related to both their probability of being implemented and their impact. These literatures suggest that the commercialization of innovations may be affected by (1) the innovating firm's internal capabilities, including the expertise and capabilities it possesses or can readily acquire, as well as the way the firm is managed or organized; (2) the organizational capabilities of prospective consumers or users of the innovation; (3) the availability of essential complementary technical components required for the development of the innovation; and (4) the external availability of complementary goods, services, and technologies that support the sale of the innovation. What we are calling "distance" or an "implementation gap" may thus be due to factors internal or external to the innovating firm. Whether internal to the firm or not, implementation gaps can affect the success with which a firm commercializes an invention or, indeed, whether an invention is commercialized at all. The premise for considering what we are calling "distance" is that innovations are not implemented in isolation;

their implementation typically depends on the availability of other artifacts, capabilities, and forms of organization within and across firms—both internal and external to the innovating firm.

Implementation gaps internal to the firm may be the consequence of constraints on existing capabilities, including manufacturing, marketing, and sales capabilities. The inventor of a new tennis racket, for example, may not be able to commercialize the product due to limited access to marketing capabilities or distribution channels. On the other hand, if the requisite capabilities are easily developed or are readily available via market transactions, then the implementation gap is less. Consider, for example, clinical testing of drugs. Over the past three decades, such capabilities have become readily available as a service. As a consequence, they represent less of a constraint on, say, a biotech firm's efforts to develop a drug and get it through the FDA approval process, assuming that the biotech firm has sufficient financial resources. Marketing and sales capabilities in the pharmaceutical industry are, however, more difficult to access or develop internally.

An external implementation gap that has constrained the commercialization of electric automobiles is the absence of a well-developed network of charging stations. Another instance of distance imposed by the environment external to the innovating firm is when customers do not possess the skills and processes that would enable adoption of a new product or it would take a substantial reorganization of their capabilities to implement the innovation. For example, Kubota, Aoshima, and Koh (2011) describe two rival chemical innovations (resists) for semiconductor production where one was readily incorporated into existing semiconductor manufacturing practices while the other, although higher in technological significance, required major readjustments in the existing production processes of the users. In this case, the resist with lower technological significance but lower distance and, in turn, lower cost of adoption dominated over the more technologically significant but higher distance resist.

Uniqueness. For uniqueness, the issue is whether anyone else could have independently commercialized a similar offering at about the same time, in which case an innovation would be judged as less unique. The argument here is analogous to Merton's (1973) arguments about simultaneous discovery in science (calculus, for example). Simultaneity may occur because two or more firms are working on developing the same innovation or because two or more firms have access, perhaps via licensing, to the same invention that would become an input to their innovative activity. Or as Marshall (1890) argued when discussing agglomeration benefits, low uniqueness may result because the ideas are "in the air," available to all to build on. In contrast, there may be cases where particular firms or inventors have special capabilities or distinctive insights that are not broadly shared, and hence the observed innovation would be unlikely to have developed had not that innovator developed them. These may include cases where the components of the idea lay fallow for a long time before somebody was able to incorporate them into the innovation. One could argue that Merck's development and introduction of statins was such a case of high uniqueness, as many firms had the chemical in their hands while failing to develop the innovation (cf. Baba and Walsh 2010). In contrast, the business model innovation of self-service grocery stores appears to have been independently invented in various parts of the country at about the same time (Zimmerman 1955). The social welfare implication of less uniqueness is that society may still reap the benefits of an innovation even if a specific innovating firm failed to pursue development of the innovation or ceased production or delivery.

Imitability. The question is how easy it is for another firm to copy an innovation once the idea of the innovation is known or introduced to the market. To the extent that an innovation is imitable, the prospects for its diffusion increase, potentially affecting a broader swath of society. As Teece (1986) highlights, imitability is a function of replicability and the strength of intellectual property protection. To the extent that patents, for example, are more easily invented around, patents constitute less of a barrier to imitation and the diffusion of the innovation. Replicability refers to others' ability to copy, notwithstanding intellectual property protection, and is likely to be a function of both the distribution of capabilities across prospective imitators and the particular characteristics of the technology, such as the complexity and observability to outside firms of the innovation or the process that produced it. An example of both the importance of others' capabilities and observability is the Toyota Production System, a process innovation. Toyota freely gave tours of its factories because it was confident that others could not readily reproduce the whole of its production process even if they saw it in action, due to its complexity and the considerable tacit and other knowledge that underpins it (Spear and Bowen 1999). An example of the role of complexity and low visibility is hybrid corn. Because the corn was a double hybrid and the parent stocks were kept secret, one could not readily tell from the final product how to copy the innovation, although with significant experimentation, one could develop rival hybrids. In contrast, once one sees a self-service grocery store, one can readily replicate the innovation absent barriers to entry or other impediments to imitation.

Also affecting replicability is the degree to which the knowledge is "sticky," meaning that it is more likely that only some firms or other entities have the requisite skills to commercialize an invention because those skills are either learned in-house through their development of the technology or developed from significant experience in the industry (von Hippel 1994). Some surgical innovations may be of this form and hence may be less imitable, at least until a new cohort of surgeons can be trained in the new methods. In contrast, other surgical innovations may involve standard skills of the profession applied in a new way and hence can be readily imitated once the new technique is publicized. Industries also may differ systematically in how practice-based versus science-based knowledge is (Jensen et al. 2007). Arora and Gambardella (1994) and von Hippel (1994) both argue that more science-based knowledge regimes are likely to provide more widespread access to relevant knowledge and hence greater imitability.

4.3.2 Further Considerations

These different attributes of an innovation do not operate independently of one another. And indeed, it is typically interactions across these attributes that would assist efforts to characterize and ultimately understand the impact of an innovation. Consider, for example, a technologically significant innovation that is deployed in an environment lacking essential complementary infrastructure: a malaria vaccine. Although technologically significant and addressing a need that is both pervasive and acute, the vaccine's administration in sub-Saharan Africa may be quite limited in the face of an implementation gap tied to a need for constant refrigeration and skilled personnel for its administration. A counterexample is provided by the technologically significant discovery (awarded the Nobel Prize in medicine) that ulcers are caused by bacteria. Utility could be quickly realized because the distance tied to the implementation of this discovery was virtually nil; physicians in industrialized nations were already employing the appropriate antibiotic for a range of other ailments. An example of an innovation, no component of which was high on technological significance at the time of its introduction but that yielded widespread utility and, in turn, impact was iTunes. The key to iTunes' success was a set of existing complementary components and capabilities, including a well-designed physical device, the iPod; easy-to-use software; and the availability of a range of digital rights agreements that enabled an extensive song catalog.

The example of iTunes raises another challenge for using surveys to assess the importance of a given innovation—time. The iTunes innovation would never have succeeded had not other innovations preceded it, from the microprocessor to the internet, the MP3 player, and so on. Surveys capture data, however, at a point in time. And many innovations may yield utility, but as suggested above, only once other foundational inventions and necessary complements and organizational changes have been realized. David's (1990) comparison of the diffusion of the dynamo to that of the computer provides a clear illustration of the point as it applies to GPTs. Similarly, it took many years to fully realize the utility of the networked computer, and hence the payoff from the various attributes of the innovation was not realized until long after its initial commercialization. Moreover, many pioneering innovations are subject over time to subsequent improvements that affect their diffusion (Rosenberg 1976). And of course, the attributes of an innovation will condition incentives that in turn affect the likelihood that an invention will be commercialized to begin with (see the middle part of figure 4.1). The implication is that survey-based measures that capture the different features of an innovation at a point in time may not be predictive of long-run impact.

Given measures of the characteristics of innovations, managers, policy makers, and economists are obviously interested in assessing their impacts on firms, industries, consumers, and so on. It is obviously the case, however, that those impacts depend on numerous other factors. A clearer understanding of these attributes and the factors conditioning their impacts, however, are key to understanding not only the *ex-post* impacts (the last arrow in figure 4.1) but also the *ex-ante* drivers of innovation (e.g., incentives to engage in R&D or to convert ideas into innovations—the first two arrows in figure 4.1). For example, if we take the case of the battery-powered electric car, we can imagine problems related to "distance" at each arrow in our diagram. To begin, there is the problem of going from R&D to ideas, which may be related to the absorptive capacity of auto firms for the knowledge necessary for electric car production (see Cohen and Levinthal 1990, and Henderson and Clark 1990). Then there is the problem of going from ideas to innovation, which may be related to automakers' capabilities related to batteries and electric motors, an aspect of the "distance" considered in this chapter. Finally, there is also the "distance" due to *ex-ante* consumer practices related to driving habits, the range of electric cars, and the availability and costs of complementary services, such as charging stations. More generally, a full understanding of the attributes of an innovation and their impacts on various aspects of social welfare depends heavily on contextual factors, including firm capabilities, appropriability conditions, market structures, the common practices of buyers, and other variables—long studied—that will interact with the different attributes of an innovation in affecting outcomes, as reflected in the last arrow in figure 4.1.

4.4 Data and Measures

The purpose of the empirical analyses below is to illustrate the usefulness of developing survey-based measures of the different dimensions of innovations for (1) increasing the interpretability of survey-based innovation measures, (2) providing new insights into the correlates and possible impacts of innovation, and (3) stimulating further empirical and theoretical work. The analysis does suffer from an important limitation: the data were not collected for the purpose at hand.[6] As a consequence, they provide a limited

6. The objective of the original project was to characterize the "division of innovative labor"—that is, the degree to which innovating firms acquired their major innovations from outside sources, the sources used, and the channels through which inventions are acquired. Our findings on the division of innovative labor for the US manufacturing sector are provided in Arora et al. (2016).

basis—but a basis nonetheless—for making our argument. In this section, we describe our data and the measures employed.

4.4.1 Data: Survey Design

Our data are from a phone survey of firms in US manufacturing and selected service sector industries (see Arora et al. 2016 for more details on the sample).[7] Our sampling frame was the Dun & Bradstreet (D&B) Selectory database. Note that we not sampling on being innovators nor on being R&D performers (in contrast to the survey efforts of Levin et al. 1987 and Cohen, Nelson, and Walsh 2000).[8]

To obtain a substantial number of innovators from each industry, we stratified our sample along multiple dimensions. To begin, we selected all the D&B cases in our population of industries.[9] The sample was stratified into 28 industries at the three- or four-digit North American Industry Classification System (NAICS) code level. Furthermore, the sampling frame was divided by size (Fortune 500; over 1,000 employees but not Fortune 500; 500 to 1,000 employees; 100 to 499 employees; 10 to 99 employees; and 1 to 9 employees) and by whether the respondent is a start-up, defined as a single-product firm that is less than five years old.

We oversampled large firms, notably firms over 1,000 employees, with Fortune 500 firms sampled with certainty across all business units.[10] We also oversampled (1) start-up firms; (2) firms from more innovative industries, using CIS data from Europe to estimate innovation rates for each industry; (3) those in NAICS code industry 533 (lessors of intellectual property) as a primary or secondary industry; and (4) less-populated industries to ensure minimum sample sizes for industry-level estimates. Other categories were undersampled. While we used the D&B industry classifications for sampling, the D&B industry classifications of respondents' industries were confirmed and, if necessary, updated based on survey responses. We use these updated industry classifications for our analyses. Furthermore, we use a postsample weighting procedure (described below) to make the data representative of

7. NORC, at the University of Chicago, administered our survey.

8. This sampling strategy is analogous to that employed by the Community Innovation Survey (CIS) in Europe and the US National Science Foundation (NSF) Business R&D and Innovation Survey (BRDIS).

9. Because all cases stay in the sample, errors in the D&B data used for stratification only affect the efficiency of the sampling, not its representativeness (Kalton 1983).

10. For the Fortune 500 firms in our sample, we collected information on the parent firm and all its subsidiaries listed in D&B in our population industries, even if those were not the main industry of the parent firm. The parent firm and its subsidiaries were grouped into business units, defined as a firm's activities within a given NAICS industry, with the parent firm and each subsidiary grouped by its primary NAICS code. The sampling unit for the Fortune 500 firms is a business unit, defined as the firm's activity in a NAICS industry. Thus a diversified Fortune 500 firm may appear multiple times in the sample. All firms other than Fortune 500 firms were assigned a single sampling unit based on their primary NAICS code, implying that we are treating these as single-industry firms.

the US firm population in manufacturing and our selected business service industries.

The survey design included cognitive testing of the questionnaire with potential respondents, pretesting of the instrument and protocol, and multiple rounds of follow-up contacts to increase response rate. We designed the survey instrument with a branching logic so that noninnovative firms received only a brief questionnaire, and firms that innovated were asked more details about their innovation process and outcomes. The sample consisted of 28,709 cases. An initial screening eliminated many cases (e.g., bakeries that are in retail, not manufacturing), leaving a final sample of 22,034. The interview protocol started with a D&B contact name—ideally the marketing manager, product manager, or for smaller firms, the business manager. We then worked through the receptionist or other contacts to find an appropriate respondent.[11]

The survey was in the field from May to October 2010. In the end, we received 6,685 responses, yielding an adjusted 30.3 percent response rate. Nonresponse bias tests comparing D&B data for respondents and nonrespondents show that the sample represents the population on firm age, being multiproduct, region, and its likelihood to export. With a 20 percent response rate, units of Fortune 500 firms were somewhat less likely to respond. Similarly, large firms, multiunit firms, and public firms were somewhat less likely to respond. With regard to industry-level response rates, pharmaceuticals had a low response rate, but still over 20 percent. A recoding of industry assignments to reflect survey responses rather than initial D&B categorizations identified another 179 out-of-population respondents.

We reweighted the sample with postsample weights based on US Census data on the population of firms in our industries, size strata, and age strata. We constructed a matrix of these three dimensions of stratification from a custom report provided by the US Bureau of the Census[12] and then constructed a set of weights for our 5,871 responses in the relevant industry and size categories that reflect the population distribution of this three-dimensional matrix. After applying these weights, our sample should represent the underlying population in terms of the industry-size / start-up distribution (Kalton 1983). These weights are used in all our empirical analyses.

For the purposes of this chapter, we exclude the very smallest establishments (less than 10 employees). The result is a sample of 5,157 cases for the manufacturing sector and 714 observations for the service sector, weighted to reflect the underlying Census-derived distribution on industry-size / start-up.

11. According to the interview script, an appropriate respondent would be "the marketing manager or another person in your company familiar with the firm's products and services." This flexibility in finding an appropriate contact person was a key rationale for using a phone survey rather than post mail or email surveys.

12. We thank Ron Jarmin and his team at the US Bureau of the Census for providing this report.

Table 4.1 **Examples of innovations in sampled manufacturing industries**

Industry	Innovation
Food	Antioxidant chocolates
Food	Live active cheddar cheese with probiotics
Beverage	Vitamin-enhanced flavored spring water
Textile	Heat-resistant yarn
Textile	New varieties of garments
Paper	Low-surface-energy light tapes resistant to air, water, detergents, moisture, UV light, and dust
Paper	Hanging folder with easy slide tab
Petroleum	Nondetergent motor oil
Chemicals	BioSolvents—water-based emulsion technology
Pharmaceutical	Oral gallium to prevent bone decay
Pharmaceutical	Inhalation anesthetics
Plastics	Styrene-based floor underlayment
Minerals	Multiwall polycarbonate recyclable panels
Minerals	Solar glass and coating technologies for solar modules
Metals	Solder system and nanofoils
Metals	New water faucets and bath products
Electronics	USB-to-GPIB interface adapter
Electronics	20-h IPS alpha LCD panel
Semiconductors	Linear voltage regulators
Semiconductors	Phase change memory
Transport equipment	Improved alcohol sensing system

Notes: Reprint of table 1 in Arora, Cohen, and Walsh (2016).

4.4.2 Descriptive Statistics

In this study, we focus exclusively on product, rather than process, innovations. Following prior innovation surveys, we asked the respondent if the firm had earned any revenue in 2009 from a new or significantly improved good or service introduced between 2007 and 2009. For those that said yes, we asked whether their most significant innovation (defined as that product innovation accounting for the plurality of 2009 sales in the respondent's market) was new to the market—that is, introduced "in this industry before any other company."[13] We do not specify a geographical boundary to the "industry" and are thus not limiting responses to a local or domestic market.[14] Table 4.1 provides illustrative examples of innovations introduced by firms in the manufacturing sector. For the purpose of this chapter, we will

13. Our new-to-the-market (NTM) figure may underestimate the percentage of firms introducing NTM innovations. For example, a firm's most significant (i.e., highest-selling) innovation may not be NTM, but it's second most significant innovation may be, implying that the firm is incorrectly classified as not being an NTM innovator. However, any bias is likely to be small because a sizable fraction of firms introduces only one innovation during the sample period (see Arora et al. 2016).

14. We also did not count as innovators firms that either reported that they introduced their "most significant innovation" outside of the 2007–9 time window or reported zero 2009 sales revenue due to this innovation.

Table 4.2a **Manufacturing: Descriptive statistics**

Manufacturing Industries (N)	NTF Inno (N)	NTF Rate (%)	Innovator (N)	Inno Rate (%)	Imit Rate (%)
Food (302)	138	39	54	13	25
Beverage and Tobacco (60)	28	43	10	18	23
Textile Mills (39)	20	49	8	26	22
Textile Product Mills (76)	28	36	12	16	16
Apparel and Leather (97)	35	33	14	12	18
Wood Product (75)	19	21	5	7	12
Paper (125)	50	31	30	16	14
Printing and Related Support (187)	85	42	18	7	33
Petroleum and Coal Products (47)	14	30	6	20	8
Chemical (except Pharma) (318)	183	52	97	25	25
Pharmaceutical and Medicine (128)	80	62	34	31	25
Plastics and Rubber (340)	185	47	74	17	26
Nonmetallic Mineral (324)	102	29	36	9	18
Primary Metal (325)	132	38	44	9	26
Fabricated Metal (426)	183	38	63	10	26
Machinery (389)	197	45	103	21	22
Computers/Electronics (except Semiconductor) (287)	202	67	108	36	29
Semiconductor and Other (302)	199	60	93	28	28
Electrical Equipment (315)	189	56	93	28	24
Transportation Equipment (344)	192	50	102	27	21
Furniture and Related Product (263)	117	41	41	14	24
Medical Equipment (136)	83	55	37	21	33
Miscellaneous (except Medical) (252)	144	55	68	26	26
Manufacturing all (5157)	2,605	42	1,150	16	24
Large (1267)	829	65	465	39	23
Medium (946)	533	54	229	23	29
Small (2944)	1,243	39	456	13	23

Notes: NTF Inno (N): Number of new-to-the-firm innovators; NTF Rate (%): Share of new-to-the-firm innovators; Innovator (N): Number of innovators (i.e., those having a new-to-the-market innovation); INNO_RATE (%): Share of innovators (i.e., those having a new-to-the-market innovation); Imit Rate (%): Share of imitators: If the respondent reports a new-to-the-firm innovation but not a new-to-the-market innovation, then it is an imitator (note that due to missing data on one or the other item, it is possible for the aggregate percentages of Innovator and Imitator to not sum to percentage of NTF).

call firms that introduce a new or significantly improved product that is new to the industry "innovators" and firms that introduce new or improved products that are only new to the firm, but not new to the industry, "imitators."

Tables 4.2a and 4.2b present summary statistics for the rates of innovation and imitation overall and by industry, where we aggregate our observations of firms into 23 manufacturing industry groups and 7 service sector industry groups, defined largely at the three-digit NAICS code level. The figures in

Table 4.2b **Selected service sector industries: Descriptive statistics**

Service industries (N)	NTF Inno (N)	NTF Rate (%)	Innovator (N)	Inno Rate (%)	Imit Rate (%)
Software Publishers (87)	63	74	30	36	36
Motion Picture and Sound (47)	28	58	8	17	40
Telecommunications (101)	64	59	20	15	42
Data Processing (83)	48	51	17	15	35
Professional, Scientific, and Tech Svc (162)	79	42	34	17	23
Engineering Svc (130)	54	35	23	13	21
Computer Systems Design (104)	63	56	23	25	28
Service all (714)	399	47	155	18	27
Large (145)	99	69	51	38	30
Medium (98)	68	64	21	20	41
Small (471)	232	44	83	17	25

Notes: NTF Inno (N): Number of new-to-the-firm innovators; NTF Rate (%): Share of new-to-the-firm innovators; Innovator (N): Number of innovators (i.e., those having a new-to-the-market innovation); INNO_RATE (%): Share of innovators (i.e., those having a new-to-the-market innovation); Imit Rate (%): Share of imitators: If the respondent reports a new-to-the-firm innovation but not a new-to-the-market innovation, then it is an imitator (note that due to missing data on one or the other item, it is possible for the aggregate percentages of Innovator and Imitator to not sum to percentage of NTF).

tables 4.2a and 4.2b and all subsequent tables are weighted to be representative of firm size and industry distributions.

Tables 4.2a and 4.2b show that 42 percent and 47 percent of firms in the manufacturing and service sectors, respectively, report introducing a new-to-the-firm (not necessarily new-to-the-market) or significantly improved products in the prior three years in manufacturing. There are significant differences in the rates of new or improved product introduction across industries. For example, at least 60 percent of firms in computers, pharmaceuticals, semiconductors and software publishing introduced a new-to-the-firm (NTF) product, while less than 30 percent of firms in wood or mineral products did so. If we limit product innovations to the introduction of something new to the market (NTM), qualifying a respondent as an innovator, we find that 16 percent of manufacturing firms and 18 percent of our service sector firms report having introduced such an innovation, with rates of 30 percent or higher in computers, pharmaceuticals, and software publishing, while wood, printing, mineral products, and metals have rates below 10 percent. As noted, in what follows, the term *innovation* refers to products that are new to the market.

Tables 4.2a and 4.2b also show that larger firms are more likely to innovate and more likely to introduce new products. In manufacturing, we find that 39 percent of small firms but 65 percent of large firms report introducing new products (i.e., new to them). For innovations (i.e., new to the market), the rates in manufacturing were 13 percent and 39 percent for small and large firms, respectively—and the rates were similar in the service sector. Thus larger firms are more likely to have at least one innovation, which is expected in light of the relationship between firm size and R&D (cf. Cohen and Klepper 1996). Interpreting the difference between an industry's rate of NTF product introductions (which include NTM and NTF) and NTM product introductions as measuring imitation (Imit Rate in tables 4.2a and 4.2b), we find that the imitation rate is relatively stable across industries in manufacturing but much less so in the service sector. It also appears to be nonmonotonically related to size in both the manufacturing and service sectors, with the medium-sized firms characterized by the highest imitation rates.

To assess the validity of our survey, we compare our manufacturing sector findings regarding innovation rates with those from other innovation surveys. The rank-order correlations between our survey-based NTM innovation rates at the industry level and other innovation-related measures, such as the percentage of firms that conduct R&D or patent, are high, above 0.7.[15] For the cross-national comparisons, one might expect differences across otherwise comparable national economies simply due to differences in the distribution of respondents across firm size classes and industries and the fact that innovation rates differ across these dimensions. Nonetheless, as compared to 42 percent of our respondents that earned revenue in 2009 from NTF products introduced since 2007, the CIS in the United Kingdom reports that about 34 percent of manufacturing respondents had introduced such a new product between 2006 and 2008. For Germany, 49 percent of manufacturing respondents report introducing an NTF product. Turning to innovation, about 38 percent of the NTF respondents in our survey had introduced a product that was NTM as well. The comparable figure for the United Kingdom is 51 percent, and that for Germany is 45 percent. Thus despite differences across the three countries in the rate at which manufacturing firms introduce new products, the share of those products that are NTM is similar. Moreover, the overall rates of product innovation are also similar to our estimate of 16 percent, ranging from about 17 percent for the United Kingdom to 22 percent for Germany. Thus our data appear to benchmark reasonably well with CIS data from Germany and the United Kingdom, which is reassuring since the question we employ to initially identify "NTM" innovators resembles the question employed in the CIS.[16] Moreover, our

15. Our patent data were obtained from PATSTAT, from which we estimated the percent of firms in each industry that had a patent application.

16. Note, however, that the means from our survey, and from the CIS, are much higher than those from the US BRDIS or Japan's National Innovation Survey. And yet the correlations are quite high between the BRDIS industry percentages and our industry percentages for the same indicators.

measure of innovation corresponds sensibly with other innovation-related measures (see Lee 2015 for a detailed analysis).

4.4.3 Measure Construction

The key questions that motivate this chapter are as follows: What do respondents mean by "innovation," and how important are those innovations? Our approach to designing our survey allows us to begin to address these issues. Rather than asking about a firm's innovations overall, as does the CIS (e.g., the percentage of sales accounted for by the firm's innovations), we ask the respondent to answer follow-on questions with respect to a specific innovation—their most important innovation—in an identified line of business, where "most important" is defined as that new or significantly improved product accounting for a plurality of their sales in the line of business.

Below we describe measures corresponding to the innovation characteristics highlighted in the prior section. It is important to recall that the survey providing the data for this analysis was not designed to develop the kind of multidimensional assessment of innovation that we are proposing. As a consequence, the attributes identified above are only partially represented and are subject to the limitations discussed below.

The measures are constructed as follows:

1. *Technological significance.* We will measure only one aspect of technological significance, novelty and nonobviousness, on the basis of whether an invention underlying the innovation had a patent associated with it—a patent filed by either the innovating firm or an outside entity such as another firm or a university if the innovation was acquired from that entity (PATENT). A patent will primarily reflect whether an examiner judged the invention to be novel and nonobvious. This measure suffers from several limitations. First, as suggested above, this measure does not reflect the second dimension of technological significance—the product performance improvement tied to the product. Second, the measure is categorical rather than continuous. Third, it is subject to the points raised above regarding patent data—that not all inventions are patented, and the propensity to patent varies across industries and firms. Fourth, the measure is tied to a patent, and in complex product industries such as computers, the technological significance of a new product transcends that of any one patentable element given that the commercialized product may embody numerous patented and unpatented elements.

2. *Utility.* We measure utility by the percentage of the respondent's sales in a line of business accounted for by their most important innovation (INNO_SALES). This measure should reflect the revenue impact of their most important innovation and thus, at least in a relative sense, the prevalence of the need that the innovation addresses. This figure, however,

depends on not only the utility buyers derive from the product but also the pricing, marketing, and other decisions made by the firm and, more generally, reflects the interaction of demand and supply conditions. Moreover, this measure only reflects the short-run market impact of the innovation, and many new products take some time before their market potential is more fully realized.

3. *Distance.* We measure only internal distance, not the external distance characterizing the external market environment discussed above. To assess distance from the respondent's existing capabilities, we use responses to two survey questions. We asked innovating firms whether, in order to commercialize the innovation, they developed new sales and distribution channels (New_Mktg) and, in a separate question, whether they had invested in new types of equipment or hired employees with distinct skills (New_EqSk). Below, we will occasionally use these measures separately. The form of this measure that we will feature, however, is whether the innovator both acquired new equipment and personnel with distinct skills *and* developed new distribution channels (NEW_CAPAB). The undertaking of either or both of these activities suggests that the innovation is substantially new to the firm in the sense that to commercialize the innovation, the firm had to acquire assets, capabilities, or relationships that they did not previously possess. A limitation of this measure is that it reflects investment decisions on the part of the firm and thus reflects not only distance but also whether the firm expected the new product in question to be valuable enough to justify the investment in these new capabilities, potentially conflating measures of distance with the other dimensions of the innovation that may condition the expected value of the innovation, such as utility or technological significance.

4. *Imitability/uniqueness.* Our survey data do not permit us to distinguish between these two related concepts. Moreover, the only survey measure that comes close to imitability is respondents' judgment of the number of firms that "have introduced or are likely to introduce" a competing innovation (INNO_RIVALS). A limitation of this measure is that it conflates two concepts: technological competition and imitability. What the measure directly reflects is the former, though presumably intensity of technological competition faced by a firm should be related to the latter.

As noted above, none of these measures are "clean" in the sense of only measuring the innovation attribute in question, and they may be conflated with other factors. For example, PATENT and NEW_CAPAB conflate what we would like to measure with the expected economic value of an innovation. At the same time, such shortcomings might be viewed more favorably: the incorporation of the expected economic value of the innovation into the firm's decision to invest in patents or capabilities might thereby make these indicators more accurate reflections of the importance of the innovation.

Despite these limitations, we argue that our measures nonetheless reflect to some degree the different dimensions of innovation identified above and provide a basis for addressing the question of how important a respondent's "most important" innovation is and in what sense.

4.4.4 Interpreting the Measures

4.4.4.1 Are the "New or Significantly Improved" Innovations Important?

Using the measures of the different dimensions, one can estimate innovation rates for which there is some confidence that the innovations in question are significant beyond the simple assessment of whether a product is simply new to the market. In this section, we build on our findings reported above that 16 percent of firms are innovators (i.e., with new-to-the-market innovations) in the manufacturing sector and 18 percent in the service sector, as shown in tables 4.2a and 4.2b. How does the innovation rate change if we focus, say, on just those innovations that garner more than 10 percent, or even 50 percent, of an innovator's sales? The rates drop markedly, to 8 percent and 5 percent, respectively, for the manufacturing sector and 11 percent and 8 percent for the service sector industries, suggesting that a sizable fraction—about half for manufacturing—that report a new-to-the-market innovation are realizing 10 percent or less of their business unit sales revenue from that new product. One qualification to this particular criterion for establishing significance is that, given that it is based on the share of a firm's own sales in a market, the percentage of sales for a new product will be affected by the size of the firm. For example, the same new product that may account for 10 percent of a large firm's sales may represent a much larger share of sales for a small firm. The consequence is that, in using this particular measure for assessing the utility of a given innovation, one typically needs to control for firm size, as we do in analyses below.

Another possible filter for assessing importance is the percentage of innovations that are sufficiently different from what firms produced or delivered previously that they had to purchase new types of equipment or hire personnel with different skills (New_EqSk) to bring the innovation to market. As noted above, this variable not only reflects distance but, given that it is a realization, also reflects a judgment of the expected value of an innovation. From table 4.3a, we see that 47 percent of innovating respondents in the manufacturing sector reported this to be the case, implying that only about 8 percent of our respondents in the manufacturing sector (i.e., 16 percent $*$ 47 percent) introduced an innovation that required such investments. What about innovating firms having to develop new sales and distribution channels (New_Mktg)? Only 6 percent of respondents (i.e., 16 percent $*$ 39 percent) in the manufacturing sector introduced an innovation requiring such activity. Finally, what is the rate at which firms undertook both of these activities to commercialize their innovations—that is, develop new distri-

Table 4.3a Summary statistics for innovation indicators for manufacturing sector

Manufacturing industries (N)	Inno Rate (%)	Inno Sales (%)	Patent Rate (%)	INNO RIVALS (N)	NEW CAPAB (%)	New Mktg (%)	New EqSk (%)
Food (302)	13	17	32	2.0	25	38	49
Beverage and Tobacco (60)	18	32	59	2.5	70	80	70
Textile Mills (39)	26	5	66	2.7	41	52	52
Textile Product Mills (76)	16	12	40	1.5	28	28	30
Apparel and Leather (97)	12	18	72	1.6	28	72	38
Wood Product (75)	7	15	3	2.7	52	76	76
Paper (125)	16	12	37	1.6	31	43	36
Printing and Related Support (187)	7	19	38	2.8	43	57	76
Petroleum and Coal Products (47)	20	11	71	4.0	24	48	29
Chemical (except Pharma) (318)	25	14	46	2.1	16	36	30
Pharmaceutical and Medicine (128)	31	31	66	2.4	7	21	42
Plastics and Rubber (340)	17	16	57	2.3	18	34	44
Nonmetallic Mineral (324)	9	13	45	2.0	12	29	25
Primary Metal (325)	9	9	36	2.0	20	31	52
Fabricated Metal (426)	10	17	41	2.0	15	22	52
Machinery (389)	21	19	58	2.1	19	35	44
Computers/Electronics (except Semiconductor) (287)	36	24	62	2.3	27	41	49
Semiconductor and Other (302)	28	23	65	2.4	30	41	56
Electrical Equipment (315)	28	20	62	2.4	15	34	34
Transportation Equipment (344)	27	26	46	1.9	23	32	47
Furniture and Related Product (263)	14	20	44	2.6	10	35	36
Medical Equipment (136)	21	27	77	2.5	42	59	67
Miscellaneous (except Medical) (252)	26	19	51	2.3	35	58	47
Manufacturing all (5157)	16	19	50	2.2	24	39	47
Large (1267)	39	12	72	2.5	16	30	45
Medium (946)	23	14	53	2.5	22	35	48
Small (2944)	13	21	46	2.1	26	42	47

Notes: INNO_RATE (%): Share of innovators (i.e., those having a new-to-the-market innovation); Inno_Sales (%): Mean % of total sales from new-to-the-market innovations; Patent Rate (%): Share of innovators that patented any part of their new-to-the-market innovation or have a patented externally sourced innovation; INNO_RIVALS (N): Mean number of rivals capable of introducing competing innovation; NEW_CAPAB (%): Share of innovators that developed new sales/distribution channels *and* bought new types of equipment or hired employees with new skills; New_Mktg (%): Share of innovators that developed new sales/distribution channels; New_EqSk (%): Share of innovators that bought new types of equipment or hired employees with new skills.

bution channels *and* acquire new types of equipment or hire personnel with different skills (NEW_CAPAB)? In the manufacturing sector, only 4 percent (i.e., 16 percent * 24 percent) of respondents meet this standard for firms' most important innovations. In the service sector, table 4.3b shows that 60 percent of innovating respondents reported that they had to purchase new types of equipment or hire personnel with different skills, implying that 11 percent of respondents introduced an innovation requiring such invest-

Table 4.3b **Summary statistics for innovation indicators for selected service sector industries**

Service industries	Inno Rate (%)	Inno Sales (%)	Patent Rate (%)	INNO RIVALS (N)	NEW CAPAB (%)	New Mktg (%)	New EqSk (%)
Software Publishers (87)	36	25	56	2.9	41	67	42
Motion Picture and Sound (47)	17	28	84	2.7	59	59	75
Telecommunications (101)	15	28	56	2.5	45	48	76
Data Processing (83)	15	44	21	2.5	68	93	70
Professional, Scientific, and Tech Svc (162)	17	26	58	2.3	45	56	56
Engineering Svc (130)	13	15	37	2.6	19	19	55
Computer Systems Design (104)	25	34	38	3.4	35	49	67
Service all (714)	18	27	47	2.8	40	51	60
Large (145)	38	26	74	3.0	46	60	54
Medium (98)	20	13	49	2.7	28	47	43
Small (471)	17	29	43	2.7	40	50	64

Notes: INNO_RATE (%): Share of innovators (i.e., those having a new-to-the-market innovation); Inno_Sales (%): Mean % of total sales from new-to-the-market innovations; Patent Rate (%): Share of innovators that patented any part of their new-to-the-market innovation or have a patented externally sourced innovation; INNO_RIVALS (N): Mean number of rivals capable of introducing competing innovation; NEW_CAPAB (%): Share of innovators that developed new sales/distribution channels *and* bought new types of equipment or hired employees with new skills; New_Mktg (%): Share of innovators that developed new sales/distribution channels; New_EqSk (%): Share of innovators that bought new types of equipment or hired employees with new skills.

ments (i.e., 18 percent * 60 percent). Similarly, 51 percent of innovators had to develop new sales and distribution channels, implying that 9 percent of respondents had an innovation requiring such activity (i.e., 18 percent * 51 percent). Only 7 percent (i.e., 18 percent * 40 percent) of respondents had an innovation that required both kinds of new capabilities. This exercise distinguishes between the larger share of firms that have reported innovation per the simple "new-to-the-market" criterion from innovations that likely differ from what the firms have commercialized before and are of much greater value given that the measure signals investment in new equipment, personnel, and sales capabilities.

Thus we suggest that using criteria based either on percentage of sales or on significant investments tied to commercialization can inform judgments about the relative importance of respondents' innovations. We are also able to flexibly apply such measures as screens to refine those judgments.

4.4.4.2 Are the Dimensions Distinct?

We have suggested that while in theory our measures should reflect distinct features of an innovation, the measures as constructed are also likely related for reasons outlined above. To assess how distinct they are from one another, we calculated the correlations among these measures, computed

Table 4.4 **Correlations (for manufacturing industries having 10 or more innovators)**

	Inno Rate	Imit Rate	Inno Sales	Patent Rate	INNO RIVALS	NEW CAPAB	New Mktg
Inno Rate	1.00						
Imit Rate	0.13	1.00					
Inno Sales	0.22	0.17	1.00				
Patent Rate	**0.43**	0.11	**0.39**	1.00			
INNO_RIVALS	0.15	**0.70**	0.22	0.08	1.00		
NEW_CAPAB	−0.15	0.14	**0.38**	0.27	−0.10	1.00	
New Mktg	−0.12	0.04	0.12	**0.45**	−0.18	**0.79**	1.00
New EqSk	−0.04	0.11	**0.51**	**0.36**	0.00	**0.79**	**0.56**

Notes: N = 32 disaggregated manufacturing industries. INNO_RATE (%): Share of innovators (i.e., those having a new-to-the-market innovation); Inno_Sales (%): Mean % of total sales from new-to-the-market innovations; Patent Rate (%): Share of innovators that patented any part of their new-to-the-market innovation or have a patented externally sourced innovation; INNO_RIVALS (N): Mean number of rivals capable of introducing competing innovation; NEW_CAPAB (%): Share of innovators that developed new sales/distribution channels *and* bought new types of equipment or hired employees with new skills; New_Mktg (%): Share of innovators that developed new sales/distribution channels; New_EqSk (%): Share of innovators that bought new types of equipment or hired employees with new skills. Bold means $p < .05$.

at the industry level, as shown in table 4.4. For the purpose of this exercise, we define our industries at a relatively disaggregated level, at the three- or four-digit NAICs code level, and apply a cutoff of at least 10 innovator observations per industry. This breakdown yields 32 manufacturing industries.[17] This analysis could not be conducted for our selected service sector industries due to too few industries that meet the 10 observation cutoff. For the manufacturing sector, we observe that while a number of these variables are correlated, it would appear that they do reflect distinct dimensions. Using our main indicators (INNO_SALES, PATENT, INNO_RIVALS, and NEW_CAPAB), we find that none of the correlations exceed 0.4, and relatively few are significant at conventional levels. We also find that each is correlated with the rate of innovation but none with a correlation coefficient above 0.5. We also observe that some of these dimensions are more closely related than others. For example, INNO_SALES, the average share of sales due to the innovation, is correlated with NEW_CAPAB, the percentage of innovating firms' investment in new types of equipment, personnel, and the development of distribution channels (r = 0.38), sensibly suggesting a link between investment in innovation commercialization and demand conditions. We also observe that our measure of the technological significance of the innovation—namely, the percentage of innovations

17. We started with 41 disaggregated manufacturing industries. After excluding manufacturing industries with fewer than 10 innovators, we ended up with a total of 32 manufacturing industries.

within an industry that are linked to a patent (PATENT)—is also correlated with INNO_SALES (r = 0.39). Although PATENT is a rather imprecise measure of technological significance given the low bar for patentability, the relationship is consistent with a link between the incentive to patent an innovation and its economic value. PATENT is also sensibly correlated with the percentage of firms within industries that claim to be innovators (r=0.43). In our correlation matrix, we also include the variable IMITATORS, which is the percentage of firms that report that they introduced a product new to the firm but not to the industry. We see that this measure is strongly and sensibly related to our measure of imitability, INNO_RIVALS (r = 0.70), our measure of the number of firms that "have introduced or are likely to introduce" a competing innovation.

4.4.4.3 Selected Cross-Industry Differences and Similarities in the Nature of Innovation

Table 4.5 ranks 24 industries on our measures of the different attributes of innovations (based on disaggregated industries spanning manufacturing and business services, again dropping industries with fewer than 10 innovators, and then aggregating to the displayed industry categories) and thus highlights important similarities and differences in the character of innovation across industries. In the table, we have highlighted the top third and bottom third of industries on each measure to illustrate the variation in innovation characteristics across industries. Some examples may help illustrate the multidimensionality of innovation and how this varies across industries. To start with some typical examples, we observe that medical devices—typically thought of as a highly innovative industry—ranks highly on most dimensions of innovativeness, particularly share of sales, the patent rate, and investments in new capabilities for commercializing their innovations, although it is only average in terms of the innovation rate (INNO_RATE). Computers and semiconductors also rank either high or average on several dimensions. On the low-innovation end, we have industries such as mineral products and metal products, which have low rates of innovation and relatively low values on several of our dimensions of innovativeness (sales, patenting, and new capabilities). We see a similar pattern in engineering services (with low rates of innovation, sales from innovation, patenting, and investment in capabilities) even though this might be seen as a technology-based industry. Hence these industries largely follow the patterns we expect, although medical equipment is more imitator dominated than many might expect. On the other hand, when we compare chemicals and plastics with pharmaceuticals, we see some telling differences. We find all three of these chemistry-based industries at or above the median for innovation, with pharmaceuticals the highest and all at or above the median on patenting, again with pharmaceuticals the highest. Pharmaceuticals stands out in terms of the share of sales from the innovation, with its 31 percent well above the

Table 4.5 Industry "innovativeness" rankings

Industry (no. of innovators)	INNO RATE	Inno Sales	Patent Rate	NEW CAPAB
Food (54)	*13*	*17*	*32*	25
Beverage and Tobacco (10)	18	**32**	**59**	**70**
Textile Product Mills (12)	16	*12*	*40*	28
Apparel and Leather (14)	*12*	18	**72**	28
Paper (30)	16	*12*	*37*	**31**
Printing and Related Support (18)	*7*	19	*38*	**43**
Chemical (except Pharma) (88)	**25**	*14*	45	*15*
Pharmaceutical and Medicine (34)	**31**	**31**	**66**	*7*
Plastics and Rubber (74)	17	*16*	**57**	*18*
Nonmetallic Mineral (36)	*9*	*13*	45	*12*
Primary Metal (37)	*13*	*10*	*41*	23
Fabricated Metal (51)	16	19	43	*16*
Machinery (86)	22	19	52	22
Computers/Electronics (except Semiconductor) (108)	**36**	24	**62**	27
Semiconductor and Other (93)	**28**	23	**65**	30
Electrical Equipment (93)	**28**	20	**62**	*15*
Transportation Equipment (102)	**27**	**26**	46	23
Furniture and Related Product (41)	*14*	20	44	*10*
Medical Equipment (37)	21	**27**	**77**	**42**
Software Publishers (30)	**36**	**25**	56	**41**
Data Processing (17)	*15*	**44**	*21*	**68**
Professional, Scientific, and Technical Svc (28)	16	**25**	55	**53**
Engineering Svc (23)	*13*	*15*	*37*	*19*
Computer Systems Design (15)	**24**	**24**	*35*	**40**
Mean	20	21	50	29
Median	17	19	46	26

Notes: Based on 37 disaggregated industries spanning manufacturing (N = 32) and business services (N = 5), again dropping industries with fewer than 10 innovators and then aggregating to the displayed industry categories, excluding Miscellaneous Manufacturing industries. Bold reflects the top tercile on a given dimension; italics indicate the bottom tercile. INNO_RATE (%): Share of innovators (i.e., those having a new-to-the-market innovation); Inno_Sales (%): Mean % of total sales from new-to-the-market innovations; Patent Rate (%): Share of innovators that patented any part of their new-to-the-market innovation or have a patented externally sourced innovation; NEW_CAPAB (%): Share of innovators that developed new sales/distribution channels *and* bought new types of equipment or hired employees with new skills.

mean, while chemicals and plastics are well below the mean at 14 percent and 16 percent, respectively. Recalling that this share-of-sales figure reflects the share of business unit sales for the innovation that accounts for a plurality of the respondent's revenue, these results suggest that drug companies are much more focused on single blockbuster innovations as compared to other chemicals industries that appear to be focused on a larger number of innovations with more modest market impacts. Also, all three show low rates of investment in new capabilities, but with pharmaceuticals the lowest by far. Hence while the innovations in chemicals, especially pharmaceuticals, are ranked highly on market impact and technical significance, they also tend to be low on our measure for distance, even compared to medical devices. These figures suggest clear differences in the nature of innovation across industries and suggest differences in innovation strategies. For example, firms in some industries tend to hew closely to existing capabilities or focus more on blockbusters.

4.5 Illustrating the Utility of Measuring the Characteristics of Innovations

4.5.1 Differences across Sectors and Industries

With these measures, we can also compare empirical patterns across sectors and industries that further reflect differences in both the nature of innovation and its impact. For example, above we saw the baseline innovation rate between the manufacturing and service sectors to be close: 16 percent versus 18 percent, respectively (See tables 4.2a and 4.2b). Once we consider impacts and "significant" innovation rates, the story changes. For example, we see that the average percent of business unit sales accounted for by the firm's most important innovations (INNO_SALES) is substantially higher in the service sector, at 27 percent, versus 19 percent for the manufacturing sector (see tables 4.3a and 4.3b). We also observed in section 4.4 that a higher proportion of respondents in services—7 percent (i.e., 18 percent $*$ 40 percent)—invested in new types of equipment and personnel and developed new distribution channels relative to the 4 percent observed in the manufacturing sector. We probe what may lie behind this pattern by comparing the sales revenue distributions of innovations in manufacturing versus software.

4.5.2 Software versus Manufacturing

In figure 4.2, we present a frequency distribution of the percentage of respondents in, respectively, the manufacturing sector and software industries, ordered by the contribution of their most important product innovation to business unit sales. For this analysis, we define software broadly to include software publishers, data processing, and computer systems design (cf. tables 4.2b and 4.3b). What we observe for the manufacturing sector is expected—namely, that the share of respondents largely declines as the reported share of business unit sales accounted for by their most important innovation increases. In other words, it is relatively rare for a recently introduced innovation (i.e., a new-to-the-market product)—even that which accounts for a plurality of a firm's sales in a market—to account for more than 50 percent of business unit sales. We find the opposite pattern, however, for software, where the percentage of respondents increases with the reported share of business unit sales accounted for by their most important innovation. Indeed, it is common for software firms' most important innova-

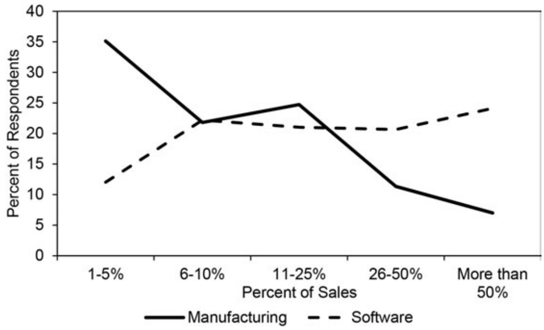

Fig. 4.2 Share of sales from innovation, manufacturing vs. software

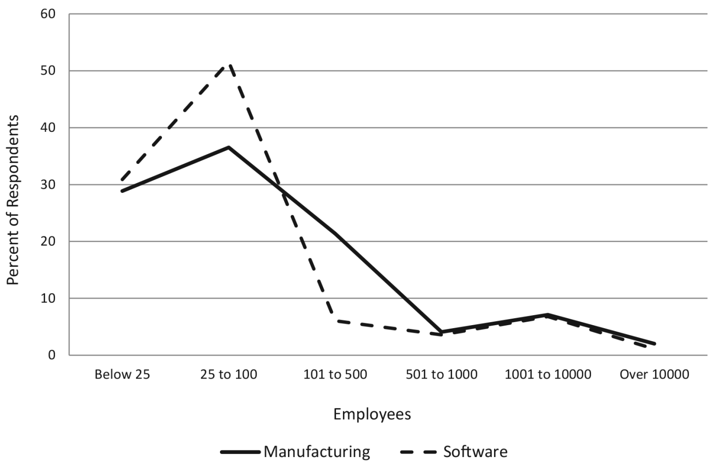

Fig. 4.3 Distribution of business unit size, manufacturing vs. software

tion to account for more than half of the business unit sales.[18] To see whether these differences are driven by differences in the size distribution between manufacturing and software, we examine the business unit size distributions. Figure 4.3 shows that the size distributions are very similar between those two sectors, with a large percentage of small firms in each, suggesting that the differences in business unit sales in figure 4.2 may not be driven by differences in the size distribution. We confirmed this by using a linear probability model, regressing a dummy variable indicating whether an innovation accounted for more than a 50 percent share of business unit sales against a dummy variable representing software (versus manufacturing), as well as

18. One qualification is that we have compared software with all manufacturing. However, when we compare software with only those manufacturing industries that may be considered high innovation intensity industries, identified as those with above-the-median industry share of sales from products that are new to the firm, we find similar differences in the frequency distributions.

the log of business unit employees, and find that software innovations are significantly more likely to account for more than 50 percent of sales, even controlling for business unit size. We find the same result if we use more than a 25 percent share as the dependent variable.

To understand the different frequency distributions in figure 4.2, we might consider that a new software product can reach a larger market more quickly and at lower cost than a new product in the manufacturing sector due to digitization and the low cost of distribution via the web. In contrast, the investment and associated adjustment costs and time lags for expanding capacity and distributing goods are much higher in manufacturing. This would suggest that in software, the cost of expansion tied to a successful product will be lower and the returns to investment in the production and distribution of a product higher than in manufacturing, consistent with the notion that greater scale can be achieved with a lower fixed cost investment in software.[19]

While the greater returns to fixed investment in product and sales capabilities may explain more rapid growth in software sales tied to a firm's highest-selling new product, it alone cannot, however, explain our figure 4.2 results showing that very high sales shares associated with this highest-selling innovation are more common in software than in manufacturing. What could provide an explanation is the possibility that software firms' most important new products are more likely to replace a prior leading product in software as compared to manufacturing; that is, software firms' leading products are more likely to cannibalize prior generations of a leading product. If this were true, we should see little change in software firms' market share tied to new product introductions. To consider this possibility, in table 4.6 we present the results of a simple ordinary least squares (OLS) probability model regressing the direction of the change in market share on INNO_SALES and log of business unit (BU) size. We code whether a respondent's market share declines (coded as "−1"), stays the same (coded as "0"), or grows ("+1"). Consistent with our conjecture, we observe no relationship between market share change and INNO_SALES in software. In contrast, in manufacturing, we see a significant positive relationship between direction of change in market share and INNO_SALES.[20]

19. If the returns to investment in production and distribution tied to innovation in software exceed those in manufacturing, we might expect to see a stronger link between the share of own-business unit sales tied to firms' most important new products (INNO_SALES) and their investment in new equipment, personnel, and distribution channels (NEW_CAPAB), as well as between INNO_SALES and a component of NEW_CAPAB—namely, whether the firm developed new marketing and distribution channels to commercialize the innovation (New_Mktg). Indeed, the correlation between INNO_SALES and NEW_CAPAB for software ($r = 0.30$) exceeds that for manufacturing ($r = 0.15$), and the correlation between INNO_SALES and New_Mktg ($r = 0.43$) reflects a much tighter link between investment in the development of new sales and distribution channels and revenues in the software industry than that observed for the manufacturing sector ($r = 0.12$).

20. Due to the large standard error on the estimate of the coefficient for INNO_SALES for software firms ($N = 54$), we cannot, however, reject the null hypothesis that the coefficients for manufacturing and software are equal ($F = 1.06$, $p = 0.3$). The results are qualitatively identical when we use an ordered logit model.

Table 4.6 **Regression of market share change on innovation sales share, for manufacturing and software**

	MS change (manufacturing)			MS change (software)		
Parameter	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)
INNO_SALES		0.006***	0.005***		0.002	0.000
		(0.001)	(0.001)		(0.005)	(0.005)
ln(BU Size)	−0.033**		−0.022	−0.162**		−0.161**
	(0.015)		(0.015)	(0.062)		(0.062)
Intercept	0.651***	0.398***	0.500***	1.263***	0.553***	1.251***
	(0.074)	(0.041)	(0.085)	(0.223)	(0.201)	(0.261)
N	899	899	899	54	54	54
R^2	0.008	0.032	0.035	0.109	0.003	0.109

Notes: OLS regression coefficients displayed with *at .10; ** at .05; *** at .01. Standard errors in parentheses.

4.5.3 Competition and Innovation

In this section, we consider whether we can use our measures of innovation and its attributes to shed light on one of the long-standing preoccupations of the literature on innovation: the link between market competition and the innovative performance of industries.[21] Using the measures constructed above, we explore a conjecture—that the link between competition and innovation may differ markedly depending on the nature of competition within industries. For this analysis, we propose dividing industries into two types—one where product innovation is central to competition and another where product innovation matters less for competition—where firms compete, for example, mainly via price or advertising. Using the same sample of manufacturing industries employed in section 4.4, we divide these industries into two groups. We will use our measure of the percentage of sales due to products that are new to the firm—but not necessarily new to the market—to coarsely distinguish between industries where competition features innovation versus industries where it does not. We again apply a cutoff of 10 observations of innovators per industry and divide the industries at the median value of this measure (i.e., the percentage of sales due to products that are new to the firm) and simply characterize the 16 industries that are above the median as innovation intensive and the other 16 industries as not.

Table 4.7 shows the means for our featured variables between the two industry groups. As shown in table 4.7, almost all the innovation indicators in the innovation-intensive industries exceed their corresponding values in the less-innovation-intensive industries. What is surprising is the relationship

21. See Cohen (2010) for a review of this vast literature.

Table 4.7 Innovation indicators for low and high innovation intensity industries

	Manufacturing		
		NTF sales	
	All (4,590)	Low (2,286)	High (2,304)
INNO RATE (%)	18	16	20
Imit Rate (%)	25	24	25
INNO SALES (%)	20	17	22
NTF Sales (%)	24	20	27
Patent Rate (%)	51	45	55
NEW_CAPAB (%)	24	21	26
New Mktg (%)	39	36	42
New EqSk (%)	46	41	51
INNO_RIVALS (N)	2.2	2.1	2.3

Notes: For industries having 10 or more innovators. Low/high based on below or equal to / above median of industry means of the percentage of sales due to new-to-the-firm innovations. INNO_RATE (%): Share of innovators (i.e., those having a new-to-the-market innovation); Imit Rate (%): Share of imitators; INNO_SALES (%): Mean % of total sales from new-to-the-market innovationsl NTF Sales (%): Mean % of total sales from new-to-the-firm innovations; Patent Rate (%): Share of innovators that patented any part of their new-to-the-market innovation or have a patented externally sourced innovation; NEW_CAPAB (%): Share of innovators that developed new sales/distribution channels *and* bought new types of equipment or hired employees with new skills; New_Mktg (%): Share of innovators that developed new sales/distribution channels; New_EqSk (%): Share of innovators that bought new types of equipment or hired employees with new skills; INNO_RIVALS (N): Mean number of rivals capable of introducing a competing innovation.

between technological competition and industry innovation rates. For this exercise, we employ our measure, INNO_RIVALS—the number of firms that "have introduced or are likely to introduce" a competing innovation—as a measure of the intensity of competition based on product innovation rather than as a measure of imitability. Comparing more- and less-innovation-intensive industries, we observe a clear difference in the relationship between the percentage of firms that are innovators (not imitators) within industries (INNO_RATE) and INNO_RIVALS. In the innovation-intensive industries, the correlation is 0.47. In the less-innovation-intensive industries, in contrast, the correlation is –0.10 and statistically insignificant.[22] This difference is consistent with the idea that in more innovation-intensive industries, competition stimulates product innovation—approximating what Aghion et al. (2005) have called "neck and neck" competition—while in less-innovative industries, where competition may largely take other forms (e.g., price), there is little relationship between the share of innovating (new-

22. We also find a sharp qualitative difference in the relationship between the percentage of firms that are innovators within industries (NTM) and the percentage of firms that are imitators (IMITATOR). In the innovation-intensive industries, the correlation is 0.46, while in the less innovation-intensive industries, the correlation is −0.30.

to-the-market) firms and firms subject to more-intense competition around product innovation. Consistent with this observation is the possibility that in innovation-intensive industries, there is greater pressure to develop and commercialize more-significant product innovations to "escape from competition" (per Aghion et al. 2005). To probe this, we examine the relationship between the average share of business unit sales attributed to the firm's most important innovation, INNO_SALES, and investment in new capabilities to commercialize the innovation, NEW_CAPAB. Across the more innovation-intensive industries, the correlation is 0.47, as compared to −0.12 in the less innovative industries. This suggests that in the innovation-intensive industries, where technological competition is more severe, firms are introducing more "distant"—and likely more valuable—innovations requiring more investment in new capabilities, while in the less-innovation-based industries, there is little relationship between the sales share attributable to new products and the need for new capabilities, suggesting that the innovations introduced in such industries are more incremental and more closely tied to existing capabilities. A substantive implication of this argument is that for models tying R&D to the intensity of competition, it may be useful to recognize that the forms of competition differ across industries, and innovation of a more substantive, perhaps more technical, sort is simply not an important means of competing in many industries.

4.5.4 Innovation-Level Indicators of Value and Outside Sources of Invention

Analyzing innovators' acquisitions of inventions from outside sources using the same data as employed here, Arora, Cohen, and Walsh (2016) also illustrate the value of our innovation-specific attributes. For the present purpose, we will build on one of the questions addressed in Arora, Cohen, and Walsh (2016): For firms that acquire their key inventions from an outside source, how does the value of those inventions vary by source? For example, how does the value of inventions acquired from customers compare with that from other sources—say, internally generated suppliers, or what Arora, Cohen, and Walsh call "technology specialists," which include universities, independent inventors, and contractors.

The extent to which a firm's innovation draws on a particular source should reflect the net surplus—the value of the invention from that source minus the cost of acquiring and commercializing it. Arora, Cohen, and Walsh (2016) report that customers are the most pervasive outside source of inventions in the manufacturing sector. A further analysis showed, however, that inventions sourced from technology specialists are of higher value and that the high share of customer-sourced inventions is associated with a relatively low cost of acquisition. Arora, Cohen, and Walsh (2016) did not, however, go further than interpreting all their measures as simply different indicators of

Table 4.8 **Different dimensions of innovativeness of innovations by source**

	Econ. val.	Distance		Tech. sig.
	Sales >50%	New_EqSk	New_Mktg	Patent
Customer	−0.06***	−0.04	0.00	−0.08**
	(0.02)	(0.04)	(0.04)	(0.03)
Supplier	0.06**	−0.19***	0.01	−0.11**
	(0.03)	(0.05)	(0.05)	(0.05)
Tech special	0.07***	0.14**	0.10**	0.28***
	(0.03)	(0.05)	(0.04)	(0.04)
Other firm	−0.03	0.00	0.02	−0.08
	(0.03)	(0.06)	(0.06)	(0.06)
Controls (R&D, size, industry dummies, parent size, age)	Yes	Yes	Yes	Yes
Obs	927	1,012	1,017	1,019
R^2	0.15	0.14	0.16	0.26

Selected results from Arora, Cohen, and Walsh (2016).

Notes: Excluded category is Internal. OLS regression coefficients displayed with *at .10; ** at .05; *** at .01. Standard errors in parentheses.

the economic value of innovation. They did not consider what particular features of innovation each of those different measures might also reflect. Reinterpreting these measures as reflecting distinct features of innovation, we relate the likelihood of scoring high on these different dimensions to the origin of these innovations—that is, whether they originate from suppliers, customers, technology specialists (universities, engineering firms, or R&D service contractors), other firms in the industry, or internally. In our framework, the different dimensions of innovations include (1) utility, measured as whether the associated sales accounts for more than 50 percent of business unit sales; (2) distance, measured as whether the innovator invests in new equipment or hires personnel with distinct skills (New_EqSk) to commercialize the innovation (distance) or develops new sales and distribution channels (New_Mktg); and (3) technological significance, measured as whether there is a patent on the innovation. Table 4.8 presents the results.[23] Since all the dependent variables in table 4.8 are expressed as dummy variables, we can compare coefficients across the specifications. We see that the impacts of particular sources vary across the different dimensions of innovation. Specifically, inventions originating from technology specialists have an especially strong association with technological significance compared to their impact on the distance or utility measures, which is consistent with the notion that innovations sourced from technology specialists are best characterized by

23. These are based on tables 5a and 5b in Arora, Cohen, and Walsh (2016).

their technological significance. On the other hand, we find a clear negative relationship between suppliers as a source and the likelihood that the innovating firm invests in new types of equipment—that is, distance as compared to its relationship with utility or technological significance. This is consistent with the notion that existing equipment suppliers in particular are unlikely to offer innovation ideas that will require their customers—that is, the innovating firms—to purchase types of equipment that are very different from what they are already employing. In other words, supplier-sourced innovations tend to be characterized by relatively low distance. This analysis suggests that our dimensions can be used to understand not just the relative value of different sources, as Arora, Cohen, and Walsh (2016) do, but also the nature of the innovations derived from different sources (e.g., their technical significance or distance). Furthermore, these analyses again show a benefit of focusing on a single innovation when asking about sources of innovation, as this is what allows comparisons of the character of innovation across the different sources of the underlying invention.

4.6 Suggestions for New Attribute-Based Innovation Measures

As noted, the survey providing the basis for our empirical analyses above was not originally designed for developing measures of all the attributes of innovation considered in our conceptual discussion. In this section, building on both our conceptual discussion and empirical analyses, we offer suggestions for other measures of the different attributes of innovation featured in our conceptual discussion. Recall that these measures should focus on a specific innovation. We will again confine our discussion to product innovations and survey-based measures.

Technological Significance. Our current measure of *technological significance* is a dichotomous measure of whether an invention underlying the innovation had a patent associated with it. As suggested above, this measure is limited. First, the technical standards for patentability are low, and second, a large fraction of inventions are not patented. To overcome the limitations of this measure, one suggestion is to ask respondents to assign scores for the invention underlying the innovations, asking respondents for their judgments regarding technological significance (No and Walsh 2010; Walsh, Lee, and Nagaoka 2016). For example, adapting language from the survey of American and Japanese inventors of patented inventions (Nagaoka and Walsh 2009), one might simply ask respondents, "Compared to other technical developments in your field during the year the focal innovation was commercialized, how would you rate the technical significance of your invention?" with the corresponding categories: *Top 10 percent*, *Top 25 percent but not top 10 percent*, *Top half but not top 25 percent*, *Bottom half*, and *Don't know*. Although this measure may not be free from potential reporting biases, it represents an expert assessment of relative technological significance.[24] This question is also targeted to technological significance apart from the innovation's economic value or impact. One may also pose a prior question to assess whether the innovation—that is, the firm's new or significantly improved product—reflects any technological advance at all and to what extent. One approach would be to ask whether the product is based on the firm's own R&D or if it embodies purchased (e.g., licensed) technology. A complementary line of questioning might assess whether the technology embodied in the new product differs markedly from competing firms' products. One would then, of course, define what "markedly" may mean—for example, employing new technological approaches to solving technical problems.[25]

To assess whether the innovation actually reflects a technological advance affecting product performance, one could inquire if the innovation was functionally superior on any performance dimension to existing products or whether it was simply different but not functionally superior (e.g., a different flavor of toothpaste or a new clothing design). To the extent that there are well-established performance metrics (e.g., clock speed for chips, conversion rate for solar cells, miles per gallon, or miles per charge), one might elicit estimates of performance improvements over existing products.

Another aspect of technological significance is whether the innovation in question provides a basis for subsequent advance. We would again suggest a question based on observable behavior or outcomes. For example, one may inquire whether the firm has a follow-on R&D project dedicated to improving the product or has contracted with another firm to do so.

Utility. Our main measure employed in our empirical analysis reflected the share of own sales linked to a new product. This measure, as noted above, is limited given that it reflects not only some measure of utility on the part of buyers but also the pricing, marketing, and other decisions made by the firm. There are, however, any number of other questions that one might ask to elicit information about utility. For example, respondents may have a sense of both the addressable market—that is, the potential market size—and the

24. Prior work suggests this may be a useful ordinal measure of technological significance. Walsh, Lee, and Nagaoka (2016) report that among patents granted in the United States and also filed in Japan and Europe (triadic patents), 15 percent of US inventors rated their patents in the top 10 percent in technical significance, and 34 percent reported being in the bottom 50 percent. Since we would expect an overrepresentation of inventions of high technical significance in a sample of triadic patents (compared to all patented and unpatented inventions), these figures suggest that inventors were reasonably accurate in their assessments of the relative technological significance of their patents. This self-reported measure has also been shown to be correlated with commercialization of the invention, project size (the number of person-months dedicated to the project), patent scope (the number of IPC classes the patent spans), and forward citations, all of which we might expect to be correlated with technological significance (No and Walsh 2010; Walsh, Lee, and Nagaoka 2016).

25. One caution in implementing these questions is that marketing or similar personnel may not be able to assess the technical contributions of their or others' innovations, requiring use of a different-respondents-for-different-questions approach, as in the NSF Business R&D and Innovation Survey.

share of the addressable market that their product reached. Presumably the size of the addressable market will relate to the product's expected growth in sales over time. Such information again, however, reflects outcomes of pricing and other decisions on the part of the firm and its rivals. We would also want to ask whether the new product is sold mainly to existing customers, new buyers in a market that the firm currently serves, or buyers in a new market. The answer to these questions would also be useful in our consideration of the dimension of "distance" discussed below. Potentially bearing on both utility and technological significance, one could also inquire whether the innovation reflects an improvement on an existing product or an altogether new product.

Other questions addressing utility would consider whose utility. For example, one could ask whether it is end consumers or firms that buy the firm's new products. Per the discussion above on whether a firm's innovation provides the basis for subsequent advance, it would also be useful to know whether the firm's innovation is employed by firms in either its industry or other industries in follow-on R&D leading to new products or technologies, which would be the case, for example, with general-purpose technologies.

Another important limitation of market-based measures of utility, as noted above, is that there are innovations for which most prospective users of a new product may not be able to afford the product (e.g., a malaria vaccine in Africa). Thus in lieu of market-based metrics, it would be useful to ask, for example, how many lives may be affected or even saved by the provision of the product. In some industries (e.g., hospitals or medicine), one could also elicit measures of improvements in patient outcomes (e.g., time until recovery, reductions in mortality or morbidity, changes in life expectancy).

Distance. As discussed above, we think of distance or the implementation gap as reflecting the degree to which either the firm's own capabilities or the external environment—particularly the absence of complementary goods or services—may constrain the firm's ability to commercialize a new invention. We suggest that our two measures employed in our empirical analysis—whether the firm needed to acquire new equipment or personnel with new skills, on the one hand, or acquire new sales or distribution channels, on the other—represent useful measures. One necessary change, however, is to separate the question of hiring new personnel from that of acquiring equipment.

Another question regarding the internal constraints on commercialization would be to inquire if the firm needed to reorganize its operations in any way to commercialize the innovation.[26] Similarly, one might consider if commercialization of the product required entirely new organizational units

26. To make this more concrete, one might ask if, in the course of commercializing the innovation, the firm had to modify any business objectives, the way decision rights are allocated in the firm, the way product or personnel performance is evaluated, or reporting structures or incentive systems or if new alliances and partnerships with other firms in previously unrelated downstream or upstream industries had to be developed.

or capabilities to produce and/or deliver the product. An example is the iPod, which required a new platform, iTunes, to deliver music and challenged an assumption that music should be sold in a physical album and that online music file sharing should be free.

To the extent that the inventions underlying an innovation originate from other industries or reflect technologies that are not typically employed by the firm, this may limit the ease with which the firm's own capabilities and practices will support the innovation or even its acquisition. Therefore, we can measure *distance* by asking the respondent if the concept for the new product originates from their own industry or from a different industry or employs technologies with which the firm has no experience.[27] We could also ask whether developing the invention required expertise from outside the firm.[28]

There is also that aspect of distance concerned with the external constraints on commercialization. Specifically, it would be useful to know if commercialization of the product required complementary products or services offered by other firms and whether the lack of such complements impeded either the quality or the availability of the firm's new product. For example, Walsh, Lee, and Jung (2016) asked if the reasons for not commercializing an invention included delays in the availability of complementary technologies or the absence of application technologies.

Replicability/Uniqueness. Currently, our measure, based on the number of firms that "have introduced or are likely to introduce" a competing innovation, not only conflates imitability with technological competition; it also does not clearly distinguish the concept of *replicability* from that of *uniqueness*. To address uniqueness, future surveys could ask if the innovating firm was aware of other firms developing similar products at the time of product introduction. For another indicator of uniqueness, one could ask firms what share of their innovation projects overlap with those of their rivals, where high overlap suggests less uniqueness.[29]

To probe replicability, one could ask if another firm introduced a competing alternative and, if so, how long it was after the innovating firm's product introduction (i.e., replicability), which is adapted from the Carnegie Mellon Survey administered by Cohen et al. (2000). Furthermore, one can also ask imitators the same question: How long was it until they introduced a competing alternative to the innovator's product innovation? Asking these questions of both innovators and imitators would provide a validity check at the industry level. One could also measure replicability at the industry level by asking about the use of reverse engineering as a source of information about competitors' products.[30] Also, for those who externally sourced their

27. Such measures resemble bibliometric measures that use information on the technological distance between the focal invention's technology class and the technology classes documented in the patent's prior art references.
28. A similar question was asked in the Carnegie Mellon Survey (Cohen et al. 2000).
29. A version of this question was asked in the Carnegie Mellon Survey (Cohen et al. 2000).
30. A version of this question was asked in the Carnegie Mellon Survey (Cohen et al. 2000).

innovation, one could also ask whether the focal firm could have acquired a similar innovation elsewhere, as was done in the Arora, Cohen, and Walsh (2016) survey. One could use this as a measure of uniqueness, especially if the measure was used at the industry level since it suggests whether innovations are available from multiple sources.

While the bulk of our discussion has been about product innovation (in part reflecting the dominance of questions about product innovation in the Arora, Cohen, and Walsh 2016 survey), one could also measure various dimensions of process innovation. *Technological significance* could be measured using similar items, asking for a ranking comparing the process innovation to others in the industry (see the discussion above for a sample item). One could also measure performance improvements, such as time or cost per unit reductions, as measures of technological significance (as is regularly modeled in the learning by doing literature). *Distance* could be measured by indicators relating to the need to purchase new equipment or hire personnel with new skills in order to implement the process innovation. Similarly, measures of engineering hours expended implementing the process innovation might be another measure of the distance from existing practices. *Uniqueness* could be measured with items similar to those used for product innovation. For example: "Could this process innovation have been sourced from another engineering firm from the one used? Could a different plant of the same firm have developed this process innovation?" One might also ask if the process innovation depended on the existence of unique equipment or unique skills among the workforce. The Fosbury flop in high-jump is one example of a significant process innovation, in terms of performance, with low uniqueness (and also high replicability). *Replicability* might be measured by the importance of secrecy for protecting the process innovation (similar to the items in the Carnegie Mellon Survey asking about the importance of secrecy for appropriating the returns to process and to product innovations, respectively). As noted above, the Toyota Production System is seen as having low replicability and hence little need for secrecy. Process innovations in the food and chemicals industries that depend on customized bacteria might be another example of low replicability. *Utility* may be measured by the share of a firm's products that benefited from the process innovation, or by the share of the firms in an industry that adopted the process innovation. Statistical quality control or lean manufacturing processes might be examples with very high utility.

* * *

In addition to the above suggestions for guiding future innovation surveys' assessments of selected attributes of innovation, we would make one additional suggestion related to survey design more generally. We would encourage surveys to address these detailed questions not only to the innovators within an industry but to the imitators as well. Many questions about the social welfare impacts of innovation turn on the degree to which firms can and do imitate others' products.

4.7 Conclusion

We suggest that with proper design, innovation surveys can provide valuable data on innovation rates that inform judgments about whether the reported innovations are important, and in what sense, and thus are more interpretable than claims that such innovations are simply "new to the market." There are several keys to doing this. First, we recommend asking respondents questions about a specific innovation in an identified line of business. In our case, the questions focused respondents on their business unit's most important innovation, defined as that which accounted for a plurality of revenue in a line of business.[31] To advance our understanding of the impact of innovation, we also recommend conceptualizing innovation as having different dimensions. We proposed five that are potentially linked to the social welfare impacts of innovation: technological significance, utility, distance (or implementation gap), uniqueness, and imitability.

The chapter also illustrates the utility of our approach, using newly collected data from an innovation survey of the US manufacturing sector and selected service sector industries to construct measures corresponding, however roughly, to the proposed dimensions of innovation. Using these data, we showed how the measured characteristics could inform judgments about the importance of innovations in different industries. By recognizing the distinct features of innovations, we also showed how these features, when combined in novel and distinct ways in selected industries, can provide a more nuanced view of innovation and its complexity. Finally, we used our constructed measures to provide some simple, illustrative insights into the nature of innovation and its impact and how that may differ across industries distinguished by sector or by the intensity of innovation competition. More importantly, in these exercises employing our measures of the different dimensions of innovation, we established empirical relationships and patterns that raise questions for future research. Future work could also test the implications of these dimensions for firm or macroeconomic outcomes—for example, incorporating our dimensions into Crepon, Duguet, and Mairesse's (1998) models. In addition, complementary qualitative studies of the development and commercialization of specific innovations may help unpack the dimensions more clearly and develop our understandings of how the various dimensions of innovations relate to firm and industry conditions, outcomes, and social welfare impacts.

31. One could instead ask respondents to focus, for example, on their most recent new product to reduce the biases that come from focusing on "most important" innovations.

References

Adner, R. 2006. "Match Your Innovation Strategy to Your Innovation Ecosystem." *Harvard Business Review* 84:98–107.

Aghion, P., N. Bloom, R. Blundell, R. Griffith, and P. Howitt. 2005. "Competition and Innovation: An Inverted-U Relationship." *Quarterly Journal of Economics* 120:701–28.

Arora, A., W. M. Cohen, and J. P. Walsh. 2016. "The Acquisition and Commercialization of Invention in American Manufacturing: Incidence and Impact." *Research Policy* 45 (6): 1113–28.

Arora, A., and A. Gambardella. 1994. "The Changing Technology of Technological Change: General and Abstract Knowledge and the Division of Innovative Labour." *Research Policy* 23:523–32.

Baba, Y., and J. P. Walsh. 2010. "Embeddedness, Social Epistemology and Breakthrough Innovation: The Case of the Development of Statins." *Research Policy* 39:511–22.

Bresnahan, T. F., and M. Trajtenberg. 1995. "General Purpose Technologies 'Engines of Growth'?" *Journal of Econometrics* 65:83–108.

Cohen, W. M. 2010. "Fifty Years of Empirical Studies of Innovative Activity and Performance." In *Handbook of the Economics of Innovation*, edited by Bronwyn H. Hall and Nathan Rosenberg, 129–213. Amsterdam: Elsevier.

Cohen, W. M., and S. Klepper. 1996. "A Reprise of Size and R&D." *Economic Journal* 106 (437): 925–51.

Cohen, W. M., and R. C. Levin. 1989. "Empirical Studies of Innovation and Market Structure." *Handbook of Industrial Organization* 2:1059–1107.

Cohen, W. M., and D. A. Levinthal. 1990. "Absorptive Capacity: A New Perspective on Learning and Innovation." *Administrative Science Quarterly* 35:128–52.

Cohen, W. M., R. R. Nelson, and J. P. Walsh. 2000. "Protecting Their Intellectual Assets: Appropriability Conditions and Why US Manufacturing Firms Patent (or Not)." NBER Working Paper No. 7552. Cambridge, MA: National Bureau of Economic Research.

Cohen, W. M., R. R. Nelson, and J. P. Walsh. 2002. "Links and Impacts: The Influence of Public Research on Industrial R&D." *Management Science* 48:1–23.

Crépon, B., E. Duguet, and J. Mairesse. 1998. "Research, Innovation and Productivity: An Econometric Analysis at the Firm Level." *Economics of Innovation and New Technology* 7:115–58.

Dahlin, K. B., and D. M. Behrens. 2005. "When Is an Invention Really Radical? Defining and Measuring Technological Radicalness." *Research Policy* 34 (5): 717–37.

David, P. 1990. "The Dynamo and the Computer: An Historical Perspective on the Modern Productivity Paradox." *American Economic Review* 80:355–61.

Fleming, L. 2001. "Recombinant Uncertainty in Technological Search." *Management Science* 47:117–32.

Giuri, P., M. Mariani, S. Brusoni, G. Crespi, D. Francoz, A. Gambardella, W. Garcia-Fontes, A. Geuna, R. Gonzales, and D. Harhoff. 2007. "Inventors and Invention Processes in Europe: Results from the PatVal-EU Survey." *Research Policy* 36:1107–27.

Griliches, Z. 1979. "Issues in Assessing the Contribution of Research and Development to Productivity Growth." *Bell Journal of Economics* 10 (1): 92–116.

Griliches, Z. 1998. "Patent Statistics as Economic Indicators: A Survey." In *R&D and Productivity: The Econometric Evidence*, edited by Zvi Griliches, 287–343. Chicago: University of Chicago Press.

Hall, B. H., A. B. Jaffe, and M. Trajtenberg. 2001. "The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools." Cambridge, MA: National Bureau of Economic Research.
Henderson, R. M., and K. B. Clark. 1990. "Architectural Innovation: The Reconfiguration of Existing Product Technologies and the Failure of Established Firms." *Administrative Science Quarterly* 35 (1): 9–30.
Hollander, S. 1965. *The Sources of Increased Efficiency: A Study of DuPont Rayon Plants*. Cambridge, MA: MIT Press.
Jaffe, A. B., and G. De Rassenfosse. 2017. "Patent Citation Data in Social Science Research: Overview and Best Practices." *Journal of the Association for Information Science and Technology* 68:1360–74.
Jensen, M. B., B. Johnson, E. Lorenz, and B. Å. Lundvall. 2007. "Forms of Knowledge and Modes of Innovation." In *The Learning Economy and the Economics of Hope*, edited byBengt-Åke Lundvall, 155–82. London: Anthem.
Kalton, G. 1983. *Introduction to Survey Sampling*. Thousand Oaks, CA: Sage.
Klevorick, A. K., R. C. Levin, R. R. Nelson, and S. G. Winter. 1995. "On the Sources and Significance of Interindustry Differences in Technological Opportunities." *Research Policy* 24:185–205.
Kubota, T., Y. Aoshima, and Y. Koh. 2011. "Influence That Distance from the Divisional Environment Has on the Innovation Process: A Comparative Analysis of ArF Resist Materials Development." IIR Working Paper. Tokyo: Hitotsubashi University Institute of Innovation Research.
Lee, Y.-N. 2015. "Evaluating and Extending Innovation Indicators for Innovation Policy." *Research Evaluation* 24:471–88.
Lee, Y.-N., and J. P. Walsh. 2016. "Inventing While You Work: Knowledge, Non-R&D Learning and Innovation." *Research Policy* 45:345–59.
Levin, R. C., A. K. Klevorick, R. R. Nelson, S. G. Winter, R. Gilbert, and Z. Griliches. 1987. "Appropriating the Returns from Industrial Research and Development." *Brookings Papers on Economic Activity* 3:783–831.
Li, G.-C., R. Lai, A. D'Amour, D. M. Doolin, Y. Sun, V. I. Torvik, Z. Y. Amy, and L. Fleming. 2014. "Disambiguation and Co-authorship Networks of the US Patent Inventor Database (1975–2010)." *Research Policy* 43:941–55.
Mansfield, E. 1968. *Industrial Research and Technological Innovation: An Econometric Analysis*. London: Longmans, Green.
Marshall, A. 1890. *Principles of Economics*. London: Macmillan.
Merton, R. K. 1973. *The Sociology of Science: Theoretical and Empirical Investigations*. Chicago: University of Chicago Press.
Nagaoka, S., and J. P. Walsh. 2009. "Commercialization and Other Uses of Patents in Japan and the US: Major Findings from the RIETI-Georgia Tech Inventor Survey." Research Institute of Economy, Trade and Industry (RIETI).
No, Y., and J. P. Walsh. 2010. "The Importance of Foreign-Born Talent for US Innovation." *Nature Biotechnology* 28:289–91.
Roach, M., and W. M. Cohen. 2013. "Lens or Prism? Patent Citations as a Measure of Knowledge Flows from Public Research." *Management Science* 59:504–25.
Rosenberg, N. 1976. "Factors Affecting the Diffusion of Technology." In *Perspectives on Technology*, edited by N. Rosenberg, 189–210. London: Cambridge University Press.
Schumpeter, J. 1934. *Capitalism, Socialism, and Democracy*. New York: Harper & Row.
Shane, S. 2001. "Technological Opportunities and New Firm Creation." *Management Science* 47:205–20.
Spear, S., and H. K. Bowen. 1999. "Decoding the DNA of the Toyota Production System." *Harvard Business Review* 77:96–108.

Strumsky, D., and J. Lobo. 2015. "Identifying the Sources of Technological Novelty in the Process of Invention." *Research Policy* 44:1445–61.

Svensson, R. 2015. "Measuring Innovation Using Patent Data." IFN Working Paper.

Teece, D. J. 1986. "Profiting from Technological Innovation: Implications for Integrations, Collaboration, Licensing and Public Policy." *Research Policy* 15:285–305.

Thompson, P. 2012. "The Relationship between Unit Cost and Cumulative Quantity and the Evidence for Organizational Learning-by-doing." *Journal of Economic Perspectives* 26:203–24.

Von Hippel, E. 1994. "'Sticky Information' and the Locus of Problem Solving: Implications for Innovation." *Management Science* 40:429–39.

Walsh, J. P., Y.-N. Lee, and T. Jung. 2016. "Win, Lose or Draw? The Fate of Patented Inventions." *Research Policy* 45:1362–73.

Walsh, J. P., Y.-N. Lee, and S. Nagaoka. 2016. "Openness and Innovation in the US: Collaboration Form, Idea Generation and Implementation." *Research Policy* 45:1660–71.

Yoon, J., and K. Kim. 2012. "Detecting Signals of New Technological Opportunities Using Semantic Patent Analysis and Outlier Detection." *Scientometrics* 90:45–61.

Zimmerman, M. M. 1955. *The Super Market: A Revolution in Distribution*. New York: McGraw-Hill.