An Evidence-Based Assessment of Research Collaboration and Team Science: Patterns in Industry and University-Industry Partnerships

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Draft: November 20, 2013

Paper commissioned for the National Research Council Study of the Science of Team Science

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Introduction to the Assessment

In the not too distant past, the mythology of science embraced the image of the brilliant, solitary researcher wrestling heroically with the great scientific challenges of the day and by dint of singular intelligence solving problems that had long eluded others. In the science of the 19th Century and earlier, the lone intellectual warrior myth sometimes contained enough truth so as to not be a great distortion (Lightman, 2008). But for many decades the portrayal of the advance of research in science, technology, engineering and mathematics (hereafter STEM) in terms of “great man history” rings hollow (Boring, 1950). Today in most STEM fields more than 90% of research studies and publications are collaborative (Bozeman and Corley, 2004) and team-based collaborative research more often leads to high impact research and to commercial uses of research as reflected in patents (Wuchty, Jones and Uzzi, 2007)

Despite significant variation by field, discipline and geography (De Stefano, et al., 2013), contemporary STEM research is dominated by collaboration, teams, networks and co-authorship. Nowadays in many areas of science collaboration is not a preference but, literally, a work prerequisite. If one’s work depends on access to samples or specimens or to extremely expensive shared equipment, then collaboration and research are essentially one in the same.

The past few decades’ trends in increased research collaboration are owing to a variety of factors, including, among others, the rapid specialization of science and the melding of fields (Porter and Rafols, 2009; Haustein, et al. 2011), new enabling collaborative technologies (Zhou, et al., 2012; Muscio and Pozzali, 2012; Tacke, 2011), resource sharing imperatives (Neveda, Georghio and Halfpenny, 1999; Ynalvez and Shrum, 2011), and new public policies

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3 For better or worse, “great man” is a term of art, not a direct denial (though perhaps a subtle one) of “great women.” In this sense, Marie Curie was for years among those listed in the “great men of science” in the pantheon.
explicitly encouraging collaboration (Ponomariov and Boardman, 2010; Wallerstein and Duran, 2010; Van Rijnsoever and Hessels, 2011).

**Decision rules for selecting articles**

We apply three guiding (i.e. flexible) decision rules for selecting articles for the review. These rules are depicted in Figure 2. The first rule addresses whether a focal article is evidence-based (in the sense of the term described above). If the focal article is not evidence-based, it is excluded from the review. For example, there are a number of very good perspective pieces on the need for more (or less) research collaboration between universities and industry, but they are excluded because they do not present a clearly-articulated research question involving use of quantitative or qualitative data.

**Figure 2. Decision rules for including and organizing articles using the framework**

- Is the focal article evidence based?
  - If yes, include.
  - If not, exclude.
- Does the focal article address research collaboration per se?
  - If yes, include.
  - If not, exclude.
- Does the focal article address attributes under more than one component of the logic model?
  - If yes, which components?
  - If yes, how will the discussion of the focal article be different across the different components?
  - If no, what is the attribute and which component does it fall under?

If the focal article “passes” the first decision rule, the next decision rule is whether the article addresses research collaboration per se, either by way of including data for variables measuring collaboration inputs, processes, outputs, and/or outcomes or by sample selection (e.g., sampling researchers affiliated with NSF centers). This rule results in the exclusion of a
number of popular empirical articles examining the connection between government support for university research and scientific productivity. However, the rule also implies that the subset of these studies that addresses empirically policies and institutions designed to facilitate boundary-spanning research collaborations (e.g., CRADAs, university research centers) are included in the review.

If the focal article “passes” the second decision rule, the last rule is determining what part of the guiding logic model the article fits. This rule is not a vital one since ours is a guiding model for organizing the literature and, of course, various research findings stand on the own. If the article examines empirically one or more of the attributes from the framework as an input, then that article is addressed under “inputs and resources.” In turn, if the same focal article models empirically yet another attribute from the logic model as an outcome, then that attribute is not addressed in the “inputs and resources” section (beyond brief mention and a cross-reference), but rather is discussed in the “outcomes and impacts” section of the review.

The Assessment of Research Collaboration Literature: Inputs and Resources for Team Science and Research Centers

Formal training at the individual and project, organizational levels

The literature on boundary-spanning research collaborations distinguishes different backgrounds and formal training at the doctoral level, albeit more typically as control variables rather than as antecedents of primary (or even secondary) interest. Most of this “controlling” has occurred with the work of Bozeman and colleagues and their series of survey- and curriculum vitae-based research on the scientific values of and participation in research collaborations by academic researchers in the US. This series of articles (e.g. Bozeman and Corley, 2004; Bozeman and Gaughan, 2007; 2011; Boardman and Ponomariov, 2007; Boardman and Corley, 2008; Bozeman and Boardman, 2013) has elicited no consistent results
connecting formal training (which Bozeman and colleagues mostly operationalize as respondents’ PhD field) to particular research collaboration strategies or behaviors. Perhaps the most consistent result across this series of articles is that there are considerable differences across fields with regard to the propensity to collaborate with industry and most find that engineering disciplines are the most likely to collaborate with industry.

A more useful operationalization of formal training for designing and implementing team science and research centers is at the project and/or organizational level, specifically addressing the heterogeneity of disciplines for a particular project or organization. The reason this is more useful is because both public and private sector research is becoming increasingly multidisciplinary due to the increasing complexity of the scientific and technical innovation required to address social, economic, health, energy, defense, and other national problems (Zerhouni 2003). Also, methodological and epistemic norms across disciplines can be quite different, sometimes diverging sharply (Snow 1964, Clark 1983, Becher 1989, Kekale 2002, Turner et al. 2002, Van Gigch 2002a, b) and therefore an impediment to boundary-spanning research collaboration (Goldman 1986, Corley et al. 2006).

There are a few studies that look at what we prefer to call “disciplinary heterogeneity” (to avoid unnecessary discussion, here, of the differences between interdisciplinary, multidisciplinary, and transdisciplinary research). Chompalov and colleagues (2002) find as disciplinary heterogeneity increases, so does productivity, but also so does heterogeneity of incentives and motives to collaborate and thusly collaborations become more hierarchical as well as more formalized organizationally.

Many other studies focus on the relationship between collaboration and disciplinary differences or collaboration and multi- and interdisciplinary issues. Some studies measure the
degree of interdisciplinary collaboration and draw conclusions based on those differences (e.g. Qin, et al., 1997; Bordons, et al., 1999; Schummer, 2004; van Rijnsoever and Hessels, 2011). Other studies are more normative, evaluating or prescribing means to overcome or exploit disciplinary differences (e.g. Hall et al., 2008; Porter et al., 2006).

**Past productivity**

There are not many studies addressing bibliometric and/or patenting productivity as an input *per se* (i.e., as a key predictor rather than as an antecedent control variable) into team science or research center processes, outputs, and/or outcomes (see Figure 1).

One example of this sort of study (i.e., conceptualizing scientific and technical productivity as an antecedent to research collaboration) are those studies focused on “star scientists,” i.e., scientists who are very productive bibliometrically because of their own innovative techniques and ideas (e.g., Zucker & Darby 1996). However, this particular “brand” of scientist is demonstrated to collaborate less to protect her or his techniques and ideas from imitation and emulation (Zucker & Darby 1996). Another example are articles focused on predicting and explaining the bibliometric productivity of team science or research centers that include lagged measures of bibliometric productivity as antecedent control variables for contemporaneous bibliometric productivity (e.g., Ponomariov & Boardman 2010).

One reason the research collaboration literature has not followed many economists in operationalizing past productivity as contemporaneous human capital is that seldom do these two literatures meet. Another reason is that bibliometric and patenting productivity have generated more interest in policy and scholarly circles as outputs and outcomes of research collaboration. A final reason may be that past research productivity may not be a valid measure of either inputs or outcomes for team science and research centers. Cronin (2001) and Garg and
Padhi (2001) for example call into question the measurement validity of research productivity as a proxies for both inputs into and outputs of collaborative research as it may occur in team science or research centers due to what they term “hypercoauthorship” wherein not all coauthors contributed expertise or human capital per se to the collaborative project and resultant article, but rather are listed as coauthors for reasons other than expertise/human capital contributions.

**Career status and past career experiences**

Past career experiences have also been shown to have an impact on research collaboration and scientific and technical productivity. Rijnsoever and Hessels (2011) find heterogeneous research experiences to correlate positively with both disciplinary and interdisciplinary research and, similarly, Aschoff and Grimpe (2011) show academic researchers who work early on in their careers with industry to be more involved with and publish more with industry based researchers later on. Ponomariov and Boardman (2010) show the rate and intensity of both interdisciplinary and university-industry co-authorship to correlate positively with academic researchers’ affiliation with university-industry research centers, using a panel of bibliometric data for 57 academic researchers over the entirety of their respective academic careers. Boardman and Ponomariov (2013) use comparative case study methodology for a purposive sample of NSF university-industry research centers to suggest that past career and educational experiences in management may have an impact on how formalized and horizontally differentiated research centers are.

Other studies assess career experiences using both more and more sophisticated constructs. Dietz and Bozeman (2005) emphasize changes in job sectors throughout scientific and engineering careers and how these affect productivity in terms of both publications and
patents. Using the curriculum vitae of 1,200 scientists and engineers from the USPTO (US Patent and Trademark Office) database, the authors show that diversity of career experiences leads to diversity in scientific and technical productivity. Specifically, the authors show that inter- and intra-sector job changes (i.e., university to industry and vice versa, university to university, industry to industry) leads to higher publishing and patenting rates.

**Social capital**

Much of the empirical work in this area emphasizes prior acquaintance and trust as an important input into research collaborations. Prior acquaintance as an input into new team science or research centers can enhance collaboration from the start due to decreased if not avoided transaction costs associated with engendering trust amongst collaborators from different disciplines, universities, firms, government agencies, sectors, and even age cohorts (Granovetter 1985, 1992, Marsden 1981, Williamson 1975, Commons 1970). One of the key findings from the general empirical literature on boundary-spanning collaboration (not necessarily research collaboration) is that acquaintance and the trust it engenders leads to progressively fewer and less formal structures and authorities for governing the collaboration (Gulati 1995).

Among the more interesting empirical studies of the role of trust in boundary-spanning research collaborations is one focused on inter-firm research collaboration. Dodgson (1993) emphasizes interorganizational (versus interpersonal) trust characterized in two case companies by what he calls communities of interest, organizational cultures receptive to external inputs, and frequent and egalitarian communication of information about the status and purpose of the collaboration.
Many other studies at the individual level of analysis show trust to correlate positively and significantly with collaboration processes, outputs, and outcomes (Sonnenwald 2007: e.g., Creamer 2004, Hara et al. 2003, Sonnenwald 2003, McLaughlin & Sonnenwald 2005, Knorr-Cetina 1999, Krige 1993). Trust has been a big emphasis in studies of research collaboration because without it collaboration in most cases does not happen (Olson & Olson 2002). Though their data are at the individual level of analysis, perhaps most relevant of these articles to the current report are the studies by Shrum and colleagues (2007) and by Zucker and colleagues (1995); both show that in team science and research centers trust is most readily engendered amongst same-discipline and same-institution researchers in multi-discipline, multi-institution research collaborations.

**Motivations and personal characteristics**

In the numerous studies surveying researchers at the individual level, many control for motivations and related characteristics such as the age, gender, and ethnicity of respondents. Melin (2000) suggests that there are many personal reasons to engage in research collaborations like team science and research centers (and also acknowledges exogenous reasons as well) but emphasizes the social aspects of collaboration as a primary motivation at the individual level of analysis. Beyond the social aspects, amongst samples of academic researchers the job security that comes with tenure has been shown to affect attitudes towards collaboration. Boardman & Ponomariov (2007) find that not having tenure negatively and significantly correlates with a willingness to work with industry among a stratified random sample of academic researchers affiliated with NSF Engineering Research Centers. Using a broader data set on a national sample of academics whether they are affiliated with a research
center or not, Corley and Bozeman (2004) find that tenure status does not correlate significantly with personal collaboration strategies.

The impact of gender on research collaboration activities and outcomes can be direct or an interaction with other individual characteristics like tenure status. Bozeman & Corley (2004) show that women tend to collaborate more than men do in academic science. This finding holds for women at all stages of their careers (e.g., tenured or not, research group leader or not) and for different types of academic careers in science (tenure track versus research faculty). The authors also find that non-tenure track women are more likely to collaborate with other women than with their male counterparts. In a more recent yet similar study Bozeman and Gaughan (2011) seek to “break” previous models suggesting that gender matters to collaboration and specifically boundary-spanning collaboration. The study showed that females collaborate more and was the first to demonstrate that the “gender effect” holds when controlling for numerous other personal attributes. Published almost simultaneously, Rijnsoever and Hessles (2011) find very similar results.

The numerous studies using the “industry involvement index” (see Bozeman & Gaughan 2007 for a detailed explanation of the index, which is a weighted gradient) finds gender to have moderate but statistically significant correlation with academic researchers’ collaboration intensity with industry, with men being advantaged compared to women (Bozeman & Gaughan 2007, Gaughan & Corley 2010).

Ethnic minority status has also been a factor in empirical and case based research on team science and research centers. Sonnenwald (2007) provides an extensive review not only of the relationship between participation of ethnic minorities in research collaborations but also
addresses field work for alleviating some of the mistrust, misunderstanding, and conflict that can arise.

Practically all of the research on the motivations and related characteristics for organizations entering research collaborations focus on private firms. A predominance of these studies provides a resource-based explanation of one sort or another (e.g., size in terms of employees and/or R&D budget). Others emphasize government incentives, geography, and leadership. The findings are quite consistent perhaps because most of these studies address private firms whose organizational environments and therefore stakeholder sets and goals are more uniform when compared to university research centers and team science.

Organizational size (usually measured as both number of employees and proportion of budget allocated to research and development) is the most frequently cited characteristic explaining which firms join industry R&D consortia and/or research collaborations with other firms. Practically all of this research finds a positive correlation between size and motivation (e.g., Angel 2002, Bayona et al. 2001, Fritsch & Lukas 2001, Santoro & Chakrabarti 2002, Kaiser 2002). But some studies show relatively unique findings. Kleinknect and Reijnen (1992) find size to decrease rather than increase the likelihood of Dutch firms collaborating with one another on research and development. Aloysius (2002) finds that firms of comparable sizes are most likely to enter into formal research collaborations with one another.

Last, some of these findings for size and motivation for firms to collaborate with one another in research may be spurious. For example, Santoro & Chakrabarti (2002) conclude that larger firms participate in university research centers to build new research capacity outside core research areas whereas smaller firms participate in centers to fulfill core research areas. But the sample of firms they use participate in different types of university research centers
with very different capacities for “radical” research and development (Ettlie & Ettlie 1984, Damanpour 1996) deviating from existing knowledge and technology versus “incremental” research and development (Ettlie & Ettlie 1984, Damanpour 1996) building predominantly on existing knowledge and technology.

Other motivations for firms to collaborate in research and development include having common precompetitive research challenges (Ouchi & Bolton 1988, Greis et al. 1995, Sakakibara 1997, Katila & Mang 2003, Mowery et al. 1998, Hayton et al. 2013) and, related, weak competition from other firms (Sakakibara 2002); spatial proximity (Fritsch 2001) and, related, being located in a large urban area (Angel 2002); having an internal champion of inter-firm research collaboration who acts as a gatekeeper to identify firms with which to collaborate in research and development (Fritsch & Lukas 2001, Mathews 2002), as well as incentives for inter-firm research collaboration from government (Sakakibara 2001, Hayashi 2003) and, related, national culture (Steensma et al. 2000).

**Materiel as inputs and resources for team science and research centers**

This component of the framework addresses the attributes that individual researchers, including their (1) tangible capital such as equipment and infrastructure, and labor such as post-docs and graduate students and (2) prior knowledge and art including past research and technology.

**Tangible capital and labor**

The literature on tangible capital for university research centers and government and university team science is sparse. Most of the work emphasizing tangible capital as inputs is from the literature on firm-firm research collaborations and, to a lesser extent, on industry consortia. In our view, the lack of emphasis in the literature on tangible capital in university
research centers and university and government team science is due to the transition over the past few decades of what constitutes competitive advantage in scientific and technical innovation at the university and national levels. However, a few studies focused on experimentation in high energy particle physics emphasize tangible capital in research centers and team science that are not firm-based (e.g., Krige 1993, Galison 1997).

Focusing predominantly on firm-firm research collaborations, Hagerdoorn and colleagues (2000) observe the popularity of the resource dependence perspective among strategic management scholars in explaining boundary-spanning research collaborations amongst private firms, which collaborate on research projects to gain access to resources and capabilities that enable them to develop and sustain competitive advantages. Others also focusing on firms (Becker and Peters 1998, Camagni, 1993) emphasize the sharing of resources to reduce uncertainty and to realize cost savings as well as economies of scale and scope. Audretsch and colleagues (2002) count firms’ network ties to universities as a tangible resource though they are really discussing the human capital in universities as much as the research laboratories and university research centers with complementary infrastructure, equipment, and critical materials. Yet, none of this literature emphasizes access to tangible capital alone, but rather emphasizes access to caches or sums of human capital and social capital and labor in addition to more tangible resources like infrastructure, critical materials, equipment, and funds.

The small literature on labor in boundary-spanning research collaborations emphasizes labor as a standalone input (rather than part of a broader cache of resources) and focuses on graduate students in university-industry research collaborations. This literature is bifurcated, with some authors suggesting that graduate students’ involvement with industry is beneficial to
technology transfer (Ponomariov 2009, Bozeman & Boardman 2013) and also to education (Bozeman & Boardman 2013), though other authors characterizing such graduate student involvement with industry as disruptive and potentially harmful to traditional graduate education (e.g., Slaughter et al. 2002, Slaughter & Rhoades 2004).

Though we treat them as one literature here, really the two perspectives constitute separate literatures. Seldom does empirical study emphasizing graduate student roles in technology transfer address outcomes related to education, like teaching and student support, and almost as a rule does the discourse (typically not empirical research) (Slaughter et al. 2002, Slaughter & Rhoades 2004) on the potentially disruptive and harmful nature of student involvement with industry go unconcerned with the potential benefits of this involvement for education as well as for economic outcomes. While both sets of results (i.e., graduate students correlating positively with technology transfer in university-industry research collaborations, graduate students experiencing negative unintended consequences) can be correct in isolation, Bozeman & Boardman (2013) address both types of outcomes to demonstrate academic researchers who work with different types of university-industry research centers also mentor and teach more graduate students. Behrens and Gray (2001) find a null relationship comparing graduate students working in university-industry research centers to their counterparts not working in these centers or comparable arrangements.

**Prior knowledge and technology (field/industry level)**

The literature on prior knowledge and technology at the field level is one that has no focused on boundary-spanning research collaborations directly, but no less it is quite important, as the state of a particular field of inquiry can have substantial impacts on the very establishment (Bozeman & Boardman 2003) and also the organization and management of
such collaborations (Boardman 2012). Conceptually, prior knowledge and technology at the field level can be “radical,” i.e., relatively divergent from existing knowledge and practice or it can be “incremental,” i.e., focused on the application of existing knowledge and practice (Ettlie et al. 1984). There are just a few studies that address the radical-incremental dichotomy as it relates to boundary-spanning research collaborations. Damanpour (1996) demonstrates collaborations focused on research and development in radical fields to have more complex organizational structures (e.g., centralized decision making, formal contracts, rules of use) than firms focused on incremental research and development. Boardman (2012) similarly finds across different types of university-industry research centers radical research and development to be more conducive to structured management practices than to incremental research and development.

Organizational capital

Here we define organizational capital broadly as anything that can be implemented at the collaboration design and implementation stages (or potentially in a redesign stage after a formative evaluation) to induce coordinated problem solving amongst the people and materiel addressed above. Our review does not address exogenous organizational capital, such as political support and popular support, insofar that these are much less manipulable by policy and program decision makers in government and industry.

We consider organizational capital to be perhaps the most important resource and input into boundary-spanning research collaborations in terms of competitive advantage in scientific and technical innovation. Research centers and team science that are not firm based will not be able to achieve “additional” (see Bozeman et al. 2013) outcomes without organizational capital because it is fundamental to the processes and activities of research centers and team science.
Yet there is not much literature directly focused on organizational capital in boundary-spanning research collaborations that are not firm based because they are predominantly informal and more difficult to observe (Hagedoorn et al. 2002). The literature on organizational capital in university research centers and team science is more focused on management challenges due to a lack of organizational capital (e.g., Boardman & Bozeman 2007, Garrett-Jones et al. 2013).

Organizational capital can be formal and informal (Barney 1995) in research centers and team science when universities and government agencies rather than firms are the “home” institutions. Most of the time, it seems these endeavors use informal coordination mechanisms to facilitate coordinated problem solving within diverse sets of scientists and engineers. This (reliance on informal organizational mechanisms) is the case typically when there are multiple institutions (Chompalov et al., 2002), there is a long history of working together among the researchers (Galison and Hevly, 1992; Krige, 1993; Knorr Cetina, 1999), and when there is trust (Gulati, 1995), as well as inertia (Li and Rowley, 2002).

One of the few studies that address organizational capital in university-industry research collaborations is a recent study by Boardman (2012). He uses as series of 21 cases of NSF university-industry research centers to describe which centers rely on informal mechanisms and which rely on formal ones to coordinate diverse sets of scientists and engineers. He finds that when informal mechanisms for coordinated problem solving such as resource interdependence and goal congruence are not there, the director implements formal structures to facilitate coordinated problem solving and vice versa.

Chompalov and colleagues (2002) identify informal organizational capital as fundamental to boundary-spanning research collaborations. Though they do not use the same
terminology (the term “organizational capital” is borrowed from the strategic management literature), the authors use the same theoretical premise (i.e., transaction costs economics as applied to organizations in Ouchi [1980]). Although they develop a typology of organizational structure for research collaborations, they argue (and find) that hierarchy is not a defining characteristic (in this they were responding to the literature by Krige on high energy particle physics experiments), but rather that the defining characteristic is consensus, which could occur for a number of reasons, including the informal mechanisms identified by Boardman (2012), i.e., goal congruence and resource interdependence.

The Assessment of Research Collaboration Literature: Processes and Activities of Team Science and Research Centers

A growing proportion of the literature on cooperative research centers – typically those that are university based – are emphasizing effective (and ineffective) management and leadership at a fundamental level – i.e., in ways that can be brought about by a number of practices – rather than by emphasizing discrete practices as “best.” Chompalov and colleagues (2002) identify approaches for managing research collaborations and these types adhere to the different combinations of organizational capital – goal congruence, resource interdependence, and formal authorities – emphasized as fundamental for coordinating inputs and resources. “Bureaucratic” collaborations are most successful when the collaboration involves multiple organizations and there must be structural component to ensure that no single organization’s interests are disproportionately served. Leaderless collaborations are too structured with rules and procedures for coordination and collaboration but without the hierarchy protecting against dominance by one organization or another. This type works when there are other informal
mechanisms keeping collaborating organizations “in line” but yet some rules and procedures for coordination across organizational boundaries are required.

Since Chompalov and colleagues (2002), few studies have assessed variation in the management and leadership of diverse sets of actors across multiple cooperative research centers and contexts, i.e., from a logic model perspective, few general studies assess the “processes” of centers. Studies of center processes have focused predominantly on specifying management challenges rather than solutions. Management in centers has been described as ad hoc and underdeveloped (Bozeman & Boardman 2003). There is evidence of negative attitudes towards commercial research (Boardman & Ponomariov 2007) and shirking (Boardman & Bozeman 2007) among center faculty due incongruence between faculty goals and center goals. Goal congruence is a formidable management challenge in NSF centers in particular, as most faculty in these centers have primary appointments in academic departments (Bozeman & Boardman 2003). Toker and Gray (2007) demonstrate challenges associated with spatial dispersion in NSF centers. How centers are responding to these challenges – and how these responses relate to center outputs and impacts – goes generally unaddressed in the literature.

Boardman (2012) describes NSF university-industry research centers as both dysfunctional organizations and organizational networks. NSF centers share attributes characteristic of collaborative networks and formal organizations. Like networks, all NSF centers are boundary-spanning. Though NSF centers vary widely in terms of research foci (Stahler & Tash 1994) and policy goals (Bozeman & Boardman 2003), all are “problem focused,” emphasizing not the extension of knowledge in a particular field or discipline per se, but rather the production of new knowledge and technology to address social and economic problems (Boardman & Gray 2010). This focus on problems rather than disciplines sees that
NSF centers are also boundary-spanning, involving faculty from multiple disciplines (and thusly from multiple academic departments and universities) and from multiple sectors (including industry, universities, and government). Boundary-spanning collaboration is regarded as the primary justification for funding centers, at the NSF and elsewhere (Becker & Gordon 1966, Ikenberry & Friedman 1972). Like new organizations, NSF centers must create leadership and authority structures as a concomitant to setting up new organizational designs. All NSF centers programs publicly solicit for proposals from teams of university faculty. Each center grant that is awarded is university-based and to be led by the principal investigator(s) who submitted the proposal. Proposals for all NSF centers programs are required to address internal organization and management, including horizontal and vertical differentiation and authority lines. However, leaders of NSF centers face a confluence of management constraints that can hinder coordinated problem solving as it occurs in both networks and formal organizations.

The Assessment of Research Collaboration Literature: Outputs, Outcomes and Impacts

Outputs and Impacts for “Knowledge-Focused” Collaborations

In most fields of inquiry, studies focusing on public policy, social or business enterprise impacts, measures of impact often disappoint owing to scarcity, undue complexity or indirect measurements and attendant assumptions, sometimes misplaced, about the ability of the available measure validly to substitute for the behavior or event one wishes ideally to measure. The study of research impacts and, by extension, research collaboration impacts, fares well on this account. While a great many measures have been suggested in connection with research output or impact, two types of measures stand out as having some face validity.
and intuitive appeal. In the case of knowledge-focused collaborations the use of citations has become widespread and increasingly powerful. In the case of property-focused collaborations, patent statistics often prove valuable. The vast majority of empirical studies of research impacts focus on one or both of these types of measures. The result is an increasingly coherent “dependent variable” but, at the same time, some predictable gaps in research.

We begin by examining studies that focus on knowledge products pertaining to research collaboration. The worldwide revolution in the use of bibliometrics, now decades old in its development (Garfield, 1979; Hood and Wilson, 2001; Godin, 2006), has been a great boon to the study of research impacts. Nevertheless, bibliometrics-based research has some important limitations with respect to understanding outputs and impacts of research. The chief problem with bibliometrics-based studies is not what they capture but what they fail to capture. In most cases, bibliometric studies do not even aspire to providing information on knowledge impacts. Many studies (e.g. Hummon and Dereian, 1989; Onel, et al., 2011) focus on the relationships of citations to social networks. Still other studies focus on citations as a direct and immediate dependent variable rather than as an expression of knowledge. Thus, for example, studies examine the effects of various dimensions of co-authoring teams on the accumulation of citations (Katz and Hicks, 1997; Persson, 2010).

To the extent that leaps in knowledge track against citations, bibliometric studies are valid and revelatory. But there are known limits to what can be captured by citations including, for example, the social and economic implications of indicators of “highly cited.” Most agree that citations can prove an excellent starting point; work that is not cited does not necessarily warrant ignoring, but a lack of citations is an excellent indicator that it has, in fact, been ignored. Nor can we assume that works that have been highly cited have been widely used in
any conventional meaning of “use of knowledge.” There is some evidence that citations are often social signs (Cronin, 1984) and that many works cited are not actually read by the person citing (though many commonly scholars who do not read entire articles do read abstracts [Whissell, 1999]). The fact that citing authors are not intimately familiar with the work of the cited author does not mean that the latter’s work has no influence, only that its influence may not be entirely substantive, that influence may be indirect, and that the influence of the knowledge itself (i.e. the embodied propositions, evidence and argument) may be confounded with any of a wide variety of social determinants of citation behavior, including personal relations, reputation of the author or the journal or even the page upon which a citation occurs in a Google Scholar search. This does not necessarily diminish either the authority or scientific standing of highly cited papers or of highly cited researchers; the point is simply that one should not draw an equation between citations and the growth of knowledge. Citations provide a good starting point, a measure that is precise, consensual, normatively meaningful, and, most important of all, easily available.

This cautionary preamble is merited because so many research evaluation and research collaboration the studies, including many of the best known studies, use citations, often to good effect, as indicators of output or impact. A general overview of research collaboration impacts (e.g. Bozeman, Fay and Slade, 2013) would perhaps include scores of such studies. However, since the focus here is chiefly on industry research, industry-university collaborations and, generally, boundary-spanning collaborations, we review only a small portion of the citation/output/impact studies.

Most citation-based studies of research output or impact focus squarely on academic science. Few if any “what-does-industry-want-from-its-university-collaboration?” studies list
citations as a “want,” except perhaps near the bottom of the list. At least one study (Lee, 2000) finds that industry’s collaborations with universities are strongly motivated by a desire to benefit from the fundamental knowledge developed by universities, but this does not imply that citations counts or impacts of citations reflect the knowledge uses intended by industrial partners (Bozeman and Rogers, 1997). Other studies (e.g. Feller and Roessner, 1995; Feller, Ailes, and Roessner, 2002) suggest the industry is more interested in access to individual scientists and to graduate students (sometimes with intent to hire them). If the intent is to directly appropriate research, the concern of industry partners often has as much to do with cost avoidance (Gray and Steenhuis, 2003), equipment access (Tartari and Breschi, 2011) or with the fit of the research to near-term needs (Bozeman and Wittmer, 2001) as with the “best” or “cutting edge,” at least as these are measured with citations.

To be sure, there are studies that focus directly on the research collaboration impacts on (citation-measured) productivity. However, almost all these studies examine university-affiliated co-authorships rather than collaborations between academic and industry scientists or collaborations among industry scientists only. There may be lessons to be gleaned but it is not clear these lessons relate directly to industry-only or industry-university collaborations. For example, Lee and Bozeman (2005) study of hundreds of academic scientists found, perhaps relevant) that the relationship of collaboration to citation-based measures of productivity is not at all straightforward. Collaboration has a strong and salutary effect on productivity if one is measuring productivity in terms of the number of articles produced (normal count) but if one reduces that number in proportion to the number of authors (fractional count) then the seeming productivity gains of collaboration vanish. The study also found that younger and mid-career scientists have greater productivity pay off from collaboration and that collaboration affects job
satisfaction. But it is not possible to determine if these findings transcend their context, chiefly collaborations among academic scientists.

Another study (Pravdić, Oluić-Vuković, 1986) potentially relevant but limited by its academic science context provides citation-based evidence that it is not only collaboration that has an impact on scientific output (in terms of the number of scientific articles produced), but also the tendency of authors to maintain a more stable set of co-authors and collaborators. While the authors did not provide hypotheses about possible causes, one can envision alternative explanations. It is possible that co-authors develop increasing trust or an improved ability to work together or that teams simply sustain diminishing transactions costs for collaboration, thereby making collaborations more efficient. It is also possible that teams stay together to wring out the “least publishable unit” (Susser and Yankauer, 1993) publication from their project, therefore elevating productivity only on the “more articles published” basis.

Despite these various caveats, there are several studies of knowledge-focused collaborations that provide more encouraging results. Caloghirou and colleagues (2001) study of university-industry collaborations in the European Framework Programs showed that firms reported substantial enhancements to their respective knowledge bases, indeed this was listed as a first benefit, followed by improvements to production processes. The study examined a large set of research joint ventures occurring during a fourteen-year period. They found that firms from smaller economy European nations were more likely to participate and more likely to benefit. Benefits occurred not only in knowledge acquisition, but also cost savings, cost sharing, and cost avoidance. But the chief benefit reported was increments to the firms’ knowledge base. The study was based on firm reports with no other supporting data.
Levy and colleagues (2009), a study sharply limited by its focus on industry collaborations in a single university, provide a finding quite relevant and, if it has external validity, important to the study of industry-university research collaboration. According to their analysis there is a strong tendency of industry-university collaborations, whatever the initial intent, to center on knowledge-focused output rather than product-focused output. In a different European setting, and with a great deal more data, Ambos (2008) and colleagues arrive at similar conclusions about the tendency of academics to push industry collaborative work away from property-focused to knowledge-focused research. In light of the incentive systems (Fulton and Trow, 1974; Ponomariov and Boardman, 2010) within most universities, not to mention the tendency of researchers to stay in their “comfort zone,” it is perhaps not surprising that such collaborations would tend to drift toward knowledge-focused (read: “publications-focused”) outputs.

**Outputs and Impacts for “Product-Focused” Collaborations**

Collaborations centering on developing intellectual property and, ultimately, commercially viable products and services, include a wide array of organizational and institutional mechanisms, ranging (at the low end of formalization) from the informal collaboration of researchers (Link, et al., 2007) in different sectors to such mechanisms as joint ventures, research consortia, multi-discipline/multi-institution university research centers (MMURCs), formal research alliances and partnerships, co-location incubator cooperative research, and research and technical assistance contracts. This list is not exhaustive (for an expanded list see Vonortas, 1997; Hagedoorn, Link and Vonortas, 2000; Hoekman, Frenken and Tijssen, 2010). Not surprisingly, given the importance of collaboration to commercialization objectives, there is a considerable relevant literature about the benefits of
collaboration. However, many such publications are reports of personal experiences, unsystematic case studies or, most common, conceptual models based on no data. While there are many evidence-based studies as well, the literature is somewhat fragmented and varies a great deal in its indicators of outputs and impacts. Aside from data based on personal reports, the most common evidence marshaled in the studies of property-focused collaboration is patent data, including patent citations (van Zeebroeck and Potterie, 2008).

In considering benefits from university-industry collaboration, it is useful to establish a baseline, namely the productivity rate when not collaborating. Morgan, Kruybosch, & Kannankutty (2001) provide such baseline information, albeit by this time somewhat dated. Using National Science Foundation data from the 1995 Survey of Doctoral Recipients and the 1995 National Survey of College Graduates, the authors analyzes responses from 204,700 scientists and engineers working in government or industry. While a variety of technical activities are examined, the chief focus for present purposes is patent rates.

Morgan and associates report that the patent activity rate (filed, but not necessarily awarded) for doctoral level scientists and engineers doctorate holders in all employment sectors is 12.1%. In industry, 20.8% were named as inventors on patent applications during the five-year period since April, 1990, more than triple the rate (6.0%) of those working in universities. Importantly, while almost all those filing patent applications from academia are doctorate-holders, industry 44.6 percent have bachelors degrees, 26.2% master’s degrees and 29.2% have doctorates. Their analysis shows that industry-based scientists and engineers have a higher rate of success developing products from patents, with 30% of patents yielding (within five years) a commercial product, process or license, compared with the academic scientists and engineers where about 20% of patents awarded resulted in a commercial product.
However, those working in higher education has a slightly higher patent granting success rate than those in industry. In academia, 41% of those named as inventors in at least one patent application in the five years studied received at least one patent, compared to a 36% “hit rate” among industry scientists. Given these baseline (no-collaboration) data, how does university-industry collaboration patent success rates compare? No truly comparable data are available.

There is little contention as to whether academic research and collaboration with industry feeds industrial organizations’ stock of intellectual property (Mansfield, 1999), even when there is not an active collaboration between academic scientists and industry. But there is also widespread agreement that the development of research-to-product can in many instances be improved and accelerated with active collaboration, including patent development and utilization (Henderson, Jaffe and Trajtenberg, 1998) but also collaborations not based on patents but on such goals as research and technical assistance, public domain research, research based on trade secrets and, often over-looked, collaborations on manufacturing technology and other production processes.

If we assume, as seems warranted (Audretsch, et al., 2002), that university-industry research collaboration often (though not inevitably) provides important benefits, then a next question is who benefits and under what circumstances? Lööf and Broström (2008) find that large manufacturing firms benefit most from collaborating with research, whereas smaller firms and service firms tend to benefit modestly if at all. This finding is consistent with a series of studies by Bozeman and colleagues, but ones focused on the benefits to firms working with federal laboratories on cooperative research agreements (see Bozeman and Papadakis, 1995; Rogers and Bozeman, 1997; Crow and Bozeman, 1998; Bozeman and Wittmer, 2001; Saavedra and Bozeman, 2004. These studies examined patent and license creation, firm
participants’ reported monetary costs and benefits, and experiences developing new products. By most indicators, first benefiting most were ones that were larger, were themselves active in research collaboration (rather than simply using federal laboratory results) and, interestingly, ones who did not have as a primary goal the near term appropriation of intellectual property. Small first tended to be much more focused on developing products from the cooperative research and, while this happened more than for larger firms, the small firms also reported lower satisfaction and lower ratio of benefits to cost.

One old (pre-Bahy-Dole legislation) but still widely used mechanism of industry-university collaboration is industry funding of university R&D. The impacts of such funding remain unclear because relatively few studies have been performed. One recent study (Hottenrott and Thorwarth, 2011) of German companies’ funding of university research indicates that there is a “skewing problem” (the authors’ terms), namely that university researchers do alter their intended research trajectories in the service of industry contracts’ objectives, arguable to determine effects on the development of knowledge-focused research. However, the authors also find that industry funding has a positive effect on applied research, at least as measured by patent filings and patent citations. Moreover, another study, using a somewhat different database, found no evidence of a skewing problems and at least some evidence that industry funding has a positive effect on knowledge-focused research.

Most university-industry collaborations are not centered on publications and do not yield patents. Even among university researchers who are strongly oriented to working with industry, most do not work with industry in developing patents. Bozeman and Gaughan’s (2007) data from the Survey of Academic Scientists, shows that among “industrially-active” academic researchers only about 5% have co-developed a patent. Lissoni and colleagues,
focusing on three European countries, report that a little more than 4% of those working with industry have developed a patent from their collaboration. In both studies, results vary considerably by field and by the nature of the university setting (Kenney and Goe, 2004) or its organizational culture (Agrawal and Henderson, 2002), but patenting is always a relatively rare outcome from university-industry outcomes. In the U.S. much more common activities include collaboration of research, consulting, technical assistance, and placement of students in industry (see Lin and Bozeman, 2006). According to Bozeman and Gaughan’s findings for a national sample of academic STEM faculty in Carnegie-Extensive universities, approximately 17% had obtained an industry grant or contract in the 12 month period preceding the study, just about the same percent (18%) who had engaged in industry research consulting during the same period. Studying German academic researchers Grimpe and Fier, 2010) report quite similar results with about 17% working as paid consultants, a similar amount reported in Haeussler and Coyvas’ (2011) study of United Kingdom and German university scientists working in the life sciences. A study (Klofsten and Jones-Evans, 2000) of science, engineering and medicine faculty in Sweden and Ireland reported a high rate of industry interaction, but most of these interactions (68%) these being limited to consulting and information exchange.  

 Outputs and Impacts for Scientific and Technical Human Capital (STHC) Impacts

Why should policy-makers be concerned with the STHC impacts of collaboration independent of the effects of collaboration on the production of knowledge and property? STHC is about the ability to sustain benefits from production of knowledge and technology and, thus, is a particularly useful perspective from a policy-making and planning standpoint. Moreover, research collaboration, including boundary-spanning collaboration, has strong potential for affecting STHC, in some cases positively in other cases less so.

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4 Some of the results reported in this paragraph are drawn from Perckmann, et al., 2013.
Since there is relatively little research proceeding directly from a STHC perspective, the research directly relevant to research collaboration is quite modest, but worth examining. At least a few studies (Bozeman and Corley, 2004; Gaughn and Robin, 2004; Corolleur, 2004; Davenport, 2004; Dietz and Bozeman, 2005; Lin and Bozeman, 2006; Woolley, et al., 2008; Boardman, 2009; Ponomariov and Boardman, 2010) have specifically taken a STHC perspective on scientific outputs and career development and several of these studies examine research collaboration directly or they are relevant to collaboration issues.

To reiterate, the STHC model focuses on the conjoining of researchers’ S&T-related human capital (e.g. formal training, experiential knowledge, skills) and their S&T-related network ties and resources and relevant social knowledge (e.g. assessments of others’ research foci, interests and abilities, knowledge of the “market” for research products, knowledge and access to particular channels for distributing knowledge). It is assumed that a researchers’ productive capacity is reflected in accumulated STHC and, further, that STHC changes regularly and in some cases even predictably with, for example, exposure to additional knowledge, additions or subtractions from social networks. It is further assumed that STHC reflects the vast majority of researchers’ capacity to produce knowledge, with the other important factors relating chiefly to resources (e.g. grants, salary, research assistance) and organizational arrangements (most important, a job and a means of making a living from research but also particular attributes and incentive systems provided by institutions). If one knows these things then, arguably, one knows all one needs about individual productive capacity. Moreover, STHC and concomitant productive capacity can be viewed as additive or at least multi-level. Thus, we can refer to an individual’s STCH but also to the accumulated STHC of a work group, a lab, a firm or a university research center. The only qualification,
not a small one, is that accumulated STHC is mediated by the ability of the “human pieces of
the organization” to not only fit together but to share and build on one another’s STHC. In
sum, STHC provides a useful perspective for understanding research collaboration but, to some
extent at least, collaboration is a vital ingredient in organizations’ ability effectively to deploy
the STHC of those employed by or affiliated with the organization. (For amplification see
Dietz, Bozeman and Gaughan, 2001).

One early study (Dietz and Bozeman, 2005) of the relation of STHC to collaboration
focused specifically on the value added of experience in industry to productivity and
collaborations. The authors analyze career mobility, specifically movement between academic
careers and industry careers but also medical careers and government positions, to determine
possible productivity effects. They use two data sets, first data from the curriculum vitae of
1200 research scientists and engineers, which they combine with patent data from the U.S.
Patent and Trademark Office. They classify job transitions according to the sector of origin
and the destination sector. For this set of scientists and engineers, the most common job
transition is academic-to-academic (62.5%) followed by industry-to-academic (8.2%). The
authors find that both inter and intra-sectoral changes in jobs throughout the career result in
higher STHC that, in turn, yields higher research productivity measured in terms of publication
and patent rates and impacts.

Several papers on scientists’ and engineers’ professional networks have bearing on the
core questions of STHC. A literature review by Audretsch and colleagues (2002) concludes
that research evidences shows that firms with network ties to universities (apart from formal
collaborations) tend to have greater R&D productivity as well as a higher level of patenting
and that these relationships provide greater capacity to the companies but also to academic
faculty and students. In another relevant study of STHC, networks and productivity, Goel and Grimpe (2011) examine both “active” and “passive” networking, with active networking measured in terms of participation in research conferences. While this presents problems inasmuch as different participants have diverse experiences at research conferences, it does provide a useful contrast to their measures of “passive” networking which pertains chiefly to interactions with ones geographically proximate colleagues. Their findings indicate that passive networking is both complement and substitutes for active networking depending on the particular character of passive networking and the setting in which it occurs. In particular, research group leadership, a passive form in their terminology, is complementary. The results indicate that not all forms of network behavior contribute substantially to STHC.

Martinelli and colleagues (2008) emphasize the importance of external relations to collaboration, arguing that academic researchers who have few external ties (i.e. S&T human capital) have especial difficulties developing collaborations. Another study (Nilsson, Rickne, & Bengtsson, 2010) focuses on the role of universities in providing supportive infrastructure for building STHC, arguing that the university incentives and environment determine a great deal about the academic researcher’s likelihood of developing STHC as part of industrial networks and activity. Related, Ponomariov and Boardman (2008) find that informal interactions between university scientists and private sector companies trigger more formal and more intense collaborations with industry. This reinforces earlier findings from Link, Siegel and Bozeman (2009) about the importance of informal university technology transfer in collaborations with the private sector.

Ponomariov and Boardman (2010) provide information directly relevant to the formation of STHC as related to research collaboration. The authors find that institutions have
strong effects on STHC and collaboration patterns. Focusing on multi-institutional university research centers they find that such centers are effective not only in enhancing overall productivity but also collaborations and these cross-sector collaborations are especially likely to yield growth in STHC of collaboration participants. In a more recent study, Bozeman and Boardman (2013) find that such university research centers serve as an important nexus for collaboration and that they serve to change STHC not only by introducing students to a wider array of work possibilities but also by providing additional support for a wider array of learning experiences for faculty, students and center affiliates.

**Assessment Questions**

In this section we return to the questions posed at the beginning of the study. In our study, as in any study examining evidence and then making recommendations, the data do not speak for themselves. We use our experience as researchers and in assessing literature to arrive at recommendations that we feel are consistent with the evidence provided here.

*Question: What does the available research on university-industry research partnerships and within-industry team science tell us about effective research management approaches and partnership models that support positive team processes and successful scientific and translational outcomes?*

We frame this question in terms of broader strategy and policy deliberations. In doing so, we find that the evidence base is relatively modest. With some exceptions we have not focused here on the micro-level management issues of teams and groups (for a review of this research see Mathieu, et al., 2008; little of this extensive research pertains to boundary-spanning collaborations between firms or between universities and firms). Instead we focus on “effective research management” in interorganizational contexts. With this more limited focus we draw two ready conclusions. First, the available evidence is minimal. Second, not only is
there little theory or research on managing boundary-spanning, inter-organizational collaborations, such literature as does exists suggests that managerial practices in such contexts is often poorly thought out and haphazard. Possibly, but not necessarily, the first problem (research scarcity) affects the second (haphazard managerial practice and managerial structures. A body of research reviewed here bears on issues pertaining to the effective management and structuring of interorganizational, boundary-spanning collaborations is the growing literature on managing multi-institutional and multi-disciplinary university research centers (e.g. Bozeman and Boardman, 2006).

**Question:** What is known about effective management approaches and models for both types of team science (university-industry partnerships and within-industry science teams) when the participating scientists are geographically dispersed?

While answers to this question are provided throughout the above review, it is worthy summarizing some key points. There are a number of factors at the organizational and team levels associated with entry and performance in inter-firm R&D alliances and industry consortia. As shown by Joskow’s (1985) research, monitoring transactions is vital to success of collaborations, especially careful monitoring of terms of contracts. Lax contract management tends to be associated with ineffective collaborations. Given that contractual relationships seem to be becoming more common (Panico, 2011), this “lesson” is perhaps more important than ever.

One of the most common findings pertaining to collaboration success, at every level and for nearly every type of collaborative institution, is that the parties to the collaboration must have a high degree of trust (Sonnenwald 2007: e.g., Creamer 2004, Hara et al. 2003, Sonnenwald 2003, McLaughlin & Sonnenwald 2005, Knorr-Cetina 1999, Krige 1993) and trust is vital for effective management of university-industry and within-industry teams and
collaborators (Doddson, 1993; Zajac and Olsen, 1993; Fulati, 1995; Davenport, et al., 1998; Tartari, et al., 2012).

The motives underpinning firms’ research collaboration have been examined by a number of authors. According to Sakakibara (1997) cost sharing and skill sharing motives are two distinct and pervasive motives for inter-firm research collaboration. Hagedoorn (1993) find similar results for firms joining R&D consortia for complementary knowledge exchanges and more recent research (Hayton, et al., 2013) supports the dual motivation of costs savings and skill sharing. Prahalad and Hamel (1990) suggest that firms joining consortia often benefit from other firms’ portfolios of core technical competencies in ways that can enhance their own technical competencies. Hamel (1991) more specifically suggests that firms benefit from consortia to internalize the technical skills and competencies of others. Another focus has been geographical proximity. According to D’Este and Colleagues (2013), it is not simple proximity that matters to research collaboration success but rather patterns of clustering, technological complementarity among firms and the interaction of clustering with complementarity patterns.

**Question:** What is known about the reasons for failure in university-industry partnerships and within-industry science teams?

Research focusing directly on failures of boundary-spanning collaboration is quite scarce. One could perhaps consider this question by assuming that factors determining failure are essentially the mirror image of those affecting success. While there is some merit to such an approach it is not ideal. It does not take into account the possibility of threshold effects (X quantity of an attribute has no effect, X+1 has extremely positive effects) and it does not take into account interaction among variables related to effectiveness.

Park & Russo 1996, Pennings et al., 1994) emphasizes the lack of formal authorities and structures (e.g., ease of entry and exit, difficult to monitor and enforce contracts) and also the lack of informal mechanisms after entry, factors such as goal congruence and resource interdependencies. Some studies suggest that formal research alliances and consortia are inherently unstable when compared to intra-firm or less complex inter-firm collaborations.

When inter-organizational collaborations rely on either formal or informal governance mechanisms rather than relying on both, failure is more likely. Oxley and colleagues (2004) and Li and colleagues (2011) identify “knowledge leakages” to competitors as a particular type of failure in those collaborations where firms share not only precompetitive but also competitive knowledge. Usually competitive knowledge is shared inadvertently but is nonetheless damaging. Collaborations facing such difficulties sustain increased transaction/coordination costs and monitoring costs and more often experience free riding and other collaborative dysfunctions (Garcia-Canal et al. 2003, Gong et al. 2007, Hennart & Zeng 2002, Hackman 1987, Steiner 1972).

**Question:** How do intellectual property and conflict of interest concerns affect the collaborative processes and scientific and translational outcomes of both types of collaborations? What are effective solutions to intellectual property and conflict of interest concerns?

Despite the rapid growth of studies of patenting and licensing, there is only a modest empirical literature relevant to the resolution of intellectual property and conflict of interest problems. That is not to say that the topic has not been addressed. Most studies focused on resolution of IP disputes are in law journals (e.g. Blackman and McNeill, 1997; Hovenkamp, Janis, and Lemley, 2002; Mandel, 2011). Since these studies are not empirical they are beyond our purview.
Even among those few potentially relevant empirical studies, most studies concerned with intellectual property problems and their remediation have only limited empirical support for their prescriptions. Still, they at least frame important issues. Sampson (2005) examines problems in firm-to-firm IPR negotiations and contracts and suggests that a key to avoiding problems is “alliance management skills.” She notes that even in firms that have quality management and a history of effectively managing their own IPR, new challenges of alliances require new and perhaps different IPR management skills.

Interestingly, some researchers indicate that governments can play an important role in lessening the likelihood of collaborative failures due to IPR problems. Research by Narula and Dunning (1998) shows that government agencies sometimes are quite helpful in mediating IPR disputes among firms that are parties to R&D consortia.

**Question: What further research is needed to improve our understanding of these two types of team science?**

In many respects this is the key issue in this assessment. The answer to this question relates to the literature examined above but, unlike the other study questions, provides no direct answers to it, only implicit answers based on what is obviously not included in the literature. The entire section below is devoted to answering the “what further research is needed?” question.

**Recommendations for New Research**

**Recommendation 1. Meta-Choice.** There is research about strategic choices made by parties to boundary-spanning research and technology collaborations and this research, while not plentiful, is generally quite useful. However, there is almost no research that tells us how participants choose among available collaborative institutions and modalities. Thus, we know something about why, in general, industrial firms decide to participate in MMURC’s, but we
do not know much about why they choose particular MMURC’s or, even more important, why they choose to participate in the MMURC as opposed to an inter-firm joint venture, a research alliance or a contractual relationship with another firm. This is particularly unfortunate inasmuch as this type of question is “knowable.” As we suggested above, self-reports are not helpful for interpreting over-determined events having multiple agents, none of whom has the “big picture.” But usually the number of people who make decisions about whether or not to participate in a collaborative institution, and which particular one, are few in number and can, if the wish to do so, provide a good account of their reasoning and discrete actions.

**Recommendation 2. Research on institutional failures and the “dark side” of collaboration.** We noted above that the literature on the collaboration of large, complex boundary-spanning collaborations is at best scant. The literature on the dark side of large-scale collaboration is non-existent. There has been at least some progress in the last decade regarding the dark side of collaboration when the collaboration focus is small-scale, especially co-authoring teams. One reason for this progress is a widespread recognition of emerging problems, especially conflict of interest and problems related to co-authorship. Many of the dark side studies are in the biomedical sciences (e.g. Rennie et al., 2000; Wainright et al., 2006; Cohen, Tarnow & DeYoung, 2004), where ethical issues have emerged around such issues as “phantom authors” and industry payments (sometimes pay-offs) for research.

Within the context of large-scale boundary-spanning collaborations, there are at least a few studies of the effects of conflict of interest, usually considering whether university researchers have been “corrupted” by their relations with industry. So far, the more systematic and empirical the focus, the less likely one is to find problems. Nevertheless, the dark side has in some cases been well documented for smaller collaborations.
The dark side issues with large-scale boundary-spanning collaborations go well beyond what is conventionally addressed in the literature. The literature tends to focus on bad behaviors or bad outcomes for academic participants in collaborations (deflected research agendas, diminished educational role) while neglecting the dark side for industry participants. We know from case studies that IP disputes are sometimes fierce and damaging, but we have little knowledge from systematic studies employing aggregate data. Similarly, we know that companies sometimes suffer (and sometimes perpetrate) industrial espionage, but we have no systematic evidence about the extent to which and ways in which this occurs in boundary-spanning or inter-firm collaborations. It is not easy to study bad behavior and disastrous outcomes, especially for firms, but it would be useful to make a start. Research might prove quite beneficial. If we again take the biomedical research collaboration research that has focused on academics, the research has led to a number of reforms, especially in journal editor’s requirements but also professional associations and even funding agencies (see for example Rennie, 2000; Marusic et al., 2004; Pichini, et al., 2005; Devine, et al., 2005).

**Recommendation 3. S&T Human Capital.** Studies of STHC collaboration, while not common, are available. However, the conceptualization has thus far been applied empirically only in university settings. Studies focus on the relation of STHC to the development of students, academic researchers’ productivity (Lee and Bozeman, 2004; Carayol and Matt, 2004), and career trajectories (Gaughan and Robin, 2004). The one study clearly relevant to business and STHC is Lin and Bozeman’s (2007) study of the effects of industry experience on academic scientists’ collaboration and productivity.

If we consider that research tells us that what most firms want from their inter-sector, boundary-spanning collaborations is access to the knowledge and skills of persons outside the
firm, then clearly the STHC focus is quite compatible with firms’ objectives. The same approaches that have been developed (unfortunately still under-developed) to measure increments to academic researchers’ STHC could be applied to industrial contexts. Indeed, such applications would in some way be even more interesting because of the diverse needs and uses of STHC in industrial settings.

**Recommendation 4: Focus on management of large-scale university-based research and collaboration centers.** The few studies that have been conducted on management selection, strategy and effectiveness in large-scale university centers with collaborative missions strongly suggest the need for more such studies. The practice, widely if informally employed in universities and government policies, of elevating cooperative agreement P.I.’s to center directorships warrants study. The notion that someone will prove a good manager of enormous and multifaceted research institutions because they are talented and productive researchers is a dangerous one that is not born out by the limited research evidence (e.g. Rogers and Bozeman, 2001; Corley, et al., 2006; Philbin, 2010; Cruz-Castro, et al., 2012).

Complex university-based research centers do not at present ensure that those in charge of managing them have significant managerial knowledge and experience. While workshops on management and management handbooks (such as those provided by the National Science Foundation’s Engineering Research Centers program) provide a useful supplement, they are no substitute for professional managerial training. More examination of the backgrounds, experiences and performance of academic managers of large, collaborative university research centers should shed some light on a variety of collaboration issues and, possibly, barriers.

**Recommendation 5. Pursue field experiments.** If the sub-literatures on research centers and team science (e.g., on NSF centers, NIH teams) can learn one important lesson from the
literatures on inter-firm R&D alliances and industry R&D consortia, it is that they the need to transition from single-case "best practices" case study research to studying large numbers of organizations in quasi-experimental and field-experimental research. The changing goals from one research center or team of scientists to the next makes inductive case study valuable chiefly for retrospective evaluation rather than prospective team/center design and implementation. Thus, should a science team at the National Cancer Institute be a best practices exemplar for other NIH centers focused on alcoholism? Or for NSF centers focused on very different scientific and technical problems? Aggregate analysis and field experiment approaches borrowed from the firm literatures on collaborative R&D, especially studies focusing on governance mechanisms (e.g., structure, goal congruence, resource dependence), are likely to prove more productive than single case studies or even multiple poorly integrated case studies.

**Recommendation 6: More impact-focused research; integrated collaborative teams to study collaboration.** If one compares the ratio of papers describing how boundary-spanning research occurs, including such topics as collaboration motivations, structuring, goals, and networking strategies, to papers identifying and explaining impacts, the clearly the scale is tilted toward answering “what?” questions rather than “so what?” questions. To be sure, the “what?” questions are important and, in at least some cases require additional attention. But if research is to be useful for other than explanatory theory purposes, then more attention should be paid to impact. This will not be easy. Let us consider why. It helps if we start by observing that there has been considerable progress mapping the impact of *individual* level collaborations on *individual* productivity (for an overview see Sonnenwald, 2007 or Bozeman, Fay and Slade,
2013). The reasons for progress are many but include the fact that citations and publication counts provide reasonably valid productivity measures.

Compared to simple collaborations, boundary-spanning collaborations are inordinately difficult to effectively and comprehensively evaluate because (1) almost all the organizations involved have their own multiple goals; (2) often there is goal conflict among the organizations party to collaboration, if not in absolute terms at least in order of priority. Impacts from complex boundary-spanning collaborations come in only two categories—those obviously difficult to measure and those that seem easy to measure but are not. For example, one of the most straightforward goals that some companies have for their collaborations is the development of technology that can result in products or process that can be brought to the market. It is easy enough to understand the appeal of this goal. However, since companies usually have a great many inputs pertaining to product development (in-house R&D, strategic choices, production capacity, manufacturing process and skills, marketing analysis and strategy, to name a few) it is nearly impossible to isolate the specific contribution of particular collaborative activities to the realization of what is an easily understood goal.

Most studies examining impacts of complex boundary-spanning collaborations rely on count data (number of patents) or self reports through interviews and questionnaires. Such studies have known but also quite significant problems. The problem with patents is that they are usually a surrogate measure and sometimes not a particularly useful one. Self-reports are often useful, but they are most useful when one is confident that the person providing the report has the full knowledge required for a valid report. Sometimes they do. So, for example, if a researcher is asked “have you ever collaborated with an employee of a government lab?” the subject has full knowledge needed to provide a potentially valid report. But if one asks a
Vice President for Research, “did the collaboration in University-Industry Center result in a product brought to market” then one faces a question that only seems to have a simple answer. The problem with self-reports is that they are notoriously unreliable when pertaining to information characterizing a whole organization and its activities (much less multiple organizations and multiple loosely-connected technically-relevant activities).

If one wanted more and better research on the impacts of complex boundary-spanning collaborations, how might one proceed? A key point is to rely on more than a single informant. In fact, it would be useful to obtain data from several persons, with different roles and perspectives, from various components of the organization and to do this within all of the participating organizations. A second point is to avoid snapshots. For obvious reasons (lack of sufficient funding and lack of time) most of the studies drawing upon unique information from people working in organizations are cross-sectional and examine a narrow time band.

From a practical standpoint how could these limitations be addressed? One easy answer is “more funding,” but without more funding perhaps more integrated, collaborative team research- a reflexive approach to understanding collaboration and teams. In the physical and natural science there has been considerable progress made owing to policy-makers requirements that center affiliates or program affiliates work together on integrated research tasks. We can perhaps assume that any funding announcement requiring teams to focus integrated research, over several years, to study multiple complex collaborations would not fail due to lack of proposals.
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