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Revisiting the Role of Collaboration in Creating Breakthrough Inventions

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Problem Definition: Is teamwork better than working alone for creating breakthrough inventions? We challenge the widely accepted affirmative answer to this question.
Academic/Practical Relevance: Extant research has consistently found that lone inventors significantly underperform teams in creating breakthroughs; thus it extols the benefits of teamwork while neglecting the role of single inventors. This paper offers an important counterweight to those empirical results by identifying a fundamental contingency under which teams might or might not outperform lone inventors: the degree of decomposability of the invention. By ignoring this contingency, past literature has systematically underestimated the role that lone inventors can play for companies.
Methodology: We use utility and design patent data for 1985–2009 to compare the effect—on the probability of creating a breakthrough—of working alone versus working with a team.
Results: For utility patents, we do find that working alone reduces the likelihood of achieving a breakthrough. Yet this disadvantage of lone inventors is not evident for design patents. We theorize that the nearly non-decomposable nature of design is a major factor contributing to lone designers' relative efficacy of achieving breakthroughs. This theory is then tested in the context of utility patents, where we can observe variation in inventions' decomposability. We find that technology inventions that are difficult to decompose also relatively advantage lone inventors compared with teams, and we demonstrate that this finding reflects greater coordination costs when such inventions are attempted by teams. If one takes a myopic view of collaboration's role, then our results suggest that working with others does not help develop outstanding non-decomposable inventions. Yet taking a long-term view reveals that lone inventors benefit more than do teams from having collaborated with others in the past. In fact, we find that past collaborations can help lone inventors outperform teams with regard to developing non-decomposable inventions.
Managerial Implications: Past research has suggested that collaboration is universally beneficial in creating breakthrough inventions. However, such efforts have ignored crucial contingencies: We show why inventors should explicitly consider both the targeted invention's decomposability and their own history of collaboration when deciding whether (or not) to work with a team on a given innovation.

Keywords: Product Design; Technology Innovation; Patents; Inventor Collaboration; Innovation Teams

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1 INTRODUCTION

Should inventors work alone, or should they collaborate in teams? Does collaboration make a breakthrough invention more likely? Empirical results—based on millions of patents and scientific papers—strongly support the notion that breakthrough innovation is more likely to come from *teams* (Wuchty et al. 2007, Jones 2009, Singh & Fleming 2010). The extent of this evidence is such that a tone of finality pervades the literature: we have come to witness the "death" of the Renaissance man (Jones 2009, p. 283); the lone inventor is a "myth" (Singh & Fleming 2010, p. 41) or a "romantic image" (Bercovitz & Feldman 2011, p. 81). Indeed, academics view teams as being "almost sacrosanct" in business (Coutu 2009, p. 2) and as dominating "across nearly all fields" (Wuchty et al. 2007, p. 1036).

Against this backdrop, our paper revisits the "lone vs. team" debate and identifies a fundamental contingency—namely the degree of the decomposability of an invention into loosely connected chunks (Simon 1969). Extant work has overlooked this contingency, yet we find that it figures prominently in determining whether (or not) team outcomes will be superior to those of its individual members. We use data on patents filed from 1985 to 2009 with the United States Patent & Trademark Office (USPTO), for utility and design (resp., function and form), to show that the relative effectiveness of teams and individuals in creating breakthrough innovations (Ahuja & Lampert 2001, Singh & Fleming 2010, Conti et al. 2014) varies depending on the invention's degree of decomposability. Hence this paper calls for scholars and practitioners in innovation management to recognize that lone inventors remain a viable means of organizing for innovation.

We develop and test three main arguments, thereby making three notable contributions to the literature on innovation management. First, we uncover an important context, *design innovation*, under which working in teams yields no significant advantage over working alone. Design, by which we mean the form or "look" of a product, is a major factor in product value and customer perceptions (Bloch 1995, Maeda 2015, Xia et al. 2016). The award of $1 billion (US) to Apple in 2012 for Samsung's patent infringement (*The Economist* 2012) attests to the economic relevance of design. Yet despite design's importance and the many case studies demonstrating clear distinctions between design and technology innovation (Verganti 2009), previous research has not challenged the assumption that collaboration fosters breakthrough invention in design as it does in technology. To the contrary, it is widely held that this assumption is generalizable to the domains of "[s]cience, music, language, art, design, manufacturing, and many other forms of creative endeavor" (Singh & Fleming 2010, p. 43). We put this claim to the test and find that—unlike technology inventions, in which a lone inventor is 17% less likely to create a breakthrough than when working with others—no such disadvantage is observed in the case of design. This result highlights an important contextual difference between design and technology—one that leads to lone inventors performing relatively better in the former field than in the latter.

Our second (and core) contribution is to investigate a mechanism that could make collaborating on design inventions fundamentally different from collaborating on technology inventions. One factor that characterizes design is that the perception of product form is fundamentally *holistic*. So when one perceives a design, its most salient feature is the "gestalt" or entirety of the design and not its individual components (Goldstone 1994; Stacey 2006; Orth & Malkewitz 2008). Thus design is nearly non-decomposable. The implication is that the task of giving form to a product is hard to partition and requires significant coordination if carried out by multiple individuals; thus a team working on design is likely to struggle should it attempt a divide-and-conquer approach to finding good holistic solutions.

Unlike design inventions, technology inventions vary in terms of their decomposability: some inventions are modular in that they can be (nearly) decomposed into well-defined "chunks" whereas others are highly integral (Simon 1969; Ulrich 1995; Schilling 2000; Pisano & Verganti 2008; Yayavaram & Ahuja 2008). Hard-to-decompose inventions often involve working with information that is "sticky" or costly-to-transfer (von Hippel 1990, 1998) and a team suffers from coordination costs when such information is distributed among its members. Because the extent to which an invention is decomposable varies widely among different technology innovations, we can explore the possibility that teams excel at creating more *modular* but not more *integral* breakthrough technology inventions. Although there is an evident advantage to adopting a team-based approach (and thus a disadvantage in relying on lone inventors) in the case of modular technology innovation, the same cannot be said of integral technology innovation; in particular, the latter resembles design innovation in that there is apparently no difference between the efficacy of teams and lone inventors at creating breakthroughs. Thus we find that the relative efficacy of teams and individuals is strongly affected by a fundamental aspect of the focal invention: its decomposability.

Although this finding certainly challenges the view that creative work is best handled by teams, we do not mean to imply that teams are irrelevant to hard-to-decompose inventions. Rather teams play a subtler role. Thus our third contribution is to show that, as regards both design and technology inventions, collaboration has persistent long-term implications even for lone inventors. More specifically, we find that the *number* of a lone inventor's past collaborators positively influences the probability of that individual creating a breakthrough invention. In other words, a lone inventor who has never collaborated tends to perform poorly, whereas one who has worked with many collaborators in the past exhibits a high probability of creating breakthroughs. We posit that past collaboration may provide a lone inventor with a learning platform and supporting resources needed to tackle the challenge of creating breakthrough inventions. Because collaboration thus yields long-term benefits for an individual inventor, our results underscore that "working alone" and "working in teams" need not be in opposition.

This study establishes that, when thinking about organizing for innovation, neither practitioners nor academics can afford to ignore an invention's degree of decomposability. When creating non-decomposable innovations, it may well be that teams are not the best way—much less the only way—to generate superior outcomes; lone inventors could play an important role in such innovation efforts. Yet this is not to say that collaboration plays no role in non-decomposable innovations. In particular, our results imply also that the *sequence* of collaboration and non-collaboration matters: working alone after significant experience collaborating with others can lead to outstanding innovation performance.

2 DEVELOPMENT OF HYPOTHESES

2.1 The literature on collaboration and innovation

Arguments in favor of teams outperforming individuals assume that resources gained from teamwork *outweigh* the coordination costs of working together (Wuchty et al. 2007; Singh & Fleming 2010). Those resources include knowledge diversity, which has multiple benefits for generating creative breakthroughs. Without diverse team members, a single inventor cannot easily access all the knowledge required to bring an idea to fruition; hence leveraging the knowledge of other team members may be necessary to make an invention work (Jones 2009). A diverse knowledge base also allows cross-fertilization of ideas and can in turn lead to improved creative outcomes (Perry-Smith & Shalley 2003). If we view innovation as a recombinant search process (Fleming & Sorenson 2001), then greater knowledge diversity increases both the number of possible combinations and the variability of outcomes (i.e., it implies fatter tails of the outcome distribution)—thereby increasing the probability that breakthroughs will be achieved. Finally, teams perform an important role in the selection of ideas by providing critical eyes that help weed out poor ideas (Singh & Fleming 2010).

Weighing against teamwork is the difficulty of effective collaboration. Experimental evidence suggests that working together may actually prevent ideas from surfacing (Diehl & Stroebe 1987; Girotra et al. 2010). In their study of brainstorming groups, Diehl and Stroebe (1987) show that team members may forget ideas while others are talking or decline to speak up if worried about peer evaluations. Teams can also fall prey to misaligned incentives (i.e., free-riding) or goal conflicts (Guzzo & Dickson 1996). Even uncertainty about the free-riding behavior of other team members can affect the extent of an individual's contribution (Hutchison-Krupat & Chao 2014). Furthermore, the effort required to coordinate and communicate ideas among team members is time consuming. In a videotape study of ten small-group meetings at a software company, Olson et al. (1992) document that nearly a fifth of the time is spent solely on coordination activities (e.g., project and meeting management) and another third on clarifying ideas. Team coordination and communication clearly require significant effort.

Notwithstanding the arguments that teamwork boosts resources *and* coordination costs both, empirical evidence of real-world inventions—as documented in patents and scientific papers—is skewed strongly toward teams (relative to individuals) in the production of breakthroughs (Wuchty et al. 2007; Jones 2009; Singh & Fleming 2010). Existing research would have us expect, ceteris paribus, that a lone inventor is less likely to create a breakthrough invention than when working with a team. Our study challenges that consensus by identifying conditions that relatively favor the lone inventor.

2.2 How does design differ?

The term "design" has many connotations (Ulrich 2011). It can be broadly defined to encompass considerations of technological constraints, business strategy, and market opportunity (Brown 2008). However, the defining characteristic of industrial design is its role in shaping the physical (aesthetic) *form* of a product (Bloch 1995; Krishnan & Ulrich 2001; Chan et al. 2018). It is in this sense that we use the term in this paper.

Teams have been shown to outperform individuals in innovation across diverse research fields, from physical science and engineering to social science and technology patents (see Wuchty et al. 2007). Why, then, should we expect a lone inventor to be any *less* disadvantaged—versus a team of inventors—in the field of design? We argue that the nature of the invention matters because it can alter the trade-off between the benefits of teamwork and its coordination costs.

Although design innovation differs from technology innovation in many aspects, one salient feature is that it tends to be holistic: the overall structure of the physical form overshadows its constituent parts (Goldstone 1994; Stacey 2006; Orth & Malkewitz 2008). For example, research on design language or "shape grammar" reveals how designs as varied as Buick automobiles and Harley-Davidson motorcycles can be viewed as the interactions among a small set of basic shapes (Pugliese & Cagan 2002, McCormack et al. 2004). Thus a product form's effect stems "not from any individual element but rather from the gestalt of all elements working together as a holistic design" (Orth & Malkewitz 2008, p. 64).

This holistic nature of design significantly influences the dynamics of any collaboration. With motorcycle design, for example, a slight shift in proportions can make a vast difference (Pugliese & Cagan 2002). Since design cannot be decomposed, it follows that team members working on a joint design problem can succeed only through extensive coordination of their efforts (Eckert 2001).

As a result, design team members must engage in a heightened level of communication even as the nature of their task renders communication difficult. The context of design magnifies the disadvantages of teamwork yet largely prevents teams from exploiting its advantages—a combination that makes the team approach less attractive in design settings. Stated more formally:

Hypothesis 1 (H1)**:** *The relative probability that an inventor working alone—versus collaborating with others in a team—will achieve a breakthrough is greater for design inventions than for technological inventions.*

2.3 The structure of technology inventions

In contrast to design, technology inventions can range over "a continuum of different structures, from highly decomposable to non-decomposable" (Yayavaram & Ahuja 2008, p. 334). Highly decomposable or "modular" structures characterize inventions that "can be partitioned into small, discrete chunks" (Pisano & Verganti 2008, p. 3). At the other extreme, non-decomposable structures characterize inventions that cannot be partitioned and are inherently "integral" (Ulrich 1995).

Our arguments concerning design carry over to technology inventions that are integral. By definition, this kind of technology invention is tightly coupled: changes in one component will affect many others (Ulrich 1995). Because optimizing the invention engages the "whole system" (von Hippel 1998, p. 640), integral technology inventions exhibit two characteristics that create coordination difficulties for teams.

First, the creation of non-decomposable inventions tend to converge only after many iterations (Smith & Eppinger 1997) and can exhibit oscillations between different solutions (Mihm et al. 2003). The lone inventor can mentally iterate, assess, and discard possibilities with ease whereas a team is typically slowed by coordination requirements. Thus iteration speed is one of the lone inventor's advantages.

Second, coordination between team members is complicated by what von Hippel (1998) calls "sticky information". That is, it may be difficult for inventors of integral technology products to describe their intentions and needs precisely and completely, which impedes productive communication. This sticky information aspect of working on integral technology mirrors the challenges that arise from the difficulty of understanding, codifying, and communicating design concepts (Stacey 2006).

Whereas the first coordination issue implies that integral inventions are associated with a *higher quantity* of communication, the second implies that such inventions involve communication of *lower quality*. Overall we expect integral technology inventions to "behave like design" in this sense: the odds that a lone inventor will achieve a creative breakthrough should match or even exceed that of a team.

At the other end of the spectrum, technology inventions can be decomposable into well-defined chunks, where each chunk consists of tightly coupled components yet the chunks themselves are loosely coupled (Simon 1969). Decomposable inventions—comprising a number of (nearly) separable chunks —are suited to an approach where roles are distributed among team members (Ulrich 1995; Baldwin & Clark 2000; Schilling 2000; Sosa et al. 2004; Kavadias & Sommer 2009; MacCormack et al. 2012; Baldwin & Henkel 2015). Thus teams reap the advantages of knowledge diversity and shared resources without incurring the disadvantages of greater coordination costs. In other words, decomposability allows team members to operate independently, entailing minimal interactions with others (Simon 1969; von Hippel 1990). We should therefore expect teams to achieve more breakthrough innovations (than a lone inventor) when an invention can be decomposed into more chunks.

In short: by exploiting variations in the decomposability of technology inventions, we establish that, in terms of creating breakthroughs, modular inventions exacerbate the lone inventor's *disadvantage* whereas integral inventions *favor* the lone inventor. These considerations lead to our next hypothesis.

Hypothesis 2 (H2)**:** *In the technological domain, the effect of working alone on achieving a breakthrough is negatively moderated by the invention's decomposability (i.e., the number of its internally inseparable chunks); so that, all else being equal, the relative probability that an inventor working alone—versus working with others in a team—will create a breakthrough invention decreases as the invention's decomposability increases.*

2.4 Past collaborators

If teams of inventors lose their advantage over lone inventors when working on non-decomposable or holistic inventions, should teams play a reduced role in the development of such inventions? What if the benefits of teams extend *beyond the task at hand*, where most research attention has been? (see e.g. Diehl & Stroebe 1987, Wuchty et al. 2007, Kavadias & Sommer 2009, Girotra et al. 2010) Below we shall argue for important collaboration benefits that extend beyond the immediate task.

First, collaboration can have a transformative effect on the participants themselves (Powell et al. 1996, Liu et al. 2018). Collaboration exposes technology inventors and designers to different ideas and perspectives (Hargadon & Sutton 1997) and thereby fosters learning, allowing inventors to internalize the skills of others (Hamel 1991). As a result, inventors who previously worked with many collaborators have an opportunity to assimilate their colleagues' skills and ultimately to apply those skills themselves. Because it enables learning, past collaboration can lead to future gains in individual output.

Second, working with others helps the inventor exploit valuable knowledge at a moment's notice. An individual who has developed "organizational memory" (Hargadon & Sutton 1997, p. 717) through extensive collaboration is well positioned to recognize and access relevant sources of knowledge when needed. Thus extensive collaboration helps build network resources that serve as channels of valuable information (Singh 2005); more succinctly, past collaborations reduce search costs (Boudreau et al. 2017). While previous collaborators are not formally involved in the inventor's current work and are unlikely to render significant assistance in time or material, they can still offer feedback on ideas (Oettl 2012) and/or identify other valuable resources (Obstfeld 2005).

Finally, the learning and resource benefits from past collaborations are more salient for a lone inventor. In the absence of a team that can serve as a "sounding board", they are more inclined to leverage the feedback of past collaborators. A network of previous accomplices can thus endow the lone inventor with some team-oriented benefits yet without imposing any team-induced coordination costs.

As a consequence, and in contrast to the literature that has established that a large network of past collaborators benefits the inventor generally speaking (Singh & Fleming 2010, Oettl 2012, Liu et al. 2018), we argue that the benefits of past collaboration are *greater* for inventors currently working alone.

Since arguments about the learning and resource benefits of past collaboration do not distinguish between design and technology inventions, we expect that the benefits that accrue to the lone inventor from past collaboration are generalizable to both types. Hence our final hypothesis:

Hypothesis 3 (H3)**:** *The relative probability that an inventor working alone—versus working with others in a team—will create a breakthrough (design or technology) invention increases as the inventor's number of past collaborators increases.*

3 DATA

We use patent grant data published online by the USPTO for the period 1975–2017. Patents that are granted to cover the invention of a "new and useful process, machine, manufacture, or composition of matter" are known as *utility patents* (USPTO 2010, pp. 2100–8); in contrast, patents granted for "new, original, and ornamental design" (USPTO 2010, pp. 1500–1) are known as *design patents*.

In the period from 1975 to 2017, the USPTO granted more than 6 million patents. To ensure comparability, we start by restricting our attention to US-based inventors. Then, while using all years of the resulting patent grant data set to calculate backward and forward measures, we focus in particular on the set of patents filed between 1985 and 2009; in this way we avoid major patent law changes and also ensure that we have enough history and a sufficient number of future citations. The resulting initial sample consists of 1,603,970 utility patents and 198,265 design patents.

3.1 Dependent variable

Top 5th percentile in citations. Forward citations have been used extensively in the literature to measure the success of patents. The reasoning behind this approach is that such citations measure an invention's importance in terms of capturing the attention of inventors who subsequently file for patents on their own innovations (Hall et al. 2005; Singh & Fleming 2010). Because a single breakthrough idea carries significantly more weight than do mediocre ideas, a breakthrough is typically defined as an instance of falling within the top tail of the relevant domain's performance distribution (Ahuja & Lampert 2001; Singh & Fleming 2010; Conti et al. 2014). Consistent with the existing literature, we therefore operationalize "breakthrough" as a binary variable, *Top5*, which is set to 1 if the focal patent's number of citations is within the top 5th percentile of the distribution within its product class (over the entire 1985–2009 time frame) and is set to 0 otherwise.

3.2 Independent variables

Sole inventor. Our main independent variable, *Sole*, indicates whether a patent's inventor is listed as being a single individual (*Sole* = 1) or as more than one person (*Sole* = 0).

Chunks. As mentioned previously, a critical construct is the "number of chunks" that constitutes a technology invention (i.e., a utility patent). The patent document does not provide a direct measure of chunks. However, the utility patent's *claims* detail how the invention's different ideas are organized and thus enable us to identify (and count) its chunks.

In a utility patent, "claims" are well-defined descriptions of an invention's novel aspects. These claims are central to the patent because they define the extent of the intellectual property to be protected. We can think of a claim as representing a single discrete "idea" of the invention (Lanjouw & Schankerman 2004; Singh & Fleming 2010). The language of a patent's claim section is highly structured and mechanistic (Faber 2001). In particular, each claim must be made in exactly one sentence, is uniquely numbered, and must begin with the invention's *subject matter*—for utility patents, a "process, machine, manufacture, or composition of matter" (USPTO 2010, pp. 2100–5).

The structured manner of claim writing allows us to measure the decomposability of utility patents via a straightforward textual approach based on identifying the different subject matters contained in each patent's claims. Consider, for example, patents 5,387,165 and 4,629,182; each patent is for the invention of a toy structure, and each makes four claims (the main visual descriptions of the patented structures are reproduced in Figure 1). Patent 5,387,165 was awarded for the invention of a "recreational equipment junction box" (a structure of interconnected tubes through which children climb or crawl). In the patent, claims 1 and 2 discuss the alternative setups of the "connective junction box", claim 3 the "connecting means", and claim 4 a "simulated play control mechanism".[1] Claims 1 and 2 relate to the same subject matter, and each describes an aspect of the invention (the junction box) without affecting the other components of the invention (i.e., connecting means or play control mechanism). Because claims 1 and 2 are simply variants of a single underlying concept, they constitute a single chunk. Claims 3 and 4 concern separate subject matters, and each is independent of the patent's other components. Since these claims concern different underlying concepts, they are considered to be separate chunks. Thus the patent highlights three different components (chunks) of the invention, each of which is essentially independent of the others; hence this patented invention is relatively decomposable.

[1] Inventors commonly use such abstract language to increase patent scope (Faber 2001), but the patent description discloses that the "mechanism" is in fact things that allow for simulated play, such as a plug-in driving wheel.

In other words, an invention like that shown in Figure 1's left-hand side is one where the inventors have ideas that are applicable to a particular chunk—but do not apply to the other chunks. We can therefore decompose such inventions into multiple chunks. An invention like that on the right-hand side is such that all of the inventors' ideas apply to a single chunk. Hence any changes to those ideas would trigger changes to the invention's entirety, because the "subject matter" of *all* their claims is "inflatable toy tunnel". This implies that the invention is non-decomposable.

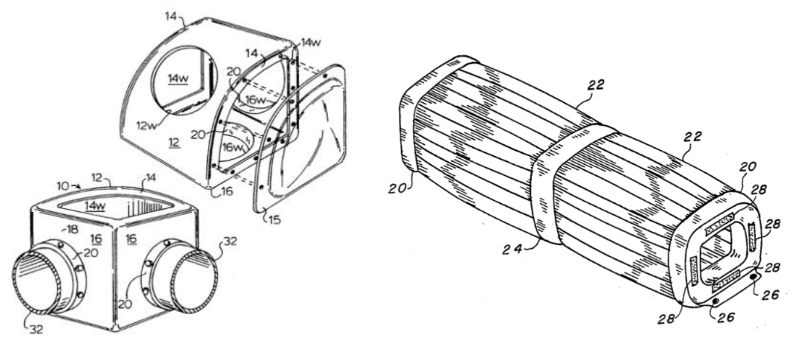

Figure 1. The main illustrations in patents 5,387,165 (left) and 4,629,182 (right)

We can, in general, identify each claim's subject matter and also distinguish between two types of claims: those that introduce and describe a *new* subject matter; and those that introduce *variations* on a subject matter described earlier in the patent's other claims (Faber 2001). Our approach to evaluating the number of chunks is based on counting the number of distinct subjects, a procedure intended to exclude what are essentially variants of the same subject. We implement this measure by identifying the claim element as the first noun (or noun phrase) in each claim; for this purpose, we use the Stanford CoreNLP program of Manning et al. (2014) to tag words (see the online supplement for details).

We use *LogChunks* to denote the (log of the)[2] number of distinct subject matters. For utility patents, the mean value of *LogChunks* is 2.0. This value corresponds to about 8 chunks on a linear scale (the mean number of claims made by utility patents is 18), with a minimum of a single chunk and a maximum (albeit rare) of more than 100 chunks. Hence about half of a typical utility patent's claims are variants of a previously defined subject matter (and so are subsumed by the corresponding chunk).

Finally, we note that the claims in design patents serve a different purpose. In line with the notion that design inventions are essentially non-decomposable, the USPTO has decreed that a design's patentability depends on its "overall" appearance and hence is based on comparisons to existing designs "as a whole" (USPTO 2010, pp. 1500–28). That is, litigants in design infringement cases are not expected to identify

[2] A log formulation is used to adjust for skewness in the distribution of independent variables; the name of each logged variable begins with the prefix *Log*. We use a "log + 1" transformation to avoid logging over zero when encountering variables that are bounded below by zero.

which *parts* of the focal invention are novel. Rather, the criterion is simply whether an average observer could differentiate the accused and patented designs holistically (Saidman 2008). So in contrast to utility patents, where each claim must distinctly point out a novel feature of the invention, design patents have only a single claim—of the form "the ornamental design of a [product] as shown"—that identifies the product to which the design applies.

Number of past collaborators. We use *LogPastCollab* to denote the log number of *unique* past collaborators of the lead inventor—excluding those directly involved with the *current* patent.

Time-varying controls based on the individual lead inventor. In addition to *LogPastCollab*, we use three other variables to capture the lead inventor's time-varying capability. First, we measure individual experience (*LogExp*), a count of the number of patents filed previously by the inventor. Second, individual experience diversity (*LogExpDiversity*) captures the unique number of different product classes in which the inventor has been granted a patent. Finally, we control (via *Assigned*, a binary indicator) for whether the patent is assigned to a company or rather to the inventor; this variable captures whether (or not) the inventor received company-level resources while working on the patented invention.

Patent characteristics. We control for the "size" of an invention. Teams potentially might have the unfair advantage of aggregating many ideas into a single patent so broad that it results in an inflated number of citations. To control for such effects, we introduce four patent-level variables. Thus our regressions include *LogClaims* (the log of the number of claims in the patent), *LogWords* (the log number of words in the claims), *LogFigures* (the log number of figures or illustrations appearing in the patent), and *Fees* (the fees charged to file the patent, deflated to 1985 US dollars).[3]

We also incorporate several variables suggested by previous research. For instance, the log number of patent classes that the USPTO assigns to the patent (*LogAssignedClasses*) captures the invention's potential application to different domains (Harhoff & Wagner 2009). We also include the log number of backward citations made by the focal patent to other patents (*LogPatentCites*) as well as the log number of backward citations it makes to other non-patent publications (*LogNonpatentCites*)—both of which model the extent to which an invention is "derivative in nature" (Lanjouw & Schankerman 2004, p. 448). Finally, we capture the scope of the invention's knowledge base by counting the number of distinct patent classes into which the patents *cited* by the focal patent fall (*LogCitedClasses*). This measure captures the extent to which an invention recombines existing technology/design classes (Fleming & Sorenson 2001).

[3] Filing fee schedules are available online from the historical editions of Appendix R of the Manual of Patent Examining Procedures; fees are a function of the number of independent and total claims, the patent's number of pages, and whether the applicant receives a discount (i.e., for being an individual, a small firm, or a non-profit entity). We do not observe—and so are unable to include—any surcharges (e.g., late fees, requests for extension, or penalties due to improperly filed patents).

4 ANALYSIS

4.1 Empirical specification

Because our dependent variable is binary (there either is, or is not, a breakthrough), we estimate a logit model. Equation (1) specifies that base model, where the dependent (indicator) variable is whether a patent p filed by lead inventor i is a breakthrough:

$$\text{logit } P(Breakthrough_{ip}) = c_i + \beta_s Sole_{ip} + \beta X_{ip}. \tag{1}$$

This specification includes: c_i, a fixed-effect term for lead inventor i; $Sole_{ip}$, an indicator for whether lead inventor i filed patent p alone or as part of a team; and X_{ip}, the set of time-varying measures that characterize the lead inventor and the patent.

Note that the lead-inventor fixed-effect term, c_i, plays two roles. First, it models the unobserved ability of lead inventors, which is necessary to avoid any "omitted variable" bias arising from the possible correlation between ability and the tendency to collaborate. For example, a lead inventor with innately higher ability to create breakthroughs would also be more likely to attract collaborators (Powell et al. 2013). Failing to account for the correlation between these factors would lead to estimates that are biased in favor of teams creating breakthroughs. Another possibility is that highly skilled inventors are more likely to prefer working alone; that correlation, if unaccounted for, would yield estimates that are biased in the other direction (Boudreau & Lakhani 2012).

The second role of the lead-inventor term is to enable comparisons between the performance of a lone inventor and the performance of teams that include this same inventor. Hence our model can capture empirically the lead inventor's likelihood of creating (unassisted) breakthroughs and also can predict whether or not the lone inventor's collaboration with other inventors increases the likelihood of breakthroughs. This approach is consistent with the approaches employed in economics and psychology to measure group synergy (Kerr & Tindale 2004; Cooper & Kagel 2005).

From an empirical standpoint, our comparison approach involves leveraging a reduced sample in which variation (across time) can be observed for each lead inventor. Our identification strategy requires that the lead inventor's career include at least one success and at least one failure to achieve a breakthrough. This requirement results in an identification sample consisting of inventors who are relatively more successful. Our final sample comprises 368,899 utility patents and 46,350 design patents; of all these patents, about 18% qualify as breakthroughs. The restricted sample provides a cleaner setup in this sense: data related to inventors who have *never* achieved a breakthrough are not used to explain breakthroughs. That said, our results are robust to linear probability, random effects, or quantile regression models that use the full sample (results in the online supplement), which maintains an aggregate breakthrough rate of 5%, and is an equivalent sample to Singh and Fleming (2010).

Our identification strategy implies a decision that merits discussion: there is heterogeneity in the teams of which the inventor is a part. Our empirical setup controls for the characteristics *only* of the lead inventor, deliberately relegating any effects of team-level variations (e.g., team size, familiarity among team members) to the error term (Wooldridge 2010). One implication of this approach is that we are comparing the lone inventor with an "average" team on which he/she is the lead inventor. In that sense, our empirical approach more closely follows the economic and psychology literature (Kerr & Tindale 2004; Cooper & Kagel 2005) than it does the works of Taylor and Greve (2006) or Singh and Fleming (2010). The key reason is that controlling for team-level variables can have the effect of making lone inventors appear less disadvantaged because they function as mediators that account for some of the advantages enjoyed by teams (Singh & Fleming 2010). Conceptually, controlling for team level variables (e.g., the total experience diversity of the team) hold those factors constant as we infer the difference (on achieving breakthroughs) between a lone inventor and a team. It implies a model that compares a lone inventor with a certain level of experience diversity, against a team that *in sum* has the same level of experience diversity—and such a benchmark is likely to make the lone inventor appear artificially better.[4]

To test H1, we first estimate β_s separately for utility patents (denoting the estimate β_s^u) and design patents (β_s^d). Separating the regressions in this way imposes the least stringent assumptions about the equivalence of coefficients across design and utility patents. If H1 holds empirically, then we would expect that $\beta_s^d > \beta_s^u$. In other words, we expect the log-odds of a breakthrough for a *design* inventor working alone (vs. working in teams) to be higher than the log-odds of a breakthrough for a *technology* inventor working alone (vs. working in teams).

We use utility patent data to show that lone inventors in *integral* technologies are similarly not disadvantaged (H2). Finally, we show (in both data sets) that lone inventors benefit from having more past collaborators (H3). To test H2 and H3, we use Equation (2); in this expression, $LogChunks_{ip}$ denotes the log number of chunks in utility patent *p* filed by inventor *i* and $LogPastCollab_{ip}$ represents the log number of unique individuals with whom lead inventor *i* had collaborated at the time of patent *p*'s filing:

$$\text{logit}\, P(Breakthrough_{ip}) = c_i + \beta_s Sole_{ip} + \beta_{sn} Sole_{ip} \times LogChunks_{ip} + \beta_{sc} Sole_{ip} \times LogPastCollab_{ip} + \beta X_{ip}. \quad (2)$$

H2 predicts that $\beta_{sn} < 0$ (the lone inventor is less successful when working on utility patents with more chunks), and H3 predicts that $\beta_{sc} > 0$ (the lone inventor's success is increasing in the number of past collaborators). Note that the linear terms $LogChunks_{ip}$ and $LogPastCollab_{ip}$ are included in X_{ip}. We de-mean $LogChunks_{ip}$ (and $LogPastCollab_{ip}$)—that is, the variables are mean-centered *after* their log

[4] Nonetheless, all our results and insights are robust to controlling for team-level characteristics. As expected the lone-inventor disadvantage is less prominent if we do control for team characteristics (as when, e.g., the lone-inventor disadvantage declines from −0.17 to −0.10 in utility patents; see Model 44 in the online supplement).

transformation—so that we can interpret the (non-interacted) coefficients as the effect at the mean number of (respectively) *LogChunks* and *LogPastCollab*.[5]

All models include a fixed effect for the filing year in order to account for systematic differences (across time) in achieving breakthroughs. We do not model product-class fixed effects because our dependent variable normalizes over product classes. We report robust standard errors clustered by the lead inventor. In Section 5 we carry out robustness tests to further rule out possible reverse causality / self-selection effects, omitted variable bias arising from unobserved time-changing variations of the lead inventor that may correlate with breakthroughs as well as potential measurement issues and other assumptions inherent to our model (see the online supplement for details of all these robustness tests).

4.2 Summary statistics and correlations

Table 1 reports summary statistics for our variables (separately for utility and design patents). Overall, design patents account for about 10% of the total number of patents. Note that a significant proportion of both types (37% of utility patents and 56% of design patents) are filed by individual inventors.[6]

Table 1: Summary statistics of variables

Variable	**Description**	**Utility**	**Design**
Top5	Indicator set to 1 only if the number of citations received by a patent is within the top 5th percentile across patents in the same class	0.18 (0.38)	0.17 (0.37)
Sole	Indicator set to 1 only if the patent is filed by a single inventor	0.37 (0.48)	0.56 (0.50)
LogPastCollab	Log of the number of past unique collaborators with whom the lead inventor has worked	2.00 (1.20)	1.16 (1.11)
LogExp	Log of the number of patents previously granted to the lead inventor	2.50 (1.29)	2.48 (1.43)
LogExpDiversity	Log of the number of distinct product categories previously granted to the lead inventor	1.55 (0.75)	1.01 (0.60)
Assigned	Indicator set to 1 only if a patent is assigned to a firm	0.90 (0.30)	0.87 (0.34)
LogChunks	Log of the number of distinct subject matters	2.02 (0.64)	—
LogClaims	Log of the number of claims	2.74 (0.80)	—
LogWords	Log of the number of words appearing in the claims	4.83 (0.60)	2.56 (0.15)
LogFigures	Log of the number of figures (illustrations) appearing in the patent	2.15 (1.03)	1.95 (0.44)
LogAssignedClasses	Log of the number of classes assigned to the patent	0.48 (0.49)	0.05 (0.20)
LogCitedClasses	Log of the number of classes cited by the patent	1.58 (0.65)	1.25 (0.52)
LogPatentCites	Log of the number of backward patent citations	2.63 (1.04)	2.46 (0.88)
LogNonpatentCites	Log of the number of backward non-patent citations	0.98 (1.27)	0.59 (0.88)
Fees	Patent filing fees (thousands of 1985 US dollars)	1.28 (0.42)	0.48 (0.20)
N	Number of patent observations	368,899	46,350

Note: Reported values are means; standard deviations are given in parentheses.

[5] We could change the model so that the non-interacted coefficients instead capture the effects at the mean of *Chunks* and *PastCollab*. Our results are not affected by that change, but this alternative is less reflective of central tendencies owing to the rightward skew of the variables.

[6] We hence observe more sole inventor patents in design. This does not systematically bias our estimations in favor of individual inventors in design because we are concerned with the difference in the proportion of breakthroughs *within* the sole (or team) subpopulation.

Table 2 presents the correlation matrix based on our utility and design patent data. There are a few variable pairs with high raw correlations (see in particular the three variables *LogPastCollab*, *LogExp*, and *LogExpDiversity*). Our analysis of the variance-inflation factors (VIF) finds that VIFs for the three variables are all below 6 (for utility) and below 4 (for design). That the VIFs are below the threshold of 10 suggest that multi-collinearity is not a major issue (Wooldridge 2012). We also continue to obtain robust results across all our hypotheses if we excluded all variable-pairs with raw correlations above 0.5 (see Models 46 and 47 in the online supplement). However, we note that these models assume that the dropped variables have zero effect on breakthroughs, an assumption which if incorrect leads to biases in the other coefficients as they absorb the dropped variables' effects (Wooldridge 2012).

Table 2: Correlation matrix for utility patent data (lower left triangle; N = 368,899) and for design patent data (upper right triangle; N = 46,350)

	Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
1	*Top5*	1.00	-0.03	-0.07	-0.20	-0.16	0.01			0.00	0.02	0.04	0.02	0.04	0.02	-0.01
2	*Sole*	-0.03	1.00	-0.40	-0.03	-0.05	-0.20			-0.05	-0.05	0.03	-0.08	-0.09	-0.01	-0.24
3	*LogPastCollab*	-0.21	-0.27	1.00	0.53	0.47	0.26			0.00	0.07	-0.06	0.04	0.16	0.02	0.41
4	*LogExp*	-0.27	-0.04	0.79	1.00	0.66	0.07			-0.04	0.06	-0.07	-0.03	0.11	0.05	0.19
5	*LogExpDiversity*	-0.23	-0.03	0.71	0.85	1.00	0.02			-0.04	0.14	0.04	0.10	0.03	-0.08	0.04
6	*Assigned*	-0.01	-0.25	0.26	0.08	0.05	1.00			-0.02	-0.05	-0.05	-0.03	0.07	0.11	0.32
7	*LogChunks*	0.07	-0.04	0.02	0.00	0.00	0.04	1.00								
8	*LogClaims*	0.07	-0.07	0.06	0.04	0.02	0.06	0.83	1.00							
9	*LogWords*	0.04	0.06	-0.11	-0.09	-0.07	-0.08	0.01	-0.04	1.00	-0.09	0.06	0.13	0.09	0.02	0.08
10	*LogFigures*	0.05	-0.02	0.02	0.03	0.02	-0.05	0.13	0.15	0.15	1.00	0.03	0.13	0.08	-0.01	-0.04
11	*LogAssignedClasses*	0.08	-0.03	-0.03	-0.06	0.00	0.02	0.01	0.02	-0.04	-0.06	1.00	0.16	-0.03	-0.03	-0.10
12	*LogCitedClasses*	0.03	-0.07	0.10	0.09	0.14	0.05	0.12	0.17	0.00	0.19	0.15	1.00	0.62	0.07	0.02
13	*LogPatentCites*	0.01	-0.07	0.14	0.16	0.11	0.05	0.15	0.19	0.06	0.27	-0.01	0.81	1.00	0.23	0.25
14	*LogNonpatentCites*	0.02	-0.14	0.13	0.08	0.03	0.12	0.08	0.15	-0.14	0.09	0.07	0.35	0.37	1.00	0.10
15	*Fees*	-0.04	-0.18	0.35	0.23	0.16	0.32	0.12	0.20	-0.07	0.09	-0.04	0.14	0.19	0.15	1.00

4.3 Results

Table 3 presents estimated coefficients for the main logit regression models used to test our hypotheses. Model 1 presents the results with respect to *utility* patents, and we can see that the coefficient for *Sole* is significantly negative at −0.17 ($p < 0.001$). This finding shows that, on average, being a sole technology inventor significantly reduces the log-odds of creating a breakthrough invention. The coefficient corresponds to a decline of approximately 17% in the probability of creating a breakthrough.[7] This result is consistent with those reported by Wuchty et al. (2007), Jones (2009), and Singh and Fleming (2010).

[7] Interpreting the coefficient as an effect on probability of breakthroughs amounts to an approximation, which is valid for small (and for small changes in) probabilities. Using p_s to denote the sole inventors' probability of breakthrough (and p_t to denote the corresponding probability when the inventor works with a team), we have
$Sole = \log p_s/(1-p_s) - \log p_t/(1-p_t) \approx \log p_s/p_t \approx (p_s - p_t)/p_t$.

Table 3: Heterogeneity in lone inventors' relative log-odds of a breakthrough

Data set Variable	***Utility*** **Model 1**	***Design*** **Model 2**	***Utility*** **Model 3**	***Design*** **Model 4**	***Utility*** **Model 5**	***Utility*** **Model 6**	***Utility*** **Model 7**
Sole	–0.17***	0.07	–0.17***	0.04	–0.15***	–0.15***	–0.15***
	(0.02)	(0.06)	(0.02)	(0.06)	(0.02)	(0.02)	(0.02)
LogPastCollab(dm)	0.03	0.08	0.03	0.04	0.02	0.03	0.03
	(0.02)	(0.07)	(0.02)	(0.07)	(0.02)	(0.02)	(0.02)
LogExp	–0.51***	–0.30***	–0.51***	–0.30***	–0.52***	–0.52***	–0.52***
	(0.03)	(0.07)	(0.03)	(0.07)	(0.03)	(0.03)	(0.03)
LogExpDiversity	0.27***	0.21	0.27***	0.21	0.27***	0.27***	0.27***
	(0.03)	(0.12)	(0.03)	(0.12)	(0.03)	(0.03)	(0.03)
Assigned	0.03	0.13	0.03	0.13	0.03	0.02	0.03
	(0.03)	(0.11)	(0.03)	(0.11)	(0.03)	(0.03)	(0.03)
LogChunks(dm)	0.17***		0.19***		0.19***	0.19***	0.19***
	(0.02)		(0.02)		(0.02)	(0.02)	(0.02)
LogClaims	0.17***		0.17***		0.17***	0.17***	0.17***
	(0.01)		(0.01)		(0.01)	(0.01)	(0.01)
LogWords	0.09***	–0.87***	0.09***	–0.86***	0.09***	0.09***	0.09***
	(0.01)	(0.18)	(0.01)	(0.17)	(0.01)	(0.01)	(0.01)
LogFigures	0.30***	0.26***	0.30***	0.27***	0.30***	0.30***	0.30***
	(0.01)	(0.07)	(0.01)	(0.07)	(0.01)	(0.01)	(0.01)
LogAssignedClasses	0.33***	0.69***	0.33***	0.69***	0.33***	0.33***	0.33***
	(0.01)	(0.09)	(0.01)	(0.09)	(0.01)	(0.01)	(0.01)
LogCitedClasses	0.02	–0.38***	0.02	–0.37***	0.02	0.02	0.02
	(0.02)	(0.07)	(0.02)	(0.07)	(0.02)	(0.02)	(0.02)
LogPatentCites	0.09***	0.29***	0.09***	0.29***	0.09***	0.09***	0.09***
	(0.01)	(0.04)	(0.01)	(0.04)	(0.01)	(0.01)	(0.01)
LogNonpatentCites	0.05***	0.07	0.05***	0.07	0.05***	0.05***	0.05***
	(0.01)	(0.04)	(0.01)	(0.04)	(0.01)	(0.01)	(0.01)
Fees	0.38***	0.43	0.38***	0.43	0.38***	0.38***	0.38***
	(0.03)	(0.33)	(0.03)	(0.33)	(0.03)	(0.03)	(0.03)
Sole × *LogChunks(dm)*			–0.07***		–0.07***	–0.07***	–0.06**
			(0.02)		(0.02)	(0.02)	(0.02)
Sole × *LogPastCollab(dm)*				0.18**	0.06***	0.06***	0.06***
				(0.06)	(0.01)	(0.01)	(0.01)
LogChunks(dm)						–0.01	–0.01
× *LogPastCollab(dm)*						(0.01)	(0.01)
Sole × *LogChunks(dm)*							0.02
× *LogPastCollab(dm)*							(0.02)
Filing-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lead-inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	368,899	46,350	368,899	46,350	368,899	368,899	368,899
Log-likelihood	–93,918	–13,146	–93,911	–13,136	–93,900	–93,899	–93,898
χ^2	12,212	432	12,208	445	12,259	12,298	12,326

Notes: Standard errors (in parentheses) are clustered by lead inventor. *(dm)* = de-meaned; FE = fixed effects.
*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

In Model 2, we run the same regression but instead on *design* patents. Here the coefficient for *Sole* is 0.07 ($p = 0.25$) and is not significantly different from zero. So in contrast with a lone technology inventor, the lone designer seems not to be disadvantaged when compared with teams. Moreover, the difference between Models 1 and 2 with regard to the sole-inventor effect is significant: 0.24 ($p < 0.001$). Thus we find support for H1. Note that this comparison is valid only if the two models have similar levels of error variances (Allison 1999). Testing the difference in a pooled data set containing both design and utility patents also yields an estimate of 0.24 ($p < 0.001$)—see also the coefficient for the *Sole* × *Design* interaction term in the online supplement's Model 42—which suggests that differences in error variances are not a major issue (Hoetker 2007). Finally, we derive similar results when using linear probability models (Models 24 and 25 in the online supplement); please note that across linear models, it is possible to compare coefficients without making any assumptions about the error variance.

We remark that the negative coefficient for experience (observed for all models) may seem to contradict the expectation that experience improves outcomes. Yet because we control for experience diversity, which is positively correlated with experience, the net effect of additional experience can be understood only when these two variables are viewed jointly. Consider, for example, a technology inventor with an average level of experience—that is, one for whom *LogExp* = 2.5 and *LogExpDiversity* = 1.55 (these values correspond to 11.2 patents over 3.7 technology classes). Adding one patent's worth of experience *within* this inventor's existing portfolio of technology domains would *decrease* her log-odds of breakthrough by 4.0%; however, if the patent were *outside* her existing set of technology domains then the benefits from extra diversity would lead to a net *increase* of 1.2% in her log-odds of a breakthrough. Thus our model's findings are consistent with results in literature on the importance of diversity (e.g., Taylor & Greve 2006; Singh & Fleming 2010).

Model 3 in Table 3 presents results that test H2. Since that hypothesis addresses technology inventions only, this model is based on utility patent data. Model 3 incorporates the additional term *Sole* × *LogChunks(dm)*, where "*(dm)*" is shorthand for "de-meaned". The coefficient for this interaction term is significantly negative (−0.07, $p < 0.001$), from which it follows that a lone inventor becomes increasingly less able to create technology breakthroughs as the invention's number of distinct subject matters increases. We thus find support for H2. Put in reverse, a lone inventor is more effective at creating breakthroughs (relative to being part of a team) for less decomposable technological inventions. Indeed, the lone inventor performs comparably to teams (−0.03, $p = 0.50$) as we approach the case of 1 chunk (where the reported value is obtained via the predictive margins, from Model 3, of *Sole*'s effect when *LogChunks* is set to zero, which corresponds to 1 chunk). Hence we find that *integral* technology innovation resembles design innovation in that the lone inventor is not significantly disadvantaged, vis-à-vis working with teams, in such pursuits.

Models 4–7 are the full models used to test H3. In Models 4 and 5 we introduce the interaction term *Sole* × *LogPastCollab(dm)* for samples based on, respectively, design and utility patents. Since the coefficient for this term is significantly positive at 0.18 ($p < 0.01$) in Model 4 and at 0.06 ($p < 0.001$) in Model 5, it follows that lone inventors become relatively more successful in creating breakthroughs than teams—with regard to both design and technology innovation—when such inventors have more past collaborators. This result supports H3. Observe also that, in both of these models, the coefficient for *LogPastCollab(dm)* is close to zero and not significant. Hence the benefits of having a large number of past collaborators accrue only to the lone inventor, as we argued in Hypothesis 3.

Finally, if the lone inventor's benefits from past collaboration are indeed wide-ranging—as indicated by our results using data on design and utility patents both—then we should *not* expect to see variation in those benefits across variously decomposable technology inventions. In Model 6 of Table 3 we include the interaction term *LogChunks* × *LogPastCollab* to test for variations in the past-collaborator effect across inventions of different decomposability; in Model 7, we also include the term *Sole* × *LogChunks* × *LogPastCollab* to test for whether the past collaborator effect might involve further interactions. However, in all cases we find that these terms are not statistically significant ($p > 0.20$). Thus we also find consistency in that the beneficial effects (for the lone inventor) of past collaborations apply across technology inventions of different decomposability.

To illustrate the interaction effect proposed by H3, the leftmost graph in Figure 2 (which is based on Model 4) plots the marginal effect of the number of past collaborators on design breakthroughs. We can see that the lines cross when the lead inventor has accumulated a relatively small number (about two) of past collaborators. Hence, *there is a large region in which the sole inventor actually outperforms teams at creating design breakthroughs*. This result underscores the importance—for an inventor's career—of establishing early collaborative ties prior to striking out on her own.

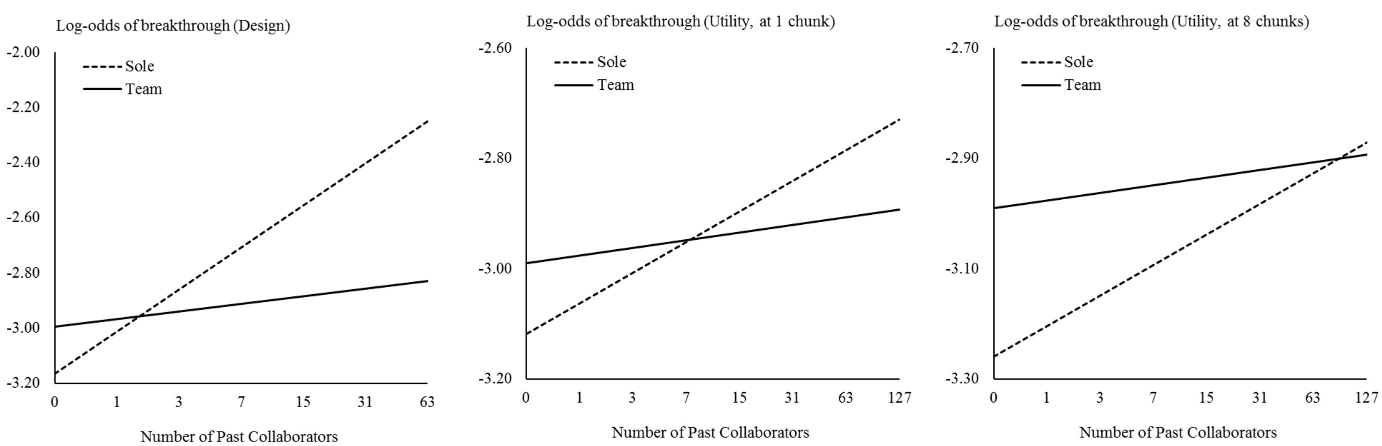

Figure 2. Marginal effects of an inventor's number of past collaborators on the log-odds of breakthrough: *left*, design patents; *middle*, utility patents consisting of 1 chunk; *right*, utility patents consisting of 8 chunks (the mean number)

The middle and right graphs in Figure 2 are both based on Model 5 and correspond to, respectively: a utility patent of 1 chunk, where the technology innovation is integral; and a utility patent of 8 chunks, where

LogChunks has been set at its mean of 2.0. The middle graph's plot resembles that of the design graph, although the lines cross at a later point; an inventor pursuing integral technology innovation starts to perform better as an individual—than as part of a team—when her number of past collaborators reaches about seven. The right graph shows that teams have a significant advantage over sole inventors when developing a technology invention of average decomposability.

The results can be summarized as follows. First, we confirm that the sole inventor is at a significant disadvantage when it comes to creating breakthrough technology inventions—although this disadvantage is not evident for *design* inventions (H1). We posit that this difference reflects the non-decomposability of design inventions (i.e., their structure is holistic). Technology inventions vary widely in terms of decomposability, hence we want to test whether the disadvantage faced by lone technology inventors varies as a function of the invention's decomposability. We find that less decomposable technology inventions tend to favor the lone inventor (H2). Finally, we show that a lone inventor with many past collaborators is more likely (than one with few collaborators) to create breakthroughs in either design or technology innovation (H3); once the number of those past collaborators reaches a certain threshold, lone inventors can outperform teams in the creation of breakthroughs.

4.4 Do non-decomposable inventions entail higher coordination costs for teams?

Teams clearly offer the individual inventor additional resources, such as access to diverse knowledge sources and a greater capacity to complete work tasks. However, teams also impose coordination costs that an individual inventor does not incur. We have argued that a lone inventor performs better on non-decomposable inventions than a team because such inventions involve higher coordination costs (than decomposable inventions). Our empirical results are consistent with this view. Yet, because teams have simultaneously more resources *and* coordination costs relative to individuals, we present further evidence that it is, in fact, the difference in coordination costs that drives the lone inventor's increased relative advantage (over a team) with regard to integral (versus modular) inventions.

So that we can better identify the effect of increased coordination costs faced by teams that seek to create non-decomposable inventions, we need to identify an exogenous variation in coordination costs that does *not* come with a commensurate change in the level of team resources. Hence, we explore how a given team would perform when its members are located in the same time zone rather than across different time zones. Because the team members do not change (we rely on team-level fixed effects to compare performance within a specific team), the essence of this approach is to hold the team's resource levels constant. At the same time, variations in time-zone dispersion as team members move across locations translate into variations in coordination costs. We exploit time-zone dispersion because dispersing team members across time zones results in coordination challenges that cannot be fully overcome by communication technology, e.g., by shrinking the time for members meet in the day (Sosa et al. 2002).

The model with team fixed effects closely follows our main model, except now we focus on patents generated only by teams. We use the same identification strategy—that is, we include a patent in the sample only if its team of inventors has achieved a breakthrough at least once over their collaborative career. Using this criterion, we identify 61,693 utility patents and 8,527 design patents. Our notion of dispersion is captured by the key categorical variable of interest, *TimeZones*, which reflects the number of distinct time zones (as inferred from the physical city and state data of individual inventors on the focal patent) in which the team operates.

Table 4: Coordination costs in teams dispersed across time zones

Data set **Variable**	***Utility*** **Model 8**	***Design*** **Model 9**	***Utility*** **Model 10**
TimeZones=2	-0.20^{+} (0.11)	0.25 (0.61)	-0.20^{+} (0.11)
TimeZones=3	-0.76^{+} (0.42)	-13.24^{***} (1.05)	-0.81^{+} (0.42)
TimeZones=4	-13.46^{***} (0.90)	—	-46.43^{***} (3.23)
LogTeamPastCollab	-0.34^{***} (0.06)	–0.06 (0.17)	-0.34^{***} (0.06)
LogTeamExp	-0.47^{***} (0.09)	-0.55^{**} (0.21)	-0.47^{***} (0.09)
LogTeamExpDiversity	0.47^{***} (0.10)	0.78^{*} (0.33)	0.47^{***} (0.10)
Assigned	0.20^{*} (0.08)	–0.07 (0.29)	0.20^{*} (0.08)
LogChunks(dm)	0.15^{***} (0.04)		0.15^{***} (0.04)
LogClaims	0.16^{***} (0.03)		0.16^{***} (0.03)
LogWords	0.02 (0.03)	-1.29^{***} (0.33)	0.02 (0.03)
LogFigures	0.38^{***} (0.03)	0.44^{***} (0.12)	0.38^{***} (0.03)
LogAssignedClasses	0.33^{***} (0.03)	0.39^{*} (0.19)	0.33^{***} (0.03)
LogCitedClasses	–0.05 (0.05)	-0.40^{*} (0.16)	–0.05 (0.05)
LogPatentCites	0.00 (0.03)	0.31^{**} (0.10)	0.00 (0.03)
LogNonpatentCites	0.01 (0.02)	0.07 (0.07)	0.01 (0.02)
Fees	0.27^{***} (0.07)	–0.35 (0.77)	0.27^{***} (0.07)
TimeZones=2 × LogChunks(dm)			–0.07 (0.06)
TimeZones=3 × LogChunks(dm)			0.15 (0.36)
TimeZones=4 × LogChunks(dm)			27.88^{***} (2.74)
Filing-year FE	Yes	Yes	Yes
Team FE	Yes	Yes	Yes
N	61,693	8,527	61,693
Log-likelihood	–16,362	–2,582	–16,361
χ^2	4,224	303	4,460

Notes: The baseline case is *TimeZones=1*. Standard errors (in parentheses) are clustered by team. *(dm)* = de-meaned; FE = fixed effects.

$^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Finally, we include the full set of patent-level controls. Yet because the analysis proceeds at the team level, we replace lead-inventor-level measures with team-level measures. In particular: *LogTeamExp* represents the total number of unique past patents created by team members; *LogTeamExpDiversity* captures the total number of unique technology/design classes in their experience set; and *LogTeamPastCollab* is the total number of unique past collaborators.

We present our analyses for utility patents (Model 8) and design patents (Model 9) in Table 4. Model 8 shows that increasing the number of time zones across which a team is dispersed has a negative effect on the likelihood of a breakthrough. The cost effect due to dispersing a team across two time zones—that is, relative to a team that is located entirely within the same time zone—has a coefficient of −0.20 ($p < 0.10$). This effect increases with the number of time zones involved, and we see a sharp drop in the log-odds of a breakthrough for teams that are dispersed across four or more time zones: −13.46 ($p < 0.001$). In the case of design innovation, we observe a similar pattern whereby design teams spread across three time zones suffer a penalty of −13.24 ($p < 0.001$) relative to a fully co-located team (we do not have any usable observations of design teams spread across four or more time zones).

In Table 4 Model 10, we consider the question of whether (or not) the time-zone penalty is greater for non-decomposable than for decomposable technology inventions. For this purpose, we interact the number of time zones with *LogChunks* of utility patents. The interaction term *TimeZones=4* × *LogChunks* is significantly positive at 27.78 ($p < 0.001$). For inventions that are decomposable, splitting teams across time zones is actually less of a detriment. Thus an increase in the number of time zones has differential effects on a team: for teams working on decomposable ideas, the negative effect of increased team dispersion is much less pronounced than for teams working on non-decomposable ideas. This difference supports our claim that invention decomposability reduces coordination costs.

5 ROBUSTNESS

One possible concern with our analysis is that the choice to work alone or as part of a team could be endogenous to the lead inventor, which would lead to biased estimates if the choice mechanism correlates with the probability of creating a breakthrough invention. That is, inventors who keep for themselves the ideas best suited to development would bias the *Sole* coefficient upward. Note that this reverse causal mechanism would work only if the inventor (a) had an informative signal of the quality of raw ideas *and* (b) behaved in ways that differed as a function of that signal. It is unclear whether inventors (and in particular, designers) actually prefer to keep the best ideas for themselves—but, if so, it would imply that inventors develop no better than average ideas when collaborating with others. Yet such behavior would certainly incur reputation costs and make it difficult for the inventor to recruit collaborators in the future. Second, even those inventors who are (for whatever reason) inclined to keep ideas to themselves may find it difficult to identify the best ones. Empirical studies have shown that idea quality is difficult to assess at the fuzzy front end, when signal content may well be low (Kornish & Ulrich 2014) or even nonexistent

Table 5: Testing for reverse causal and selection effects

Dataset	***Utility***	***Design***	***Utility***	***Design***	***Utility***	***Design***	***Utility***	***Design***
Model	Experience	Experience	Matching	Matching	Instruments	Instruments	Career-block FE	Career-block FE
	Model 11	**Model 12**	**Model 13**	**Model 14**	**Model 15**	**Model 16**	**Model 17**	**Model 18**
Sole	–0.15*** (0.02)	0.05 (0.07)	–0.10*** (0.02)	0.03 (0.07)	–0.21*** (0.04)	–0.08 (0.09)	–0.15*** (0.02)	0.01 (0.06)
LogPastCollab(dm)	0.01 (0.02)	0.05 (0.07)	0.04 (0.04)	0.12 (0.14)	0.00 (0.02)	–0.01 (0.09)	–0.06** (0.02)	–0.08 (0.07)
LogExp	–0.51*** (0.03)	–0.31*** (0.10)	–0.53*** (0.06)	–0.22* (0.10)	–0.53*** (0.03)	–0.31*** (0.06)	–0.33*** (0.03)	–0.23** (0.08)
LogExpDiversity	0.27*** (0.03)	0.20 (0.11)	0.19** (0.07)	0.10 (0.22)	0.27*** (0.04)	0.22^{+} (0.12)	0.19*** (0.04)	0.14 (0.13)
Assigned	0.02 (0.03)	0.13 (0.11)	0.07 (0.06)	0.09 (0.21)	0.03 (0.03)	0.14 (0.12)	0.07 (0.03)	0.13 (0.12)
LogChunks(dm)	0.19*** (0.02)		0.22*** (0.04)		0.20*** (0.02)		0.18*** (0.02)	
LogClaims	0.17*** (0.01)		0.15*** (0.03)		0.17*** (0.02)		0.17*** (0.02)	
LogWords	0.09*** (0.01)	–0.86*** (0.18)	0.07** (0.03)	–1.21** (0.41)	0.09*** (0.01)	–0.86*** (0.14)	0.07*** (0.01)	–0.81*** (0.18)
LogFigures	0.30*** (0.01)	0.27*** (0.07)	0.31*** (0.02)	0.35** (0.13)	0.30*** (0.01)	0.27*** (0.08)	0.33*** (0.01)	0.35*** (0.06)
LogAssignedClasses	0.33*** (0.01)	0.69*** (0.09)	0.29*** (0.03)	0.76*** (0.20)	0.33*** (0.01)	0.69*** (0.10)	0.34*** (0.01)	0.67*** (0.09)
LogCitedClasses	0.02 (0.02)	–0.37*** (0.07)	0.03 (0.04)	–0.25 (0.13)	0.02 (0.02)	–0.37*** (0.06)	–0.01 (0.02)	–0.41*** (0.07)
LogPatentCites	0.09*** (0.01)	0.29*** (0.04)	0.06* (0.03)	0.38*** (0.08)	0.09*** (0.01)	0.29*** (0.04)	0.11*** (0.01)	0.33*** (0.05)
LogNonpatentCites	0.05*** (0.01)	0.07 (0.04)	0.07*** (0.02)	0.14* (0.07)	0.05*** (0.01)	0.07^{+} (0.04)	0.06*** (0.01)	0.04 (0.04)
Fees	0.38*** (0.03)	0.43 (0.32)	0.25*** (0.06)	–0.76 (0.62)	0.37*** (0.03)	0.41 (0.34)	0.32*** (0.03)	0.26 (0.35)
Sole × LogChunks(dm)	–0.07*** (0.02)		–0.09* (0.04)		–0.09** (0.03)		–0.08*** (0.02)	
Sole × LogPastCollab(dm)	0.08** (0.02)	0.16* (0.07)	0.04* (0.02)	0.13^{+} (0.07)	0.14*** (0.03)	0.32^{+} (0.17)	0.04** (0.02)	0.14* (0.06)
Sole × LogExp(dm)	–0.02 (0.02)	0.02 (0.07)						
Filing-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lead-inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Inventor × 5-year blocks	
N	368,899	46,350	105,109	11,409	368,899	46,350	227,633	35,313
Log-likelihood	–93,899	–13,136	–26,772	–3,401	–93,893	–13,134	–68,738	–10,661
χ^2	12,275	447	3,651	165	29,356	926	7,434	326

Notes: Standard errors (in parentheses) are clustered by lead inventor. *(dm)* = de-meaned; FE = fixed effects.

$^{+}$ $p < 0.10$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$

(Dahan et al. 2011). Hence an idea's true value might simply be too obscure, at the outset of team formation, for inventors to benefit from a strategy of "reserving" ideas.

Nonetheless, if high-quality ideas *are* being reserved then it is reasonable to suppose that inventors improve their discrimination skills (i.e., identifying good vs. bad ideas) with experience. In that case we should expect to see a significant positive interaction between *Sole* and *LogExp*, or patenting experience; see Models 11 and 12 in Table 5 for (respectively) utility and design data. The reported coefficients for that interaction term are not significant, and our main results continue to hold.

Furthermore, if we view innovation as the recombination of existing ideas (Fleming & Sorenson 2001) and if the inputs to such recombination are indicative of ex ante quality, then we can use nonparametric matching of inventions that use similar inputs to reduce any bias resulting from idea selection. Consider a lead inventor who has been granted solo patents that cite other patents in a set of patent classes. A natural match would consist of patents that the same lead inventor was granted as part of a team and that also cite patents from the same set of patent classes; in this case, we can perform a regression based on these matched pairs. We define a *match* as any two patents—from the same inventor—that are more than 50% similar as measured by the Dice (1945) index.[8] The regression results for this set of matched patents are reported in Table 5 as Models 13 and 14, and all our results hold for the matching model (albeit in Model 14 the coefficient testing H3 is only marginally significant; $p < 0.10$). These outcomes suggest that our findings are not substantially affected by the endogenous choice of an inventor to work alone or with a team, which may be influenced by the estimated quality of their patentable ideas.

As an alternative, we can leverage an instrumental variables technique to create exogenous variation of the propensity to work alone or in teams. Motivated by the work of Fleming, Mingo and Chen (2007), we use as an instrument the log number of unique lawyers (*LogLawyers*) engaged previously by the lead inventor. One can reasonably suppose that the breadth of legal assistance engaged previously affects the likelihood of inventors meeting other inventors (outside their network of past collaborators) and hence affect the team formation tendency; this establishes the relevance requirement. That said, we also argue that the lawyers themselves do not directly affect the odds that any particular invention is a breakthrough; this is the exclusion restriction.

Because our model is nonlinear, we avoid bias by using the two-stage residual inclusion method (that is, a control function approach; Terza et al. 2008) rather than the two-stage predictor substitution method. In the former approach first-stage residuals (intuitively, the unobserved tendency to work alone induced by our instrument; Wooldridge 2015) are controlled for in the second stage. Given the existence of interactions between *Sole* and the exogenous variables *LogPastCollab* and *LogChunks*, we can also control for

[8] Let C_s (resp., C_t) denote the set of classes cited by the patent that an inventor worked on alone (resp., with a team); then the Dice index is calculated as $D = 2|C_s \cap C_t|/(|C_s| + |C_t|)$.

interactions between the residuals and those exogenous variables (i.e., denoting the first stage residuals as $\hat{r}$, we control for $\hat{r}$, $\hat{r} \times$ *LogPastCollab,* and $\hat{r} \times$ *LogChunks* in the second stage). To account for errors in the first stage on the second stage, we report standard errors obtained using clustered bootstrapping on the lead inventor (Wooldridge 2015, p. 428). We note that the *LogLawyers* instrument is not weak: its use significantly improves model fit when predicting tendency to work alone (*Sole*) in both technology innovation (likelihood ratio LR = 27.7, $p < 0.001$) and design innovation (LR = 6.4, $p = 0.01$). The values reported in Models 15 and 16 of Table 5 show that our results are robust to using this approach (although the results for H3 in Model 16 is marginally significant at $p < 0.10$). The Durbin-Wu-Hausman test of endogeneity (which is equivalent to testing if the new controls in the second stage are jointly different from zero; Wooldridge 2015) is not statistically significant for both the utility and design data. We report our first-stage results in the online supplement (Models 57-58 in Table 13).

Biases may also arise if we have failed to capture some time-varying characteristics of the lead inventor that are correlated with the time-varying aspects that we do measure (e.g., the pool of his past collaborators), leading to bias in the coefficient. One example of such an uncaptured time-varying variable is fame, which might simultaneously affect both the size of the lead inventor's collaborator pool and his likelihood of creating a breakthrough. If we assume that such unobserved factors evolve slowly, then they can be modeled nonparametrically (as in Models 17 and 18) by allowing inventors—over the stages of their respective careers—to exhibit a greater (or lesser) ability to create breakthroughs. Such modeling is enabled by first "bucketing" the inventor's career into five-year time spans and then modeling fixed effects on each inventor for each of those buckets. Thus we ensure that comparisons across contexts (i.e., sole versus team) apply only to distinct five-year buckets of the inventor's career. As shown by Models 17 and 18 in Table 5, our results are robust to this alternative specification.

We conduct additional analyses to deal with other omitted variable and measurement issues. We first discuss analyses related to measurements of decomposability (results presented in Table 6 of the online supplement provide robustness to all our findings). While the USPTO has strict rules of invention relatedness to prevent inventors from cobbling together unrelated inventions into a single patent (saving filing fees in the process, but which would have artificially inflated our chunks measure), we can deal with this potential issue in two ways beyond controlling for invention size by the number of claims, words, and figures. First, we can incorporate two additional interactions: one between *Sole* and *LogClaims* and another between *Sole* and *LogWords*. We find no statistically significant moderation effect of working alone (*Sole*) with respect to either the number of ideas in a patent (*LogClaims*) or the extent of discourse needed to document those ideas (*LogWords*). Hence teams are not better at creating inventions with broader (i.e., more variations of) ideas requiring more words to document; rather, they are better at creating inventions with more chunks.

Second, we create alternative measures of decomposability that need not scale with the invention's size. We replace *LogChunks* with *GSI*, a distribution-based measure based on the Gini–Simpson index (or 1 minus the Herfindahl–Hirschman index) of claims over chunks. As compared with a count-based measure, *GSI* is finer in that it considers how claims are distributed across chunks. So even when we are comparing two inventions with the same number of chunks, *GSI* can judge one of them to be more decomposable if its claims are more evenly distributed across the chunks. Alternatively, we measure decomposability via the network-based Modularity *Q* index (Newman 2006, Blondel et al. 2008). To calculate this measure, we first assess the strength of the connection between any two chunks by counting the number of claims that mention both of them; we then use the Modularity *Q* index to assess the degree of clustering in the network that connects those chunks. This approach allows us to derive a measure of decomposability that is more aggregated because it incorporates how chunks are linked to each other.

Tables 11 and 12 of the online supplement report the results of additional robustness tests to other omitted variable / measurement issues, and all our findings are robust to these alternatives. First, design patents are significantly cheaper to file compared to utility patents, which may make design patents relatively more suitable for the sole inventor. We put this conjecture to the test (by adding the interaction term *Sole* × *Fees* to our main model), and find that sole inventors are indeed relatively better at generating breakthroughs for low cost technology inventions. We do not see a similar effect in design. That said, all our results are robust in these alternative models. In particular, there remains a significant interaction of *Sole* × *LogChunks.* Hence, we find robust indications that non-decomposability relatively favors the lone inventor and that fee differences across design and technology patents is not a major confounding factor affecting their relative effectiveness.

Second, our models do not explicitly model product class and firm heterogeneity because most of their effects are absorbed by lead-inventor fixed effects. However, we can model these factors explicitly by creating separate fixed effects for the cases in which a given lead inventor works on inventions in different product classes or works for different firms. Doing so allows us to absorb heterogeneity across classes into the fixed effects. Again, all our results are robust to such an alternative specification.

Moreover, in setting lead inventors as the basis of comparison, our main model implicitly assumes that such inventors are the most instrumental in breakthroughs. We therefore test our results against a benchmark that instead uses a randomly selected team member as the basis of comparison. Our results are robust to this variant basis of comparison as well.

Our final two alternative models are as follows. First, instead of using inventor identifiers derived from Singh and Fleming (2010), we use the unique inventor identifiers proposed by Li et al. (2014) for all utility patents from 1975 to 2010. Second, we run models that test the sensitivity of our findings to alternative ways of measuring breakthroughs—defining “breakthrough” inventions using the top 1 percentile (rather than the top 5 percentile).[9] Once again, all our findings are robust to these variations.

6 DISCUSSION

How should we conceptualize the relationship between a lone inventor and a breakthrough innovation? Scholars have variously described the breakthrough single inventor as a myth, a romantic image, or a dead phenomenon (Jones 2009; Singh & Fleming 2010; Bercovitz & Feldman 2011). Such views render the significant fraction of patents that are filed by individual inventors (viz., 44% of all patents granted during 1985–2009) as long shots or even frivolous. By examining the areas in which individual inventors might outperform teams, our study identifies important contingencies affecting the usefulness of inventive collaborations.

We argue that the cost–benefit trade-off for teams can change dramatically across different types of inventions. Design innovation—unlike technology inventions—tend to be non-decomposable (holistic); the importance of the whole (i.e., the gestalt) overshadows its individual components. In fact, our analysis reveals that the 17% lower probability of a lone inventor (versus one working with others) in achieving a technology patent breakthrough is *not* observed for design patent breakthroughs. The difficulty of decomposing design and merging the work of different designers may explain why Philippe Starck insists on “never collabora[ting]” (Beard 2013, p. 144).

The results for design patents extend to technology inventions of an integral nature. Thus we identify a moderation effect whereby a lone inventor is no worse at creating breakthroughs (than when working with others in a team) when working on technology inventions that are relatively non-decomposable—in other words, inventions that cannot be easily partitioned into separate chunks. While the probability of a breakthrough for a lone inventor working on a technology invention of average decomposability would be 15% lower relative to teams, an inventor working on an integral invention has a non-statistically significant penalty of 3% when working alone. Our finding that integral technology inventions mimic design (in that lone inventors are not disadvantaged, as compared with teams, in creating breakthroughs) lends credence to our argument that non-decomposability is the main reason why the results for design patents differ so markedly from those for utility patents.

We emphasize that the empirical evidence—for teams having less advantage, over lone inventors, when developing integral (rather than modular) technology inventions—does not constitute a formal test of our

[9] We can also consider the effect of the lone inventor across the entire distribution of outcomes as opposed to focusing just on the upper tail (i.e., breakthroughs) using quantile regressions or logit regressions focusing on the lower tail—that is, on failures. These results are in Tables 8-10 in the online supplement. Our regression results are consistent with existing literature (Singh & Fleming 2010). We also find support also for our thesis whereby we find that the lone inventor disadvantage (relative to teams) is significantly reduced when it comes to design or integral technology inventions.

assertion that the holistic nature of design is what reduces the advantage of a team approach to innovating in that realm. Since there is not much observable variation in design decomposability, we could test the effect of invention decomposability only on utility patents. However, the internal consistency of our theoretical arguments is a strong indicator of why working in teams is unlikely to yield the same benefits in design innovation as it does in technology innovation.

In contrast to the extensive literature on managing modular systems (Baldwin & Clark 2000, Schilling 2000, Sosa et al. 2004, MacCormack et al. 2012, Baldwin & Henkel 2015), our study thus shifts research attention toward the management of tightly integrated systems. It establishes that, when creating integral systems, managers must re-evaluate the widely accepted view that "teams outperform individuals". Approaches to innovation should distinguish the extent of additional resources and coordination costs associated with teams, factors that depend on the focal invention's decomposability. Thus the sole inventor is less disadvantaged in creating tightly integrated inventions because they entail significant coordination demands when developed by a team. Supporting evidence of this argument is provided by varying team location across time zones, and thereby coordination costs, while holding team composition constant. One important practical implication of this result is that, if a team is tasked with developing a non-decomposable invention, its members should be co-located to avoid exacerbating the coordination costs imposed by that invention's structure.

More generally, our findings suggest that aligning the structure of the innovation task (creating a modular vs. an integral system) with the collaborative structure (working with others vs. working alone) is a critical decision that significantly affects the chances of breakthrough. Managers can avoid—or, at least, minimize—coordination pitfalls if they ensure that invention and collaborative structures "mirror" each other. Hence our work speaks also to the technology management literature that considers the architecture of products when deciding on how best to organize for innovation (Henderson & Clark 1990; von Hippel 1990; Sosa et al. 2004; Gokpinar et al. 2010; MacCormack et al. 2012). We extend this stream of literature by providing conceptual and empirical foundations for the role that an invention's decomposability should play in the decision about individual vs. team level innovation (Puranam 2018). This is an important decision whenever managers consider innovation team formation within entrepreneurial or corporate settings.

To the extent that coordination costs reflect information stickiness, our work also sheds light on the relationship between an invention's structure and the "stickiness" of the information needed to design it (von Hippel 1990, 1998). Our findings suggest that integral structures are more likely to be associated with sticky information which reduces any team advantage during the innovation effort whereas modular structures seem to "unstick" the information thus facilitating the distribution of the innovation effort across multiple team members and ultimately making teamwork more advantageous. Further, our empirical approach to measuring an invention's decomposability offers an avenue by which future research could explore the implications of this connection between an invention's structure and information stickiness on collaborating within or across organizational boundaries (Lakhani et al. 2013).

Far from suggesting that teams are irrelevant for holistic innovation, we take a more nuanced view, likewise refuting the binary notion that either teams or the lone inventor must dominate. For instance, the IDEO design firm is renowned for collaborative design (Hargadon & Sutton 1997). However, its fostering of collaboration may be motivated by factors other than the belief that teams are invariably better at creating breakthroughs. Collaborative meetings at IDEO are largely devoted to building network access and capabilities; working together allows one to learn about the abilities of others, and through awareness of different viewpoints it improves cognitive "suppleness" of the individual (Sutton & Hargadon 1996). We find evidence supporting this view: having worked with a large number of people in the past makes the lone inventor more effective at creating breakthroughs. Indeed, when working on a *technological* invention of average decomposability, an inventor with an average number of past collaborators would find it worthwhile to always collaborate—if they had chosen to work alone, they would have suffered from a 15% reduction in probability of breakthrough; however, our model also shows that the most prolific collaborators—those in the top 5th percentile in terms of number of past collaborators suffer from a much smaller penalty, a 4% reduction in probability of breakthroughs. Further, they are 38% better at creating *design* breakthroughs *alone* (and 9% better at independently creating integral utility breakthroughs). These results suggest that firms and entrepreneurs should not neglect individual work, especially individuals who have built up an extensive collaborative network—in defiance of Philippe Starck's "never collaborate". Indeed, the patent database does contain designs resulting from his collaboration with others early in his career.

Our robust results support the notions that a lone inventor is not disadvantaged, in comparison with a team, when creating a non-decomposable invention and she may even outperform teams after establishing a broad network of past collaborators. However, we should exercise caution in supposing that the concept of a "lone inventor" is strictly captured by the *absence* of patent co-inventors. Like previous work based on patent data, we consider interpersonal collaboration only when it is significant enough to merit co-ownership of an invention, yet this is not to imply that lone inventors are isolated from the world. The literature on collaborative design (e.g., Hargadon & Sutton 1997; Brown 2008) acknowledges that designers interact with users, colleagues, and other experts for the purpose of inspiring and refining ideas—even when the interactions do not amount to co-ownership (Molotch 2003). Future research could seek to establish empirically the effect of loose and informal collaborations (i.e., in which co-ownership is not anticipated) on inventive output. Distinguishing between different forms of collaboration would inform a more nuanced understanding of just what role collaboration can (and should) play in the creation of holistic inventions.

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