1042-2587

The Power and Effects of Entrepreneurship Research

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This study summarizes and analyzes average statistical power and effect sizes in empirical entrepreneurship research. Results show that statistical power was higher than expected, and was particularly high in studies employing archival measures. Statistical power has also increased over time. Effect sizes were higher than expected, a finding that remained consistent for different levels of analysis and across multiple subdomains. We discuss these findings, compare them to related disciplines, and draw implications for the design of future studies.

Statistical power and effect sizes of empirical studies are important components of a discipline's research methodology (Maxwell, 2004). Collectively, efforts to deal with statistical power and effect sizes have the potential to contribute to the statistical validity of empirical studies, meaning that neglecting them may limit the ability to base conclusions on the research (Scandura & Williams, 2000). When statistical inference testing is dominant, common practice calls for surveying and calculating the statistical power and average effect sizes of empirical research particular to the field (Chase & Chase, 1976; Maxwell; Rossi, 1990).

Reviews of statistical power and effect sizes have played important roles in informing and developing several social science disciplines such as marketing (Sawyer & Ball, 1981), accounting (Borkowski, Welsh, & Zhang, 2001), and psychology (Clark-Carter, 1997; Rossi, 1990). Reviews of this type have also been completed for a variety of subdisciplines within management, including international business (Brock, 2003), industrial/organizational psychology (Mone, Mueller, & Mauland, 1996), and strategy (Mazen, Hemmasi, & Lewis, 1987).

To date, however, statistical power and effect sizes associated with empirical entrepreneurship research have not been assessed and reported. This is an important omission in the entrepreneurship domain's published record for several reasons. First, a macro

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DOI: 10.1111/j.1540-6520.2009.00316.x

understanding of statistical power can point to where the field is and ought to be heading with respect to certain aspects of research design. Howard, Maxwell, and Fleming (2000) note that if aggregate statistical power is too low, it leads to a body of evidence in which results appear to be contradictory in nature (see also Boyd, Gove, & Hitt, 2005a; Ferguson & Ketchen, 1999). Conversely, if empirical research is characterized by high power, scholars may wish to consider the effect size of their research questions because even small effects occurring in the population can be statistically significant (Thompson, 2006).

Second, a review of statistical power allows comparison in this dimension of a focal domain to other domains within social science. As an academic discipline strives to establish itself as a unique entity, it is important to demonstrate that researchers are held to the same level of methodological rigor as colleagues in related disciplines (Harrison & Leitch, 1996). Statistical power is a critical methodological dimension on which scholars evaluate research involving statistical inference tests (Boyd, Gove, & Hitt, 2005b; Cohen, 1988). Hitt, Boyd, & Li (2004, p. 15) note that "inattention to statistical power is one of the greatest barriers to advancing the strategic management paradigm," and we suggest the same may be said of entrepreneurship.

Third, a review of effect sizes within entrepreneurship research can facilitate meta-analytic rationale in study design (Thompson, 2005). Scholars conducting statistical inference tests ought to explicitly invoke prior effect sizes for their research stream and relationships under consideration when planning their studies (Kline, 2004). This is not simply limited to replication studies; even groundbreaking research should be designed and placed in the context of the effects of prior related literature (Harris, 1991; Henson, 2006). Doing so will make researchers less inclined to overemphasize the effects of a single study and, looking back, allows them to be more confident of results that are comparable to prior research.

Last, an examination of reported effect sizes within the entrepreneurship domain is particularly important because entrepreneurship is an applied discipline. Because of this, entrepreneurship research is often concerned with dependent variables of interest to the business community (e.g., new venture survival, the likelihood of acquiring funding, and the performance of initial public offerings [IPOs]). The ability to provide large-effect recommendations in such a field would be of great value to practicing and aspiring entrepreneurs. A review of effect sizes of empirical entrepreneurship research and of particular literature streams within entrepreneurship will provide scholars with an improved understanding of the extent to which they are describing and predicting practical phenomena.

In earlier work, scholars traced entrepreneurship's evolution as a discipline in a qualitative manner (Low & MacMillan, 1988; Sexton & Smilor, 1985). Subsequent reviews focused on the definition of entrepreneurship and the field's central issues (Daily, McDougall, Covin, & Dalton, 2002; Gartner, 1990; Sarasvathy, 2004). These efforts yielded valuable insights that helped establish conceptual boundaries (Shane & Venkataraman, 2000). In addition to these qualitative assessments, a sufficient body of empirical entrepreneurship research has emerged to allow for quantitative assessment (Combs & Ketchen, 2003; Ireland, Reutzel, & Webb, 2005). Toward this end, we meta-analytically review reported effect sizes and calculate average statistical power in entrepreneurship research. We also examine several factors that may influence average statistical power. Further, we consider specific contexts within entrepreneurship research that are likely to be characterized by unique effect sizes. This study concludes by placing the results in the context of prior reviews in related disciplines and drawing conclusions for the direction of empirical entrepreneurship research.

Conceptual Background

Cohen (1962) was the first to conduct a systematic review of statistical power in a single discipline; additionally, he is often credited with introducing power considerations to scholars. Encouraged by the attention brought to an issue of such clear and substantive merit, researchers in business disciplines closely followed the procedures Cohen outlined to evaluate the publication record of their own discipline. These included reviews of empirical research in marketing (Sawyer & Ball, 1981), management (Mazen, Graf, Kellogg & Hemmasi, 1987), information systems (Baroudi & Orlikowski, 1989), and accounting (Lindsay, 1993). The recent trend, however, is toward more specific reviews of statistical power. Some of these reviews cut across disciplines to examine statistical power for a particular methodology (e.g., Aguinis, Beaty, Boik, & Pierce, 2005; Cashen & Geiger, 2004). Others dig deeper within a field to examine statistical power for a particular subdiscipline, such as operations management (Verma & Goodale, 1995), behavioral accounting (Borkowski et al., 2001), and international business (e.g., Brock, 2003).

An advantage of discipline and subdiscipline reviews of statistical power is that they serve as a comparative benchmark to related fields. The results of 19 power surveys in prevailing fields that traditionally serve as referent disciplines for entrepreneurship research are presented in Table 1. Overall average statistical powers for all 19 power surveys, weighted for the number of studies reviewed, are .26 for small effects, .67 for medium effects, and .86 for large effects. The studies presented in Table 1 are comparative across disciplines, with the chief differences being due to minor changes in the definitions

Table 1

Average Statistical Power Levels in Related Disciplines

Discipline	Author(s)	N	Tests	Small	Med.	Large
Accounting	(Borkowski et al., 2001)	96	NA	.23	.71	.93
Accounting	(Lindsay, 1993)	43	NA	.16	.59	.83
Communication	(Chase & Tucker, 1975)	46	1,298	.18	.52	.79
Communication	(Katzer & Sodt, 1973)	31	1,671	.23	.56	.79
Education	(Brewer, 1972)	47	373	.14	.58	.78
Info. tech.	(Baroudi & Orlikowski, 1989)	57	149	.19	.60	.83
International business	(Brock, 2003)	374	1,138	.29	.77	.93
Mgmt and app. psych.	(Mone et al., 1996)	210	26,471	.27	.74	.92
Marketing	(Sawyer & Ball, 1981)	23	475	.41	.89	.98
Psychology	(Clark-Carter, 1997)	96	1,243	.17	.59	.82
Psychology	(Sedlmeier & Gigerenzer, 1989)	54	NA	.21	.50	.84
Psychology	(Chase & Chase, 1976)	121	3,373	.25	.67	.86
Psychology	(Cohen, 1962)	70	2,088	.18	.48	.83
Social work	(Orme & Combs-Orme, 1986)	49	3,114	.31	.76	.92
Sociology	(Spreitzer & Chase, 1974)	34	1,049	.55	.84	.94
Management	(Cashen & Geiger, 2004)	43	77	.29	NR	NR
Management	(Mazen, Graf, et al., 1987)	84	7,215	.31	.77	.91
Strategic management	(Ferguson & Ketchen, 1999)	18	24	.26	.67	.88
Strategic management	(Mazen, Hemmasi, et al., 1987)	44	3,665	.23	.59	.83
Median		49	1,270	.23	.64	.85

Weighted Mean .26 .67 .86.
NA, not applicable; NR, not reported.

of small, medium, and large effects that were imposed to create greater consistency across different types of statistical tests.

Expecting researchers to consider statistical power in the design of their studies might be likened to expecting more stringent control for Type I errors by changing the critical probably of null hypothesis rejection from .05 to .01; the benefit will be increased reliability of statistical inferences, but there are also costs involved. The primary cost associated with higher power is achieving sufficiently large sample sizes. This has direct implications on the time and energy put forward by the researcher in data collection efforts and is particularly important for field data where researchers must deal with low response rates and difficult-to-access subjects. An important consideration here is the extent to which a small sample represents a larger population. For example, Keh, Foo, and Lim's (2002) sample of entrepreneurs may not be representative of entrepreneurs on the whole but it is likely a very good representation of Singaporean or even Asian entrepreneurs, who themselves constitute an important area of study.

Another cost of higher power is brought about by the need for researchers to subjectively select an appropriate effect size for their study. Doing this is neither a simple nor intuitive task. Cohen (1988) proposed a conventional notation in which certain effect size values serve as operational definitions of the qualitative adjectives "small," "medium," and "large." Scholars suggest that effect size should be considered within specific research domains (Aguinis et al., 2005; Ward, 2002). Rossi (1990) argues that consideration of more specific research domains affords a unique advantage in that actual observed effect sizes may be obtained via meta-analysis, and follow-on power calculations may then be conducted both with Cohen's benchmarks and with the potentially more accurate domain-specific benchmarks. An understanding of domain-specific average effect sizes is, therefore, an important step toward sound research design (Breaugh, 2003). Thompson (2005) recently reviewed various types of effect sizes, arguing that statistical inference tests should begin with an estimate of effect size based on meta-analytic rationale. Thompson (2002) defines meta-analytic rationale as both (1) the prospective formulation of study expectations and design by explicitly invoking prior effect sizes and (2) the retrospective interpretation of new results, once they are available, via explicit and direct comparison with prior effect sizes in related literature. Reviews such as ours facilitate this approach to research design.

Statistical Power and Effect Size in Entrepreneurship Research

Cohen (1988) suggests a broad rule of thumb for researchers wishing to protect against both Type I (rejecting a true null) and Type II (failing to reject a false null) errors: Type I is about four times as grievous as Type II. Researchers seeking to balance risk between the two types of error set alpha equal to .05 and then seek a beta of .20 (four times as much). This implies that statistical inference tests will have an 80% probability of detecting an effect. Cohen's prescription is a widely cited standard for power sufficiency (e.g., Aguinis et al., 2005; Ferguson & Ketchen, 1999). Therefore, we frame our discussion about power sufficiency with the underlying assumption that, on average, an 80% probability of detecting an effect is sufficient. However, there may be exceptions to this rule. For example, when examining the antecedents of new venture feasibility, a researcher may conclude that Type II error is more serious than usual, requiring a lower beta (e.g., Krueger, 1993).

As we can see in Table 1, average statistical power within each related discipline that has been reviewed was insufficient to detect small effects. The same can be said of medium-sized effects, with the exceptions of marketing (Sawyer & Ball, 1981) and sociology (Spreitzer & Chase, 1974). At the same time, every domain was also characterized by sufficient statistical power to detect large effects, with the exception of three reviews in which nearly sufficient power was found (i.e., .78 or .79). Notably, all three of these reviews were in disciplines outside of those commonly associated with business schools. Because entrepreneurship research is related to and derived from the disciplines reported in Table 1, we expect that average statistical power within entrepreneurship will follow a similar pattern. That is, we expect that average statistical power of entrepreneurship studies are sufficient to detect large effects but insufficient to detect medium or small effects.

In addition to calculating average statistical power in entrepreneurship research, we consider segments of entrepreneurship literature that may explain differences in statistical power. This approach is consistent with Maxwell (2004), who posits that the ready availability of large archival data sets may be one explanation why some studies, such as those found in marketing (Sawyer & Ball, 1981), enjoy higher statistical power. Scholars have considered the importance of differences between archival and perceptual measures for reliability and validity (Shortell & Zajac, 1990), but there are also implications for statistical power. Researchers using perceptual measures may argue that the criterion for statistical power should be relaxed for their studies, given the difficulties associated with data collection. For example, the literature indicates that environmental dynamism is an important construct of interest in entrepreneurship research (Phan, 2006). Whereas some have measured dynamism using archival information (e.g., Lyles, Saxton, & Watson, 2004), others have measured this construct with perceptual measures via surveys (e.g., Miller, Droge, & Vickery, 1997). There is merit to both types of measures (Boyd, Dess, & Rasheed, 1993), but it is easier to increase sample size and, therefore, statistical power in archival studies. So, we expect that average statistical power of entrepreneurship studies is lower when perceptual measures are employed.

Ferguson and Ketchen (1999, p. 390) note that, "in analyzing past research, perhaps the total set of studies should be segmented with some of the earlier, groundbreaking studies held to less stringent standards regarding power than current work." Consistent with this notion, we suggest that, as science progresses, scholars should embrace a higher standard for statistical power. Stated differently, science that is in an earlier stage of paradigmatic development could allow for studies with lower statistical power. Scholars completing their work, reviewers, and editors may recognize the limitations of conducting studies in areas of research with lower paradigmatic development and be more lenient with respect to required power levels. Scholars have found evidence of increasing levels of statistical power in other disciplines. For example, Brock (2003) found an increase in the statistical power of international business studies throughout the 1990s. Mone et al. (1996) found no significant increase over time in psychology and management research, but this may have been due to their limited (i.e., 3-year) sampling window because Aguinis et al. (2005) found an increase in the same literature using a wider time frame. These increases are likely due to advancement of the discipline from groundbreaking, exploratory research to examination of better-defined constructs and relationships. Entrepreneurship research has made important strides over the last decade (Chandler & Lyon, 2001), and we expect these strides will be manifested in the form of increasing levels of statistical power over time.

With respect to effect sizes, Cohen (1988) suggested that small to medium effects are considered the norm, not the exception, in social sciences. Ward (2002) confirms this contention in her recent survey of power and effect size in the psychology literature, finding that average effect size across 157 articles corresponded most closely with

Cohen's benchmark for medium effects. In a similar review of three top-tier applied psychology journals, Aguinis and colleagues (2005) conducted a systematic effort to contact all authors who posited a moderated relationship in order to gain the necessary information to calculate effect size, whether or not it was reported in the published article. Even accounting for the downward bias in observed effect size that is characteristic of moderated effects, these authors found that average effect sizes were small. Within the management domain, Mazen, Hemmasi, et al. (1987) transformed the absolute estimates of relationships from 12 separate meta-analyses to effect sizes using Cohen's formulae, reporting an aggregate effect size across studies consistent with Cohen's benchmark for small effects. Given this evidence, we expect to find similar results with a review of average effect sizes in the entrepreneurship domain.

This conclusion is consistent with the modest average effect sizes found in recent entrepreneurship meta-analyses, such as those conducted by Combs and Ketchen (2003) and Daily, Certo, Dalton, and Roengpitya (2003). Entrepreneurial constructs exist in various dimensions that researchers may configure in many combinations, such that any single study is necessarily circumscribed in scope. Because of this, it is unreasonable to expect any one study to comprehensively incorporate all relevant variables to account for large amounts of variance (Boyd et al., 2005b). Note, however, that smaller effect sizes do not necessarily imply that relationships are less meaningful. Breaugh (2003) provides a number of illustrations wherein studies with small effect sizes have important implications for science and practice. Given these arguments, we expect to find the average effect size of our review will yield small to medium effects.

Some suggest that reviews of effect size may benefit from being oriented toward the specific research situation at hand (Aguinis et al., 2005; Ferguson & Ketchen, 1999). This position reflects the notion that effect size distinctions are relative "to the area of behavioral science or even particularly to the specific content and research methods being employed" (Cohen, 1988, p. 25). For this reason, Aguinis et al. examine effect size for different literature streams, specifically comparing research on personnel selection and work attitudes to other areas within applied psychology. The motivation behind such comparisons is that literature streams are often characterized by a common set of constructs and relationships, and effect size distinctions are dependent on the set of relationships under consideration (Trusty, Thompson, & Petrocelli, 2004). For example, Eden (2002) argued that the importance of any particular effect size depends on the nature of the outcome studied.

Following this line of reasoning, we also compare effects among different literature streams within entrepreneurship research to test if there are any areas of study characterized by uniquely high or low effect sizes. We expect to find distinctions among average effect sizes in these different streams owing to differences in relationships under consideration. For example, one promising area of research lies at the intersection of social network analysis and entrepreneurship. Fischer and Pollock (2004) considered the effects of social capital during a firm's IPO, finding that network embeddedness decreases the likelihood of firm failure during the 5 years following an IPO. Shane and Cable (2002), on the other hand, considered the role of network ties for emerging ventures, examining the likelihood of receiving seed-stage financing. Using similar independent variables, the IPO literature concerns itself with survival over time, whereas the new venture literature considers network ties as a strategy for obtaining financial capital. Bodies of empirical research that regularly examine different relationships are likely to yield different average effect sizes (Thompson, 2005). We expect, therefore, that average effect size examined in empirical entrepreneurship research is statistically different for subdomains within entrepreneurship.

Level of analysis is one of the most important content distinctions within entrepreneurship studies (Davidsson & Wiklund, 2001). Early research emphasized the individual level, which remains important (Ireland, 2007), but the field has incorporated consideration of many different levels, including entrepreneurial teams (Chowdhury, 2005), entrepreneurial firms (Wiklund & Shepherd, 2005), and industrial and societal implications of entrepreneurship (Phan, 2006; Tan, 2005). Each of these is marked by its own unique set of research questions. Relationships between variables observed at one level may be different from relationships observed at a higher or lower level (Low & MacMillan, 1988). Therefore, there are likely to be differences between average effect sizes reported in research investigating entrepreneurs themselves (individual level) versus research on the entrepreneurial team (group level), new ventures (organization level), or aggregate levels such as industry or society (Davidsson & Wiklund; Shaver & Scott, 1991). In sum, we expect that average effect size examined in empirical entrepreneurship research is statistically different for different levels of analysis.

Methodology Sample

We examined empirical studies from eight leading journals that publish entrepreneurship research. Tahai and Meyer (1999) provide an extensive list and ranking of the most influential management journals with a view toward aiding management scholars in journal selection for research and publication. Their sampling window ended in 1994, so we reordered their journal rankings based on citation data through 2006. To do so, we used the Hirsch index (h-index), which measures the global citation performance of a set of articles (Egghe & Rousseau, 2006). The h-index is defined as the unique number *h* such that, for a general group of papers, *h* papers received at least *h* citations, while the other papers received no more than *h* citations. Our choice was to use only the top five general management journals (as ranked by h-index) that regularly publish empirical entrepreneurship research. These were the *Academy of Management Journal* (*AMJ*), *Strategic Management Journal* (*SMJ*), *Journal of Management* (*JOM*), *Management Science* (*MS*), and *Organization Science* (*OS*). We then added the top two journals dedicated exclusively to publishing entrepreneurship research, *Entrepreneurship Theory and Practice* (*ETP*) and *Journal of Business Venturing* (*JBV*) and the top international business journal, *Journal of International Business Studies* (*JIBS*). Scholars have recognized the journals we selected as the leading journals that feature entrepreneurship as a regular part of their published body of work (Chandler & Lyon, 2001). Last, the topic of venture capital has a much stronger presence in the finance literature than in the entrepreneurship literature. Therefore, we added the 10 most highly cited studies on the subject of venture capital that fell within our sampling window; these came from a variety of finance journals.[1]

We chose a 10-year sampling window (1997–2006) for our analysis. Prior reviews in related disciplines often use a 5-year sampling window (e.g., Borkowski et al., 2001; Verma & Goodale, 1995). However, because the hypotheses suggest a trend, a longer time frame was necessary. Therefore, we followed Brock (2003), who examined the same issue for international business research using 10 years of data.

Measures

For consistency, we followed several conventions associated with previous surveys in other disciplines (Borkowski et al., 2001; Brock, 2003; Mazen, Hemmasi, et al., 1987;

1. Thank you to an anonymous reviewer for recognizing this important addition.

Sawyer & Ball, 1981). We identified statistical inference tests in each article that directly examined hypotheses (Mazen, Graf, et al., 1987). We set the Type I error significance criterion to $\alpha = .05$, the assumed two-tailed tests (nondirectional), and the logically equivalent one-sided test for chi-square and F distributions. While this latter convention may have led to a slight underestimation of power in some cases, it avoids the more serious problem of inflated significance levels (Orme & Combs-Orme, 1986). For comparison with other disciplines, the effect sizes used to determine statistical power were those Cohen (1988) defined as small, medium, and large.

Cohen (1992) discussed the method for calculating power postinvestigatively, and we made use of statistical software for calculating power in accordance with these standards (Faul, Erdfelder, Lang, & Buchner, 2007). We did not include empirical studies using simulations based on computer-generated data nor did we include studies employing procedures for which statistical power could not be calculated with established formulae. We identified empirical tests in each article that directly addressed hypotheses. These were distinguished from secondary tests, such as manipulation checks or reliability estimates, that were not included in the analysis and from tests of inferential statements that were not hypothesized. This yielded a total of 2,582 statistical tests found in 330 empirical studies, an average of slightly less than eight tests per study. We then calculated the statistical power for small, medium, and large effect sizes for each individual test (Borkowski et al., 2001; Brock, 2003).

Variance in definitions of entrepreneurship (e.g., Alvarez & Barney, 2004; Davidsson, 2005; Sharma & Chrisman, 1999) complicated the task of identifying entrepreneurship research and classifying it into different literature streams. We did not, for example, include studies on "innovation" unless they were definitively aligned with entrepreneurial activity because there are multiple areas of inquiry outside of entrepreneurship that address innovation (e.g., Somech, 2006). We also did not include studies on strategic renewal, although one could reasonably argue that renewal is an important component of entrepreneurship (Sharma & Chrisman). We recognize that there is some level of idiosyncrasy to the process of identifying entrepreneurship research. To enhance our review's objectivity, we did not rely on search terms. Instead, two individuals scanned the abstracts of every article published in the focus journals during our 10-year sampling window. We discussed and resolved articles that were not clear, which were rare.

To initially develop a classification system, each of two coders independently classified a number of articles into individually chosen topic areas. Comparing results, the coders agreed that most empirical entrepreneurship research could be categorized into the dominant literature streams identified by Ireland et al. (2005). Specifically, the coders separated articles into categories based on dependent variables that examine new venture strategy and performance (e.g., Gilbert, McDougall, & Audretsch, 2006), corporate entrepreneurship (e.g., Dess et al., 2003; Ireland, Covin, & Kuratko, 2009), IPOs (e.g., Deeds, DeCarolis, & Coombs, 1997), family firms (e.g., Rogoff & Heck, 2003), venture capitalism (Hsu, 2006), small to medium enterprises (e.g., Lubatkin, Simsek, Ling, & Veiga, 2006), entrepreneurial traits and cognition (e.g., Choi & Shepherd, 2004), and international entrepreneurship (George, Wiklund, & Zahra, 2005). We added categories specifically for family firms and venture capitalism based on our own belief that research on these topics may exhibit unique effect sizes compared with other literature streams. We did not classify the topics of individual statistical tests but rather classified studies into topics at the study level. Some studies address dependent variables that fit into more than one category, in which case the coders selected the category that best represented the primary focus of the hypotheses.

Analysis and Results

The first finding in our review was that statistical power was higher than expected. Average statistical power for large effect sizes was close to 1 (i.e., .96), well above the target .80 ($p < .01$). This suggests that, when entrepreneurship researchers investigate a phenomenon that exhibits a large effect in the population, on average, it is almost certain that they will have sufficient power to detect it. When we considered the more common medium effect sizes, we found that average statistical power was .86, also in excess of the target .80 power level ($p < .01$) and well in excess of the .67 found in other social science disciplines. This suggests that, on average, entrepreneurship researchers will correctly detect medium effect size phenomena 84% of the time. Average statistical power for small effect sizes was .40, which was also higher than the average of .23 found in other disciplines ($p < .01$) but well below the .80 required by Cohen's (1988) rule of thumb. Table 2 shows a summary of average statistical power by journal outlet.

We then calculated average statistical power for research in which scholars could potentially loosen the criterion for statistical power. Specifically, we coded all statistical tests as to whether the primary data collection used perceptual measures or archival measures. A two-sample *t*-test showed that the average statistical power of entrepreneurship studies using archival data was higher than that of studies incorporating perceptual data ($p < .01$).

The second test for differences of statistical power within our sample examined the influence of time. Following prior studies that evaluate the trend of statistical power over time (Aguinis et al., 2005; Brock, 2003), we examine Pearson's r between the year of publication and the statistical power of each study. The correlation between these two variables is .11, which is small but significant ($p < .05$). Average statistical power of empirical entrepreneurship research increased during the 10-year window we examined.

Similar to the results on statistical power, we found that average reported effect size in entrepreneurship research was also higher than expected. We did not calculate postinvestigative effect sizes based on sum of squares or other information (Kier, 1999); instead, we chose to include only those R^2-type effect sizes that authors explicitly reported

Table 2

Summary Statistics of *Post Hoc* Statistical Power Calculations

Journal	Power for meta-analytic ES (.28)
JOM	.94
AMJ	.89
ET&P	.87
OS	.87
SMJ	.86
JIBS	.85
MS	.84
JBV	.78

ES, effect size.

(Breaugh, 2003). This yielded 204 studies with observed effect sizes, or 62% of the total number of studies examined. The overall meta-analytic observed effect size in entrepreneurship research, weighted for sample size, was .28 (standard deviation [SD] = .01). A *t*-test comparison to Cohen's (1988) benchmark for medium effects is significant in the opposite direction than predicted ($p < .01$). Thus, explained variance did not correspond with small to medium effects but did correspond with medium to large effects.

Observed effect size was not significantly different based on research subdomain or level of analysis. We coded all studies according to their research stream, including start-up firms, small to medium enterprises, corporate entrepreneurship, IPOs, family firms, entrepreneurial traits and cognition, international entrepreneurship, and venture capital. Because of positive skewness, we transformed observed effect sizes by their .15 root (Box & Cox, 1964). This resulted in an approximately normal distribution (skewness = −.16). Analysis of variance (unbalanced ANOVA) on the transformed effect sizes found no statistically significant differences ($p = .82$). This suggested that average observed effect size is fairly robust across subdomains within entrepreneurship research.

Similarly, we compared the mean and median effect sizes for individual-, group-, and firm-level analyses of the primary constructs for each study, as well as other analyses that did not fall into those three most common levels. ANOVA, again unbalanced, on the transformed effect sizes showed no statistically significant differences across levels ($p = .32$). Table 3 summarizes these results.

Table 3

Summary Statistics of Meta-Analytic Reported Effect Sizes

					95% confidence interval	
Analysis	N	%	Median ES	Mean ES (SD)	Low	High
Research stream						
New venture strategy and performance	45	22	.25	.30 (.19)	.20	.31
Small-to-medium enterprises	21	10	.22	.23 (.14)	.14	.27
Corporate entrepreneurship	40	20	.22	.25 (.14)	.21	.25
Initial public offerings	17	8	.24	.26 (.13)	.14	.39
Family firms	16	8	.21	.26 (.20)	.11	.31
Entrepreneurial traits & cognition	24	12	.24	.30 (.18)	.20	.34
International entrepreneurship	25	12	.24	.30 (.20)	.14	.35
Venture capital	16	8	.24	.26 (.12)	.13	.36
Construct level						
Individual	43	21	.23	.25 (.02)	.21	.29
Group	14	7	.33	.33 (.05)	.23	.43
Firm	140	68	.23	.28 (.02)	.24	.29
Other	7	4	.26	.37 (.09)	.19	.54
All studies	204	100	.23	.27 (.01)	.25	.30

ES, effect size.

Discussion

The results of our survey of statistical power in entrepreneurship research provide interesting findings that stand in contrast to those of previous reviews conducted in other disciplines. For example, we found average statistical power levels to be higher than expected. Our results also show that there are situations in which scholars may relax the criterion for statistical power, such as for entrepreneurship studies that make use of perceptual data. For example, Keh et al. (2002) provide some interesting and important insights about the cognitive processes of entrepreneurs by examining a relatively small number of owners of the top small and medium enterprises in Singapore via survey data collection. We also find that average statistical power appears to have increased over time. Average observed effect size was higher than we predicted, and this finding was robust across levels of analysis and subdomains within entrepreneurship research.

These results may encourage entrepreneurship researchers who argue that the field is making advances in the pursuit of scholarly legitimacy (Busenitz et al., 2003). Although there are many facets to establishing a research field's legitimacy, our findings at least reflect broad awareness of the importance of statistical power within the field, even if it is often not reported. Our results may be an indication that entrepreneurship researchers are likely to consider statistical power either before or when completing their studies and that statistical power is at least one consideration for publication in peer-reviewed journals. This is confirmed anecdotally by renewed emphasis on power estimation in some of the most popular analysis software packages used by entrepreneurship scholars, such as stpower in Stata and glmpower in SAS. A comparison to other disciplines and journals suggests that entrepreneurship scholars are developing a body of evidence based on empirical work with statistical power that exceeds the average of the broader management domain. Further, our finding that average statistical power has increased over the past decade provides some evidence that methodological rigor is improving.

Several factors likely contribute to or account for the positive results about statistical power found in this review. It is reasonable to expect that the increasing attention journals have devoted to matters of statistical power and effect size has affected authors, reviewers, and editors (Murphy & Myors, 2004). Also, entrepreneurship research has, to some degree, struggled as a discipline to define itself within the larger community of scholars in business schools (Bruyat & Julien, 2000; Venkataraman, 1997). This struggle may affect the statistical power of entrepreneurship research in two ways: (1) Entrepreneurship researchers may overcompensate by employing larger than necessary sample sizes. (2) Reviewers may be suspicious of underpowered studies in the entrepreneurship domain. Lastly, because the field of entrepreneurship is emerging and is still establishing standards, there may be a tendency to underestimate the expected population effect size and, consequently, overestimate the required sample size.

The finding that average statistical power in entrepreneurship research was higher than expected provides some unique insights for the field's direction. If a scholar expects statistical power of a research design under consideration is high, then he or she might consider reducing sample size to save time and effort. Alternatively, when designing their study, if researchers anticipate a large effect size, they may wish to consider whether that effect is so obviously present that they should examine a less obvious but possibly more meaningful hypothesis involving a smaller effect size. For example, instead of merely testing whether a model yields better than random events, researchers may wish to compare their model with others that have previously been shown to have good predictive ability. Also, in highly powered research studies, even small effects occurring in the population can be statistically significant, suggesting that estimates of expected effect size may be especially important in entrepreneurship research. For example, it was particularly important for Schulze, Lubatkin, and Dino (2003) to conceptually justify the nature and direction of relationships between owners and directors in family firms, given the large sample size of their data set and small effect sizes under study.

In retrospect, there may be several arguments that help explain our findings about effect size. Entrepreneurship research is not purely experimental or theoretical (Walster & Cleary, 1970). The dependent variables in entrepreneurship research are usually oriented toward strategic outcomes that often interest practicing entrepreneurs. If an outcome variable is particularly resistant to intervention or bears the weight of life-or-death importance, then small effect sizes may still be quite noteworthy (Thompson, 2005). Strategic outcomes fulfill neither condition, suggesting that researchers may look for phenomena accounting for greater explained variance. Also, as an emerging discipline, entrepreneurship research may still be focused on macro relationships where variance is more readily explained. As the field develops, more fine-grained relationships with smaller effects in the population may become more frequent. So far, however, such a trend has not emerged. Supplementary analysis of effect size by year revealed no significant correlation, suggesting that effect sizes on the whole are not necessarily or at least not yet becoming smaller over time.

Entrepreneurship researchers may be encouraged by the results of our review of reported effect sizes. First, reported effect sizes were larger than expected. This suggests that researchers are explaining a significant degree of variance of practical outcomes. Second, reported effect sizes were fairly robust across streams of research and levels of analysis. Although we did not expect this outcome, it eases the task of estimating expected effect sizes in study design. Scholars might consult Table 3 as an initial guide to expected effect size within the range of indicated confidence levels.

There are, however, both advantages and disadvantages to our findings about effect size. Given that entrepreneurship researchers rarely have access to the entire population of interest, it is important that the relationship between two or more variables under study have a reasonably large effect size so that findings about the relationship will not be due entirely to chance. For example, Florin, Lubatkin, and Schulze (2003) use social capital theory to explain relationships between human and social capital and a venture's ability to accumulate financial capital. Effect sizes of the relationships under examination were large, allowing them to use a smaller sample size. Another example comes from Zahra, Neubaum, and El-Hagrassey (2002), who encountered medium to large effect sizes in their study of the relationship between competitive analysis and new venture performance. Expected effect size allowed them to employ a smaller sample size, 228 firms, which was particularly important, given their survey data collection method.

At the same time, large effect sizes can also hinder a field's growth. One potential problem is that scholars could gain unreasonable expectations of medium to large effect sizes and feed a pattern of uncharacteristically low power. Ferguson and Ketchen (1999) provide an excellent review of how this phenomenon played out among scholars examining the relationship between organizational configurations and performance. Over time, the body of studies examining this relationship became underpowered, such that only 8% of the configurations-performance research was able to detect small effects and less than half could detect medium effects. Fichman (1999, p. 296) provides an insightful analysis of how a "focus on explaining variance can have detrimental consequences for theory development."

Further, our finding that entrepreneurship research is characterized by medium to large effect sizes does not diminish the potential contribution of small effect size relationships. Martell, Lane, and Emrich (1996) provide an interesting example of how even a small gender-bias effect in performance ratings can build on itself over time to have a very large effect on the number of women being promoted. In another study, the small amount of explained variance found by Dushnitsky and Lenox (2005) is offset by their ability to explain broad trends in corporate venture capital investment. In this case, explaining even a small amount of variance is important when it applies to vast sums of money on which rest the fortunes of many firms.

Limitations and Future Research

While our findings yield some surprising insights, especially in comparison to past reviews and other disciplines, a few words of caution are in order. For example, there are some limitations to reviews of statistical power and how to interpret average statistical power. Following previous studies, we assumed that the reliability of reported results is a function of the sample size of each statistical test. We also assumed that the measures used are perfectly reliable, which is, of course, an upper bound. Unreliable measures will serve to decrease statistical power such that actual power levels will be lower than those calculated in this review.

Although average statistical power was higher than expected, this does not mean that all entrepreneurship studies exhibit an ability to avoid a Type II error. Average statistical power is only an overall indicator of a body of research; however, we may not interpret high average statistical power for the whole domain at the level of an individual study. We believe that this review takes an important step toward Rossi's (1990) exhortation to conduct statistical power surveys in more specific research domains. At the same time, we suggest that future research might carry the exercise to the next level of detail, surveying specific constructs (e.g., Lyon, Lumpkin, & Dess, 2000) or methods (e.g., Aguinis, 1995) within the entrepreneurship domain.

Our review of entrepreneurship literature has focused on a select set of journals, several of which mainly publish work in the management domain. However, entrepreneurship research spans various other disciplines that measure unique constructs with their own expected effect sizes and statistical power (Ireland & Webb, 2007). Future research may take a more inclusive approach, examining entrepreneurial phenomena in journal outlets from such areas as accounting, finance, marketing, psychology, sociology, and economics, among others.

Lastly, our approach to examining the effect size of various topics within entrepreneurship is based on classifying the dependent variable of interest for each study. This is justified in that studies generally examine a single dependent variable or a set of dependent variables that fall within a particular research domain. However, future research should consider effect size groupings at an even greater level of detail. Although outside the scope of this review, it would be particularly useful for scholars to be able to reference meta-analytic effect sizes for more specific constructs and relationships of interest within entrepreneurship. Along these lines, further classification could be performed on the basis of the independent variables under study. This would facilitate examination of effect size variation both within topics and between dependent and independent variables. Carrying this kind of review to the next level of detail would be especially useful given that there are a limited number of meta-analyses devoted to empirical entrepreneurship research.

REFERENCES

Aguinis, H. (1995). Statistical power problems with moderated multiple regression in management research. *Journal of Management*, *21*, 1141–1158.

Aguinis, H., Beaty, J.C., Boik, R.J., & Pierce, C.A. (2005). Effect size and power in assessing moderating effects of categorical variables using multiple regression: A 30-year review. *Journal of Applied Psychology*, *90*, 94–107.

Alvarez, S.A. & Barney, J.B. (2004). Organizing rent generation and appropriation: Toward a theory of the entrepreneurial firm. *Journal of Business Venturing*, *19*, 621–635.

Baroudi, J. & Orlikowski, W. (1989). The problem of statistical power in MIS research. *MIS Quarterly*, *13*, 87–106.

Borkowski, S., Welsh, M.J., & Zhang, Q. (2001). An analysis of statistical power in behavioral accounting research. *Behavioral Research in Accounting*, *13*, 63–84.

Box, G.E.P. & Cox, D.R. (1964). An analysis of transformations. *Journal of the Royal Statistical Society*, *26*(2), 211–246.

Boyd, B.K., Dess, G.G., & Rasheed, A.M.A. (1993). Divergence between archival and perceptual measures of the environment: Causes and consequences. *Academy of Management Review*, *18*, 204–226.

Boyd, B., Gove, S., & Hitt, M.A. (2005a). Consequences of measurement problems in strategic management research: The case of Amihud and Lev. *Strategic Management Journal*, *26*, 367.

Boyd, B., Gove, S., & Hitt, M.A. (2005b). Construct measurement in strategic management research: Illusion or reality? *Strategic Management Journal*, *26*, 239–257.

Breaugh, J.A. (2003). Effect size estimation: Factors to consider and mistakes to avoid. *Journal of Management*, *29*, 79–97.

Brewer, J.K. (1972). On the power of statistical tests in the American Educational Research Journal. *American Educational Research Journal*, *9*, 391–401.

Brock, J. (2003). The power of international business research. *Journal of International Business Studies*, *34*, 90–99.

Bruyat, C. & Julien, P.A. (2000). Defining the field of research in entrepreneurship. *Journal of Business Venturing*, *16*, 165–180.

Busenitz, L.W., West, G.P., Shepherd, D., Nelson, T., Chandler, G.N., & Zacharakis, A. (2003). Entrepreneurship research in emergence: Past trends and future directions. *Journal of Management*, *29*, 285–308.

Cashen, L.H. & Geiger, S.W. (2004). Statistical power and the testing of null hypotheses: A review of contemporary management research and recommendations for future studies. *Organizational Research Methods*, *7*(2), 151–167.

Chandler, G.N. & Lyon, D.W. (2001). Issues of research design and construct measurement in entrepreneurship research: The past decade. *Entrepreneurship Theory and Practice*, *2*(4), 101.

Chase, L.J. & Chase, R.B. (1976). A statistical power analysis of applied psychological research. *Journal of Applied Psychology*, *61*, 234–237.

Chase, L.J. & Tucker, R.K. (1975). A power-analytic examination of contemporary communication research. *Speech Monographs*, *42*(3), 29–41.

Choi, Y.R. & Shepherd, D.A. (2004). Entrepreneurs' decisions to exploit opportunities. *Journal of Management*, *30*, 377–395.

Chowdhury, S. (2005). Demographic diversity for building an effective entrepreneurial team: Is it important? *Journal of Business Venturing*, *20*, 727–746.

Clark-Carter, D. (1997). An account of statistical power in research published in the British Journal of Psychology. *British Journal of Psychology*, *88*, 71–83.

Cohen, J. (1962). The statistical power of abnormal-social psychological research: A review. *Journal of Abnormal and Social Psychology*, *65*(3), 145–153.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. New York: Academic Press.

Cohen, J. (1992). A power primer. *Psychological Bulletin*, *112*(1), 155–159.

Combs, J.G. & Ketchen, D.J. (2003). Why do firms use franchising as an entrepreneurial strategy? A meta-analysis. *Journal of Management*, *29*, 443–465.

Daily, C.M., Certo, S.T., Dalton, D.R., & Roengpitya, R. (2003). IPO underpricing: A metaanalysis and research synthesis. *Entrepreneurship Theory and Practice*, *27*, 271–296.

Daily, C.M., McDougall, P.P., Covin, J.G., & Dalton, D.R. (2002). Governance and strategic leadership in entrepreneurial firms. *Journal of Management*, *28*, 387–412.

Davidsson, P. (2005). *Researching entrepreneurship*. New York: Springer.

Davidsson, P. & Wiklund, J. (2001). Level of analysis in entrepreneurship research: Current research practice and suggestions for the future. *Entrepreneurship Theory and Practice*, *25*(4), 81–99.

Deeds, D.L., DeCarolis, D., & Coombs, J.E. (1997). The impact of timing and firm capabilities on the amount of capital raised in an initial public offering: Evidence from the biotechnology industry. *Journal of Business Venturing*, *12*, 31–46.

Dess, G.G., Ireland, R.D., Zahra, S.A., Floyd, S.W., Janney, J.J., & Lane, P.J. (2003). Emerging issues in corporate entrepreneurship. *Journal of Management*, *29*, 351–378.

Dushnitsky, G. & Lenox, M.J. (2005). When do firms undertake R&D by investing in new ventures? *Strategic Management Journal*, *26*, 947–966.

Eden, D. (2002). Replication, meta-analysis, scientific progress, and AMJ's editorial publication policy. *Academy of Management Journal*, *45*, 841–846.

Egghe, L. & Rousseau, R. (2006). An informetric model for the Hirsch-index. *Scientometrics*, *69*, 121–129.

Faul, F., Erdfelder, E., Lang, A.G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods, Instruments, and Computers*, *39*, 175–191.

Ferguson, T.D. & Ketchen, D.J. (1999). Organizational configurations and performance: The role of statistical power in extant research. *Strategic Management Journal*, *20*, 385–395.

Fichman, M. (1999). Variance explained: Why size does not (always) matter. *Research in Organizational Behavior*, *21*, 295–331.

Fischer, H.M. & Pollock, T.G. (2004). Effects of social capital and power on surviving transformational change: The case of initial public offerings. *Academy of Management Journal*, *47*, 463–481.

Florin, J., Lubatkin, M., & Schulze, W. (2003). A social capital model of high growth ventures. *Academy of Management Journal*, *46*, 374–384.

Gartner, W.B. (1990). What are we talking about when we talk about entrepreneurship? *Journal of Business Venturing*, *5*, 15–28.

George, G., Wiklund, J., & Zahra, S.A. (2005). Ownership and the internationalization of small firms. *Journal of Management*, *31*, 210–233.

Gilbert, B.A., McDougall, P.P., & Audretsch, D.B. (2006). New venture growth: A review and extension. *Journal of Management*, *32*, 926–950.

Harris, M.J. (1991). Significance tests are not enough: The role of effect-size estimation in theory corroboration. *Theory and Psychology*, *1*, 375–382.

Harrison, R.T. & Leitch, C.M. (1996). Discipline emergence in entrepreneurship: Accumulative fragmentalism or paradigmatic science? *Entrepreneurship, Innovation, and Change*, *5*(2), 65–83.

Henson, R.K. (2006). Effect-size measures and meta-analytic thinking in counseling psychology research. *The Counseling Psychologist*, *34*, 601–629.

Hitt, M.A., Boyd, B.K., & Li, D. (2004). The state of strategic management research and a vision of the future. In D. Ketchen & D. Bergh (Eds.), *Research methodology in strategy and management* (Vol. 1, pp. 1–31). New York: Elsevier.

Howard, G.S., Maxwell, S.E., & Fleming, K.J. (2000). The proof of the pudding: An illustration of the relative strengths of null hypothesis, meta-analysis, and Bayesian analysis. *Psychological Methods*, *5*, 315–332.

Hsu, D.H. (2006). Venture capitalists and cooperative start-up commercialization strategy. *Management Science*, *52*, 204–219.

Ireland, R.D. (2007). *Random thoughts about interesting entrepreneurship research*. Paper presented at the annual meeting of the United States Association of Small Business and Entrepreneurship, Orlando, FL.

Ireland, R.D., Covin, J.G., & Kuratko, D.F. (2009). Conceptualizing corporate entrepreneurship strategy. *Entrepreneurship Theory and Practice*, *33*, 19–46.

Ireland, R.D., Reutzel, C.R., & Webb, J.W. (2005). Entrepreneurship research in AMJ: What has been published, and what might the future hold? *Academy of Management Journal*, *48*, 556.

Ireland, R.D. & Webb, J.W. (2007). A cross-disciplinary exploration of entrepreneurship research. *Journal of Management*, *33*, 891–927.

Katzer, J. & Sodt, J. (1973). An analysis of the use of statistical testing in communication research. *Journal of Communication*, *23*, 251–265.

Keh, H.T., Foo, M.D., & Lim, B.C. (2002). Opportunity evaluation under risky conditions: The cognitive processes of entrepreneurs. *Entrepreneurship Theory and Practice*, *27*(2), 125–148.

Kier, F.J. (1999). Effect size measures: What they are and how to compute them. In B. Thompson (Ed.), *Advances in social science methodology* (pp. 87–100). New York: JAI Press.

Kline, R.B. (2004). *Beyond significance testing: Reforming data analysis methods in behavioral research*. Washington, DC: American Psychological Association.

Krueger, N. (1993). The impact of prior entrepreneurial exposure on perceptions of new venture feasibility and desirability. *Entrepreneurship Theory and Practice*, *18*(1), 5.

Lindsay, R.M. (1993). Incorporating statistical power into the test of significance procedure: A methodological and empirical inquiry. *Behavioral Research in Accounting*, *5*, 211–236.

Low, M.B. & MacMillan, I.C. (1988). Entrepreneurship: Past research and future challenges. *Journal of Management*, *14*, 139–162.

Lubatkin, M.H., Simsek, Z., Ling, Y., & Veiga, J.F. (2006). Ambidexterity and performance in small-to medium-sized firms: The pivotal role of top management team behavioral integration. *Journal of Management*, *32*, 646–672.

Lyles, M.A., Saxton, T., & Watson, K. (2004). Venture survival in a transitional economy. *Journal of Management*, *30*, 351–375.

Lyon, D.W., Lumpkin, G.T., & Dess, G.G. (2000). Enhancing entrepreneurial orientation research: Operationalizing and measuring a key strategic decision making process. *Journal of Management*, *26*, 1055–1085.

Martell, R.F., Lane, D.M., & Emrich, C. (1996). Male-female differences: A computer simulation. *American Psychologist*, *51*, 157–158.

Maxwell, S. (2004). The persistence of underpowered studies in psychological research: Causes, consequences, and remedies. *Psychological Methods*, *9*, 147–163.

Mazen, A.M., Graf, L., Kellogg, C., & Hemmasi, M. (1987). Statistical power in contemporary management research. *Academy of Management Journal*, *30*, 369–380.

Mazen, A.M., Hemmasi, M., & Lewis, M.F. (1987). Assessment of statistical power in contemporary strategy research. *Strategic Management Journal*, *8*, 403–410.

Miller, D., Droge, C., & Vickery, S. (1997). Celebrating the "essential": The impact of performance on the functional favoritism of CEOs in two contexts. *Journal of Management*, *23*, 147–168.

Mone, M.A., Mueller, G.C., & Mauland, W. (1996). The perceptions and usage of statistical power in applied psychology and management research. *Personnel Psychology*, *49*, 103–120.

Murphy, K.R. & Myors, B. (2004). *Statistical power analysis: A simple and general model for traditional and modern hypothesis tests*. Mahwah, NJ: Lawrence Erlbaum Associates.

Orme, J.G. & Combs-Orme, T.D. (1986). Statistical power and Type II errors in social work research. *Social Work Research and Abstracts*, *Fall*, 3–10.

Phan, P.H. (2006). Dynamism as a necessary property of entrepreneurial systems. *Journal of Business Venturing*, *21*, 149–151.

Rogoff, E.G. & Heck, R.K.Z. (2003). Evolving research in entrepreneurship and family business: Recognizing family as the oxygen that feeds the fire of entrepreneurship. *Journal of Business Venturing*, *18*, 559–567.

Rossi, J.S. (1990). Statistical power of psychological research: What have we gained in 20 years? *Journal of Counseling and Clinical Psychology*, *58*, 646–656.

Sarasvathy, S.D. (2004). The questions we ask and the questions we care about: Reformulating some problems in entrepreneurship research. *Journal of Business Venturing*, *19*, 707–720.

Sawyer, A. & Ball, D. (1981). Statistical power and effect size in marketing research. *Journal of Marketing Research*, *18*, 275–290.

Scandura, T.A. & Williams, E.A. (2000). Research methodology in management: Current practices, trends, and implications for future research. *Academy of Management Journal*, *43*, 1248–1264.

Schulze, W.S., Lubatkin, M.H., & Dino, R.N. (2003). Exploring the agency consequences of ownership dispersion among the directors of private family firms. *Academy of Management Journal*, *46*, 179–194.

Sedlmeier, P. & Gigerenzer, G. (1989). Do studies of statistical power have an effect on the power of studies? *Psychological Bulletin*, *105*, 309–316.

Sexton, D.L. & Smilor, R.W. (1985). *The art and science*. Cambridge, MA: Ballinger.

Shane, S. & Cable, D. (2002). Network ties, reputation, and the financing of new ventures. *Management Science*, *48*, 364–381.

Shane, S. & Venkataraman, S. (2000). The promise of entrepreneurship as a field of research. *Academy of Management Review*, *25*, 217–226.

Sharma, P. & Chrisman, J.J. (1999). Toward a reconciliation of the definitional issues in the field of corporate entrepreneurship. *Entrepreneurship Theory and Practice*, *23*(3), 11–28.

Shaver, K.G. & Scott, L.R. (1991). Person, process, choice: The psychology of new venture creation. *Entrepreneurship Theory and Practice*, *16*(2), 23–45.

Shortell, S.M. & Zajac, E.J. (1990). Perceptual and archival measures of Miles and Snow's strategic types: A comprehensive assessment of reliability and validity. *Academy of Management Journal*, *33*, 817–832.

Somech, A. (2006). The effects of leadership style and team process on performance and innovation in functionally heterogeneous teams. *Journal of Management*, *32*, 132–157.

Spreitzer, E. & Chase, L.J. (1974). Statistical power in sociological research: An examination of data-analytic strategies. Unpublished research note, Bowling Green State University.

Tahai, A. & Meyer, M.J. (1999). A revealed preference study of management journals' direct influence. *Strategic Management Journal*, *20*, 279–296.

Tan, J. (2005). Venturing in turbulent water: A historical perspective of economic reform and entrepreneurial transformation. *Journal of Business Venturing*, *20*, 689–704.

Thompson, B. (2002). "Statistical," "practical," and "clinical": How many kinds of significance do counselors need to consider? *Journal of Counseling and Development*, *80*, 64–71.

Thompson, B. (2005). Research synthesis: Effect sizes. In J. Green, G. Camili, & P.B. Elmore (Eds.), *Complementary methods for research in education* (pp. 583–603). Washington, DC: American Educational Research Association.

Thompson, B. (2006). *Foundations of behavioral statistics: An insight-based approach*. New York: The Guilford Press.

Trusty, J., Thompson, B., & Petrocelli, J.V. (2004). Practical guide to implementing the requirement of reporting effect size in quantitative research in the Journal of Counseling and Development. *Journal of Counseling and Development*, *82*, 107–110.

Venkataraman, S. (1997). The distinctive domain of entrepreneurship research. In J.A. Katz (Ed.), *Advances in entrepreneurship, firm emergence, and growth* (pp. 119–138). Greenwich, CT: JAI Press.

Verma, R. & Goodale, J. (1995). Statistical power in operations management research. *Journal of Operations Management*, *13*, 139–152.

Walster, G.W. & Cleary, T.A. (1970). Statistical significance as a decision rule. In E.F. Borgatta & G.W. Bohrnstedt (Eds.), *Sociological methodology* (pp. 246–254). San Francisco: Jossey-Bass.

Ward, R.M. (2002). Highly significant findings in psychology: A power and effect size survey. Doctoral dissertation, University of Rhode Island.

Wiklund, J. & Shepherd, D. (2005). Entrepreneurial orientation and small business performance: A configurational approach. *Journal of Business Venturing*, *20*, 71–91.

Zahra, S.A., Neubaum, D.O., & El-Hagrassey, G.M. (2002). Competitive analysis and new venture performance: Understanding the impact of strategic uncertainty and venture origin. *Entrepreneurship Theory and Practice*, *27*(1), 1–28.

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The authors would like to gratefully acknowledge the valuable comments of David Ketchen (Lowder Eminent Scholar and Professor of Management, Auburn University) and Bruce Thompson (Distinguished Professor of Educational Psychology, Texas A&M University).