Does Experience Determine Performance?
A Meta-Analysis on the Experience-Performance Relationship

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Abstract
The impact of experience on entrepreneurial performance has been widely tested. Although experience is expected to positively impact performance, results are varied. This research synthesizes the current literature by determining systematic sources of variation through both exploratory and ordered probit analyses. Results reveal that start date for data collection and form of experience tested pose a major impact on the probability of obtaining a positive estimate for the experience-performance relationship. This research further emphasizes the need for tightened standards across the experience-performance literature in order to equip both academics and practitioners with better information.

Introduction

Interest in the characteristics of entrepreneurial selection and performance has increased over the past several decades as demonstrated in the business and economics literature. A great deal of that literature explores characteristics of the entrepreneur related to the human, financial, and social capital factors that influence firm performance (Gimeno-Gascon, Folta, Cooper, & Woo, 1997; Caputo & Dolinsky, 1998; Baron & Markman, 2003; Goetz & Freshwater, 2001; Markman & Baron, 2003; Anderson & Miller, 2003; Bosma, van Praag, Thurik, & de Wit., 2004; Lynskey, 2004; Lee, Florida, & Acs, 2004; Montgomery, Johnson, & Faisal, 2005). Many authors have concluded that investments in human capital augment entrepreneurial performance (Brüderl & Preisendörfer, 1998; Cooper, Gimeno-Gascon, & Woo, 1994; van Praag & Cramer, 2001), and have attempted to use those results to explain variation in performance across entrepreneurial firms. As such, human capital is one of the most studied factors of entrepreneur performance.

Education has emerged as the single most investigated feature of human capital, with hundreds of studies dedicated to exploring the impact of educational attainment on both entrepreneurial selection and performance (e.g., Bates, 1990; Blanchflower, 2000; Caputo &

Dolinsky, 1998; Cooper, Folta, Gimeno-Gascon, & Woo,1992; Cooper et al., 1994; Evans & Jovanovic, 1989; Davidsson & Honig, 2003). Since the definitions employed and results received concerning the relationship between human capital and entrepreneurship have been mixed, van der Sluis, van Praag, and Vijverberg (2003) conducted a meta-analysis of empirical studies exploring the impact of education on entrepreneurship in industrialized countries. One of the most informative conclusions of their research indicated that education positively and significantly influences overall performance, but does not impact the decision to become an entrepreneur.

Much of the same literature also investigates experience as a determinant of entrepreneurial selection and performance (Cooper et al., 1994; Evans & Jovanovic, 1989; Taylor, 2001; Bates, 1990). Mincer (1974) contended that education and experience are the primary determinants of individual earnings for employees. Empirical support for this theory in the case of entrepreneurs has also been established by a number of researchers (de Wit & van Winden, 1989; Cooper et al., 1994; Taylor, 2001; van Praag & Cramer, 2001; Bosma et al., 2004). The empirical results related to experience and performance, however, have been varied. In addition to positive impacts, a large number of insignificant effects (e.g., Astebro & Thompson, 2007; Boden &Nucci, 2000; Bosma et al., 2004; Dyke , Fischer, & Reuber, 1992; Gill, 1988; Gimeno-Gascon et al., 1997; Keeley & Roure, 1990; McGee , Dowling, & Megginson, 1995; Roper, 1999; Shrader & Siegel, 2007) and some negative effects (e.g., Alba-Ramirez, 1994; Brüderl & Preisendörfer, 1998; Dyke et al., 1992; Flota & Mora, 2001; Hundley, 2001; Shrader & Siegel, 2007; van de Ven , Hudson, & Schroeder, 1984) have been obtained. The mixed results have arguably stemmed from variations in the specification of both experience and performance (Cooper & Gimeno-Gascon, 1992); thus, making comparison across studies difficult.

In their study of the effect of experience on performance for technology firms, Reuber and Fischer (1994) argued that determining the types of experience predictive of firm performance may provide practitioners with improved tools to assess business plans and/or loan applications. Likewise, a greater understanding of experience as a performance indicator may assist in the development and improvement of Extension and other government-sponsored programs targeted towards entrepreneurs. Reuber and Fischer (1994) noted that even authors who did not determine a significant relationship between entrepreneurial experience and performance have been cautious to conclude that experience does not pose a substantial impact on performance. The authors argued that the mixed findings likely result from the varying specifications of performance across the literature.

To shed new light on the experience-performance relationship, this research compiles, analyzes, and describes empirical studies measuring the effect of experience on entrepreneurial performance in industrialized countries from 1980 to 2007. The systematic compilation of empirical results provides the authors the tools to conduct a meta-analysis using the current set of primary empirical results. Meta-analysis employs statistical techniques to determine study-specific factors contributing to variance in results, and is divided into two segments. The first segment describes the primary trends and effects found in the experience and entrepreneurship literature via an exploratory analysis. In the second segment, moderator variables representing specific characteristics of the studies are tested for their impact on the direction of estimated effects.

Background

Becker (1975) described human capital as the skills, experience and education in which an individual or firm invests. Although education is the most studied form of human capital due to the relative ease of gathering this information, experience has been said to add to an individual what education alone cannot (Becker, 1975). Mincer (1974) argued that experience impacts earnings of wage employees beyond the level of schooling. He specified experience as the potential number of years in the labor force (i.e., current age less years of schooling less the age of the individual at the time schooling began). This experience indicator has often been used in the economics-based entrepreneurship literature (e.g., de Wit & van Winden, 1989; Cooper et al., 1994; Taylor, 2001; van Praag & Cramer, 2001). Cooper et al. (1994) contended that firms with greater resource endowments, such as preparation and experience, may be placed in a better position to survive both shocks to the business environment and poor business decisions. Cooper et al. (1994) acknowledged that in spite of the increasing amount of literature on the topic, a clear depiction of the impact of initial resources on firm performance has not been determined. Other studies have proposed similar thoughts on the matter (Reuber & Fischer, 1994; Reuber & Fischer, 1999).

A number of economists have explored experience as a determinant of self-employment earnings (e.g., Tucker, 1985; Robinson & Sexton, 1994; Lentz & Laband, 1990; Kidd, 1993). In a meta-analysis of factors affecting the success of new ventures, Song, Podoynitsyna, van der Bij, and Halman (2008) analyzed 31 studies and identified the 24 most widely researched factors of success for new technology ventures (NTV). Using Pearson correlations, they discovered that both founders' marketing experience and industry experience were positively and significantly correlated to the success of NTV's. Additionally, they determined that research and development experience, and founders' experience with start-ups were not significant factors in determining NTV success.

Although Song et al. (2008) found that some factors of experience significantly impacted NTV success, literature reviews related to the experience-performance relationship have shown that results across the literature are inconsistent (Reuber, Dyke, & Fischer, 1990; Reuber & Fischer, 1994; Cooper & Gimeno-Gascon, 1992; Cooper et al., 1994). Reuber & Fischer (1999) argued that no consistent, direct relationship has been found to exist between owner/founder or management team experience and venture performance. Their contention is that these fragmented results are likely a result of the variety of experience and performance measures employed, the wide range of control variables used, and large differences in model specification (Reuber & Fischer, 1994; Reuber & Fischer, 1999).

[Place Table 1 approximately here]

Table 1 illustrates the types of experience explored thus far, as well as the number of estimates for each experience specification that appears in the literature. The two most common categories of experience tested to date have been management experience and prior ownership and/or entrepreneurial experience. Estimated effects by category for the most common experience measures are reported in Table 2.

[Place Table 2 approximately here]

Just as experience has been defined in a number of ways, performance likewise has multiple interpretations. Maes, Sels, and Roodhooft (2005) noted that several performance, success, or survival models appear across the literature, representing both financial and non-financial measures of performance. Cooper and Gimeno-Gascon (1992) contended that the wide variety of performance measures throughout the literature complicates the direct comparison of results across those studies. Classifications of performance have ranged from profits to marginal survival to earnings to reaching an economic threshold, often depending on the constructs of the study and the dataset available to the researchers. Earnings, employment, and growth, when growth is defined as any element of growth (e.g., growth in profit, earnings, number of employees, etc.), have been the most-used performance indicators.

Data and Methods

The thoughtful and comprehensive overviews of the literature relating experience and performance by Reuber and Fischer (1994), Cooper and Gimeno-Gascon (1992), and Reuber and Fischer (1999) have highlighted the lack of a definitive relationship between experience and performance. Since practitioners, such as venture capitalists, believe that experience constitutes an important component of firm performance, researchers have continued to test this relationship, employing various definitions and assembling a pool of mixed results. The continued work on this topic has further compounded problems with comparisons across studies, since researchers exploring the experience-performance relationship continue to add variable specifications in search of meaningful and consistent results. With such a wide variety of variable specifications, a traditional literature review related to the effect of experience on performance is useful, but insufficient in determining systematic sources of variation.

Song et al. (2008) argued that the inconsistent results seen in the literature may appear due to the use of differing methodologies, diversity of study design, differences in specifications of measures, omission of variables in regression models, and samples that are not easily comparable. Meta-analyses are generally employed to integrate the results of the available set of primary empirical studies to remedy such issues as those mentioned above (Song et al., 2008).

Although meta-analyses were formally developed in experimental research settings (Waldorf & Byun, 2005), meta-analysis has now become a common methodological tool across many disciplines, such as psychology, education, the sciences, and medical research (Florax, de Groot, & de Mooij, 2002).

Meta-analysis involves analyzing a sample of primary empirical studies using regression techniques. As such, the estimated effect reported in the primary study serves as the dependent variable. The independent, or explanatory, variables consist of selected moderator variables, which represent characteristics of the research design and data structure. These variables account for potential study-specific sources of variation. Meta-analysis pinpoints issues leading to variation in results across studies and summarizes important relationships occurring in the literature (Waldorf & Byun, 2005). Thus, in combining the summary and synthesis of research, meta-analysis extends the knowledge and information provided by the primary studies in a particular area of research to determine sources of variation for the reported results (Waldorf & Byun, 2005).

Data

Since the twofold objective of this study is to analyze and summarize the data, as well as to determine study-specific factors contributing to variance found across studies, it is imperative to gather the relevant literature. To ensure that the relevant literature is included in the analysis, published experience and entrepreneurship literature from 1980 to 2007 and unpublished work, from 2000 to 2007 (when available) are represented. Since van der Sluis et al. (2003) had conducted an extensive search of the education-performance literature, the current study began investigating the literature via the reference list from their research. Other relevant studies were gathered using *EconLit*, *Business Source Premier* (Ebsco), and *Google Scholar* searches (keywords: entrepreneurship, experience, performance) as well as by follow-up searches from citations located via the database searches. The dataset contains research published in 37 journals and two working papers. Table 3 summarizes the studies used in the analysis, as well as the number of experience-performance estimates found in each study.

[Place Table 3 approximately here]

Table 3 lists a representative sample of studies rather than the complete set of experience-performance studies conducted to date. Since robust datasets for the self-employed are often difficult and expensive to obtain, a number of studies use the same datasets. Although the analyses themselves are often very different, when the same dataset is used the issues of independence for the meta-analysis would be further jeopardized if each study was included in the database. When datasets were repeated, the study with the most robust technique and highest level of information was retained for the meta-analysis. The following studies were eliminated due to data set repetition: Bates (1990), Brüderl et al. (1992), Cooper et al. (1989), Cooper et al. (1994), and Lentz and Laband (1990).

Only studies providing information related to the direction and statistical significance of the estimated effect of the experience-performance relationship are included in the analysis. Van der Sluis et al. (2003) were forced to focus on the direction rather than the magnitude of the estimated effect via an ordered probit model, due to the overwhelming difficulty in comparing sizes of estimated effects taken from models differing with regards to both definitions of key variables and model specification. Since a good deal of similarity exists between the experience-performance literature and the education-performance literature, the present meta-analysis likewise focuses on the direction of the effect, rather than magnitude.

Exploratory Analysis

In conducting a meta-analysis, the estimated effect of experience on performance serves as the dependent variable. The moderator variables are then recorded for each effect for the study from which the estimate originated. As shown in Table 2, of the 262 total estimated effects across the experience-performance literature, the occurrence of negative effects is limited. There are only two experience measures for which insignificant effects do not outnumber significant ones outright – traditional experience and related activities experience.

Moderator variables were selected in an attempt to identify study-specific sources of variability. Researchers using meta-analysis, often choose moderator variables to represent differences in time and location, quality of publication outlet, sample size, industry differences, and estimation methods; thus, data for the current study was recorded for each of these characteristics. Two performance specifications were included to assess the relationship between the performance measure employed and the estimate obtained. Additionally, experience measures were tested to provide insight into the effects of specific forms of experience. Table 4 lists all variables employed in the analysis, their definitions, and summary statistics for each variable.

[Place Table 4 approximately here]

Table 5 illustrates sample size variation by effect category (i.e., negative, insignificant, or positive). Only 22 of the estimated effects were negative; however, on average, negative effects came from much larger datasets than insignificant or positive ones. This information indicates that negative results appear the most robust in terms of sample size, on average, followed by positive results.

[Place Table 5 approximately here]

The binary moderator variables are assessed with respect to the proportion of estimated effects. Results are shown in Table 6. The z-value statistic reported beneath the proportion values represents a test of difference in proportions between the indicator variable and its respective reference for each estimated possibility.

[Place Table 6 approximately here]

Results from the test of proportions reveal a number of significant differences. For example, the technology industry exhibits a significantly higher proportion of positive estimated effects and a significantly lower proportion of insignificant estimate effects than other industries. This may suggest that experience is more valuable for those entering the technology industry, since human capital may play an important role as a signal of industry knowledge and productivity.

Datasets from the US produce a significantly larger proportion of negative estimated effects than data from other countries. This is contrary to the findings of van der Sluis et al. (2003), in which the US was found to possess a level of competitiveness and market accessibility that positively and significantly contributed to variability across the literature. With regards to estimation method, using OLS estimation produces a significantly lower proportion of positive effects and a significantly higher proportion of insignificant effects than other statistical methods.

From investigating specification of performance, studies employing growth as the performance measure produce a significantly higher proportion of insignificant estimates than other definitions of performance. When earnings are employed as the performance measure, there are a significantly lower proportion of positive results and a significantly higher proportion of negative results than other measures of performance. This may suggest that experience enhances other types of performance more dramatically than earnings.

Industry experience has a significantly higher proportion of negative estimates when compared to other forms of experience, while related activities experience has a significantly higher proportion of positive estimated effects than other forms of experience. Intuitively, since related activities experience and industry experience are relevant, both would be expected to produce a higher proportion of positive results. However, when compared to other measures, it appears that activities related to business ownership produce a significantly higher proportion of positive estimates. The use of traditional, Mincerian experience (current age less years of schooling less age when schooling began) produces a significantly lower proportion of insignificant effects than other experience measures, while start-up experience demonstrates a significantly higher proportion of insignificant estimated effects.

The impact factor of the journals in which studies were published is reported to determine whether publication bias towards higher quality publications may be expected to occur. Impact factors were obtained from the ISI Web of Knowledge Journal Citation Reports (2006), based on the most current rankings available. Waldorf and Byun (2005) contended that researchers conducting meta-anlaysis studies often suggest that their databases reveal some level of publication bias towards positive results. In their meta-analysis related to environmental issues and transport economics, van den Bergh and Button (1997) asserted that the general propensity of the economics literature has been to publish positive results. Figure 1 illustrates the average impact factor by category of experience and estimated effect.

[Place Figure 1 approximately here]

Insignificant and positive estimated effects, on average have been prevalent in higher quality journals, when impact factor proxies journal quality. It is important to note that of the 22 negative estimated effects published in the literature, 31% were published in journals with no reported impact factor. This may suggest some bias against negative results by higher quality journals.

Figure 2 illustrates the estimated effects for experience measures across average year of publication. On average, significant effects have been published more recently in the literature than insignificant ones. Negative effects likewise have been published slightly more recently, on average, than positive effects. However, as shown in Figure 1, positive effects have been published in higher quality journals, on average.

[Place Figure 2 approximately here]

Figure 3 illustrates the average starting and ending years for studies across estimated effect. The figure shows that, on average, the difference between the start and ending dates for data collection differs quite markedly across estimated effect. Negative effects appear to have been obtained from studies that have an average of approximately three years between the starting and ending dates for data collection. Insignificant effects have a slightly smaller difference with an average of two years between the beginning and ending dates of data collection. The most striking difference is the eight year lag, on average, between starting and ending dates of data collection for positive estimated effects. This suggests that perhaps longer periods of data collection allow sufficient time for the effects and value of experience to be recognized in performance level.

[Place Figure 3 approximately here]

Ordered Probit Models

The exploratory portion of this analysis describes how specific moderator variables contribute to the variation across the literature. The relationships previously revealed, however, may not sufficiently identify the true sources of variation that have occurred in the literature. Since specifications of both experience and performance vary so widely, the direction and significance of the estimated effects will provide the most information via a limited dependent variable model meta-analysis. Both van der Sluis et al. (2003) and Waldorf and Byun (2005) used ordered probit models in their analyses, arguing that ordered probit models are appropriate since the three effect categories provide a natural ordering based on the calculated t-statistic.

Conceptual motivation for the ordered probit follows the general method of Waldorf and Byun (2005). If y* is chosen to represent the effect sizes reported for the effect of experience on performance, then the values of y* will fall in some range between negative and positive infinity. We follow Waldorf and Byun's (2005) assumption that the variations of y* follow a linear regression model of the form:

(1) $$y^{*} = X\beta + \varepsilon$$

where X serves as the matrix of quantifiable moderator variables, β is the vector of parameters, and ε represents the normally distributed error term. Rather than utilizing the exact values of y, a three-part ordered classification of the estimated effect sizes of y* is used:

Category 1 – Negative Estimates $y = 0 \text{ if } y^{*} < 0$

Category 2 – Insignificant Estimates $y = 1 \text{ if } 0 < y^{*} < \mu$

Category 3 – Positive Estimates $y = 2 \text{ if } \mu < y^{*}$

After standardizing y*, the threshold of zero separates Category 1 from Category 2, while the parameter μ separates Category 2 from Category 3. In setting the threshold separating Categories

1 and 2 at ‘zero’, only one parameter estimate must be calculated to differentiate the three categories from one another. The following probabilities are obtained when the error term is normalized to a mean of zero and standard deviation of one,

$$\begin{aligned} &P(y=0) = P(y^* \le 0) = P(X\beta + \varepsilon \le 0) = P(\varepsilon \le -X\beta) = \phi(-X\beta) \\ (2)\qquad &P(y=1) = P(0 < y^* \le \mu) = P(y^* \le \mu) - P(y^* \le 0) = \phi(\mu - X\beta) - \phi(-X\beta) \\ &P(y=2) = P(\mu < y^*) = 1 - \phi(\mu - X\beta) \end{aligned}$$

where Φ represents the standard normal distribution function. To make certain P(y=1)>0, it is necessary that μ be greater than zero. A positive *β* parameter indicates that a direct relationship exists between the moderator variable X and the probability of receiving a positive result, and likewise indicates a negative effect on the probability of receiving a negative result. Conversely, a negative *β* parameter reveals that the probability of receiving a positive result decreases as the moderator variable (X) increases. It is important to note, however, that the sign of the *β* parameter does not establish the effect of X on the probability of receiving an insignificant result.

Waldorf and Byun (2005) argued that the marginal effects, when evaluated at the means, present greater indication of the magnitude of the probabilities for all three categories when changes are made to the exogenous variables. The marginal effects for continuous exogenous variables are calculated as such:

$$\begin{aligned} &\frac{\partial P(y=0)}{\partial x} = -\phi(\beta' x)\beta \\ (3)\qquad &\frac{\partial P(y=1)}{\partial x} = (\phi(-\beta' x) - \phi(\mu - \beta' x))\beta \\ &\frac{\partial P(y=2)}{\partial x} = \phi(\mu - \beta' x)\beta \end{aligned}$$

When dummy variables are employed in the analysis, Greene (2000) stated that the marginal effects are defined as the changes that occur in probabilities as X moves from X=1 to X=0.

Because using unweighted observations in the meta-analysis may assign greater value to studies which reported more than one estimate (Stanley, 2001), weighted observations are likewise used in the formulation of model results. The weight used for the observations of an observed categorical effect is inversely proportional to the number of estimated effects obtained from a specific study (Waldorf & Byun, 2005). Following the method of Bijmolt and Pieters (2001), the observed effect *k* from a particular study *s* is given the following weight:

$$(4) \qquad w_{ks} = \frac{M}{M_s S}, \forall s = 1,...,k = 1, M_s$$

where M represents the total number of estimated effects in the database, M_s indicates the number of estimated effects from a particular study, s, and S signifies the total number of studies under analysis. The weight is then attached to each observation in the analysis using the importance weighting tool in STATA10.

Results

The ordered probit analysis was run in both weighted and unweighted form as shown in Table 7. For the unweighted model, impact factor positively and significantly increases the probability of obtaining positive estimated effects. Although the unweighted model indicates that some publication bias may occur against negative results in higher quality publication outlets, the weighted model does not reveal the same significant result. The marginal effects indicate that higher impact factors increase the probability of obtaining a positive estimate for the impact of experience on performance by approximately 11.9% and 7.7% in the unweighted and weighted models, respectively. Although the year of publication was expected to yield additional insight into publication bias, it does not appear to be a significant determinant of variation.

[Place Table 7 approximately here]

The date data collection began negatively and significantly impacted the probability of obtaining a positive estimated effect for experience across both models, while the date data collection ended posed a positive and significant impact on the probability of obtaining a positive estimate for the unweighted model. The unweighted model suggests that a longer time period between starting and ending dates of data collection significantly increases the probability of obtaining a positive effect for the experience-performance relationship. Across both models, however, a more recent start date for data collection poses a significant, negative impact on the probability of receiving a positive estimate for experience.

The exploratory analysis indicated that larger sample sizes typically supported negative results. The ordered probit analysis, however, shows that sample size has no significant effect. The marginal effects provide little increased insight. Contrary to expectation, the technology industry exerted negative and significant effects across the two models, indicating that the technology industry increases the likelihood of obtaining a negative estimate for the experience-performance relationship. For both the unweighted and weighted models, the technology industry was shown to decrease the probability of obtaining positive effects by 26% and 22%, respectively.

The direction of both the country and OLS moderators is negative for the two models, as expected. Neither serves as a significant factor, however, in determining variability across studies. Additionally, the growth and earnings measures of performance follow the expected negative direction, but neither is found to explain a significant amount of variation.

Based on the test of proportions from the exploratory analysis, both traditional experience and related activities experience were expected to increase the likelihood of obtaining positive results for the effect of experience on performance. While management, industry, ownership/entrepreneurship, and start-up experience were expected to exert negative influences. When compared to other forms of experience, however, all the experience variable moderators in the model positively impacted the probability of obtaining a positive estimate. Management, industry, and related activities experience were positive and significantly increased the probability of obtaining positive estimates for both models. Ownership/entrepreneurial experience and start-up experience were found to positively and significantly impact the probability of obtaining a positive estimated effect for the unweighted model, while traditional experience was found to positively and significantly increase the probability of obtaining a positive result for the weighted model. Marginal effects indicate that industry experience increases the probability of obtaining a positive impact by the greatest amount. For example, in the weighted model, industry experience increases the probability of obtaining a positive estimated effect by 54.1%. The second greatest impact comes from the management experience specification, since using management experience in an analysis is shown to increase the probability of obtaining a positive estimated effect by 40% in the weighted model.

Discussion and Conclusions

Although a large number of studies have been conducted in which the experience-performance relationship is tested, several difficulties have arisen in drawing comparisons and subsequently definite conclusions from their result since the empirical results have been mixed (Cooper & Gimeno-Gascon, 1992; Reuber & Fischer, 1994). From the results of the meta-analysis, several study-specific characteristics appear to account for a good deal of the variation across the literature. Within the confines of this study, moderator variables representing publication bias and type of experience appear to be largely responsible for variation among studies investigating the experience-performance relationship.

The quality of publication outlet, when represented by journal impact factor, indicates that higher ranked outlets increase the probability of obtaining a positive estimate for the impact of experience on performance. This indicates that some publication bias may be present in favor of positive results. In viewing the marginal effects, impact factor increases the probability of obtaining a positive effect by as much as 12%. If results were randomly chosen from a normal distribution, then an equal number of positive and negative results would be expected across the literature; thus, a disproportional amount of positive results to negative ones is surprising.

Since impact factor appears to account for a portion of the variation found in results, additional tests for publication bias would provide depth to those results. In their meta-analysis of minimum wage studies, Card and Krueger (1995) determined that publication bias against insignificant results was present. The marginal effects from the current study indicate that higher impact factors decreased the probability of insignificant results by a larger magnitude than negative ones.

The starting and ending dates of data collection likewise pose an interesting result. The exploratory analysis reveals that positive results had, on average, eight years between the starting and ending dates of data collection, while insignificant and negative results had two and three year differences, respectively. Many firms struggle in earlier years of operation, which may not allow for the experience of the entrepreneur to impact firm performance from an empirical standpoint. However, when provided sufficient time, these results indicate that experience may heighten the performance of the venture beyond that of less experienced entrepreneurs.

For the unweighted model, data collected from the technology industry was found to increase the probability of obtaining a negative estimate for the impact of experience on performance. Although a closer look must be taken at the primary empirical studies to support this hypothesis, it may be possible that the experience of a large number of entrepreneurs in the technology industry come from unrelated industries. As such, the experience may not necessarily positively contribute to the performance of the firm under consideration.

Perhaps the most interesting results obtained from the ordered probit analysis come from the moderators representing experience measures. The current study confirms the argument of Reuber and Fischer (1994; 1999), which suggested that the difference in experience measures appears to account for the greatest amount of variation in results across the literature. Under the weighted model, the marginal effects indicated that industry experience had the largest impact on the probability of obtaining a positive result, followed by management experience. The large impact of industry experience on the probability of obtaining a positive estimate is not particularly surprising since industry experience is typically considered among the most relevant forms of experience. Industry experience was found to increase the likelihood of obtaining a positive impact by 54%, while management experience was found to increase the probability of a positive effect by 40%.

Further study related to relevance of experience, particularly management experience, would greatly enhance the literature. Although negative results may appear counter-intuitive, there are sound explanations related to why a negative result may be obtained for different measures of experience. For example, suppose the sample at hand measured success for start-up firms randomly selected from the technology industry and also tracked the experience of the founder. Traditional experience, in terms of age, maturity, and life experience would be expected to positively impact the firm. Management experience would likewise be anticipated to heighten the performance of the firm, if it was relevant to the firm at hand. However, entrepreneurs may create firms outside their breadth of industry or related experience. If the lead entrepreneur on a technology start-up had experience managing a fast food restaurant in college, that management experience would not necessarily be expected to increase firm performance by the same standards as an entrepreneur who had management experience with Google, Yahoo, or some other more relevant firm prior to launching his/her own technology venture. Despite the fact that both situations are considered management experience, the latter situation would obviously be expected to have a greater impact on the performance of a technology firm.

Start-up experience can be thought of in much the same way as the management experience example. If an entrepreneur in the technology industry decides to launch a barbecue restaurant, then the start-up experience gained in the technology industry may not be particularly helpful. The financial management experience gained through the technology start-up may not be particularly useful in mastering the art of ordering food stock, barbecuing the meat, or in dealing with customers or employees in a restaurant setting. Entrepreneurs often venture beyond their realm of past experience in undertaking new ventures, and despite having management or start-up experience, the experience gained may not be particularly relevant to the new firm. Thus, when hypothesizing about the effect of experience, relevance of that experience may be central in determining the firm's subsequent performance.

Further study of the primary literature would be required to determine if the majority of empirical models in individual studies include all management experience in an individual's lifetime, or just the management experience relevant to the firm. An empirical analysis of the subsamples would then allow for testing of differences between directly related and unrelated forms of experience on performance. Further research of this topic will help determine whether experience is more valuable if it is complementary to the current venture.

This research has uncovered some of the systematic sources of variation across the experience-performance literature. The results of the meta-analysis highlight the need for increased standards across the literature related to how experience should be measured. In economics there is a tendency to “try, try again” when it comes to determining the impact of experience on performance, rather than attempting to confirm prior results. Attempts at innovation rather than confirmation have led to a wide variety of measures having been tested, making casual comparison of results across studies extremely difficult.

In addition to the academic implications related to study design, data, and methods, practitioners, such as loan officers and Extension specialists may also take away valuable information from the meta-analysis. From the results at hand, it appears that industry experience greatly increases the probability of heightened performance for the firm. Additionally, management experience and experience in activities relevant to business ownership significantly impact the probability of obtaining a positive effect on firm performance. Further study will determine whether the management experience needs to be relevant to the industry at hand, or if general management experience is a sufficient indicator. Such information will provide both relevant and important points of discussion for small business practitioners in encouraging entrepreneurs to obtain additional forms of experience prior to launching a business.

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Table 1. Experience Measures Tested across the Entrepreneurship Experience-Performance Literature and the Number of Estimates for Each Measure

Experience Measure	**No. of Estimates Across Literature**
Management Experience	45
Ownership/Entrepreneurial Experience	43
Traditional Experience	40
Start-up Experience	35
Related Activities Experience	34
Industry Experience	18
Experience squared	16
Wage Experience	6
Marketing Experience	6
Finance Experience	4
Supervisory Experience	3
Tenure	3
Tenure Squared	3
R&D Experience	2
Manufacturing Experience	2
Joint Experience (Team)	2
Total	262

Table 2. Estimated Effects by Experience Measure

	Experience	Management Experience	Ownership/ Entrepreneurial Experience	Related Activities Experience	Start-up Experience
Negative	4	1	1	2	2
Insignifican	18	26	29	15	25
Positive	18	18	13	17	8

Table 3. Studies Included in the Meta-analysis and the Number of Estimated Effects Associated with Each Study

Study	No. of estimates	Study	No. of estimates
Alba-Ramirez (1994)	2	Harada (2003)	3
Arribas and Vila (2007)	1	Harada (2004)	1
Astebro and Thompson (2007)	1	Hundley (2001)	8
Buam and Silverman (2004)	1	Keeley and Roure (1990)	2
Bernhardt (1994)	2	Kidd (1993)	4
Boden and Nucci (2000)	4	Lussier (1995)	2
Bosma, Van Praag, Thurik, and de Wit (2004)	12	Macpherson (1988)	2
Brown and Sessions (1998)	2	Maes, Sels, and Roodhooft (2005)	1
Bruderl and Preisendorfer (1998)	12	Mcgee, Dowling, and Megginson (1995)	6
Colombo, Delmastro, and Grilli (2004)	34	Montgomery, Johnson, and Faisal (2005)	6
Dahl and Reichstein (2005)	2	Reuber and Fischer (1994)	6
Dahlvquist, Davidsson, and Wiklund (2000)	2	Robinson and Sexton (1994)	1
Dolton and Makepeace (1990)	3	Roper (1999)	6
Duchesneau and Gartner (1989)	1	Roure and Keeley (1990)	2
Dyke, Fischer, and Reuber (1992)	75	Sandberg and Hofer (1987)	2
Eisenhardt and Schoonhoven (1990)	2	Shrader and Siegel (2007)	20
Flota and Mora (2001)	3	Stuart and Abetti (1990)	2
Gill (1988)	2	Tucker (1985)	1
Gimeno, Folta, Cooper, and Woo (1997)	12	Van de Ven, Hudson, and Schroeder (1984)	2
Hamilton (2000)	12		

Table 4. Variable Definitions and Summary Measures for All Experience Measures

Dependent Variable					
EFFECT	Categorical Effect	Proportion			
	Negative: y = 0	0.084			
	Insignificant: y = 1	0.569			
	Positive y = 2	0.347			
Moderator Variables		Mean	Std. Dev	Min	Max
IMPFACTOR	Impact factor of journal	1.073	0.848	0	3.194
YRPUB	Year published	1998	6	1984	2007
DBEGIN	Date data collection began	1987	5	1974	2000
DEND	Date data collection ended	1991	5	1978	2004
SAMPSIZE	Sample size	1052	2749	14	22176
IND	Technology industry	0.267	0.443	0	1
COUNTRY	US	0.344	0.476	0	1
OLS	Ordinary Least Squares Estimation	0.504	0.501	0	1
GROWTH	Growth as performance measure	0.177	0.382	0	1
EARN	Earnings as performance measure	0.263	0.441	0	1
TRAD	Traditional experience	0.153	0.360	0	1
MGTEXP	Management experience	0.172	0.378	0	1
INDEXP	Industry experience	0.069	0.253	0	1
OWNENTEXP	Ownership/entrepreneurial experience	0.164	0.371	0	1
RELACTEXP	Related activities experience	0.130	0.337	0	1
STARTEXP	Start-up experience	0.134	0.341	0	1

Table 5. Sample Size Variation across Experience Measure and Effect Categories

Effect	# of Estimates	Median Sample Size	Average Sample Size	Standard Deviation
Negative	22	1475	3426	5025
Insignifican	149	198	425	707
Positive	91	391	1505	3601

Table 6. Binary Moderator Variables and Effect Types for Traditional Experience

Binary Moderator Variables and Effect Types		Experience			
Moderator Variable		No. of Estimates	Proportion of Estimates		
			Negative	Insignificant	Positive
IND	Yes	70	0.071	0.386	0.543
	No	192	0.089	0.635	0.276
	z-value		-0.4419	-3.6111***	4.0137***
COUNTRY	Yes	90	0.133	0.567	0.300
	No	172	0.058	0.570	0.372
	z-value		2.084**	-0.0481	-1.1639
OLS	Yes	132	0.091	0.720	0.189
	No	130	0.077	0.415	0.508
	z-value		0.4081	4.9727***	-5.4103***
GROWTH	Yes	46	0.043	0.696	0.261
	No	216	0.093	0.542	0.366
	z-value		-1.0906	1.9147*	-1.3564
EARN	Yes	69	0.145	0.638	0.217
	No	193	0.062	0.544	0.394
	z-value		2.1272**	1.3480	-2.6413**
TRAD	Yes	40	0.100	0.450	0.450
	No	222	0.081	0.590	0.329
	z-value		0.3971	-1.6468*	1.4816
MGTEXP	Yes	45	0.022	0.578	0.400
	No	217	0.097	0.567	0.336
	z-value		-1.6411	0.1351	0.8154
INDEXP	Yes	18	0.222	0.333	0.444
	No	244	0.074	0.586	0.340
	z-value		2.1915**	-2.0893**	0.8967
OWNENTEXP	Yes	43	0.023	0.674	0.302
	No	219	0.096	0.548	0.356
	z-value		-1.5701	1.5310	-0.6779
RELACTEXP	Yes	34	0.059	0.441	0.500
	No	228	0.088	0.588	0.325
	z-value		- 0.5667	-1.6095	2.0043**
STARTEXP	Yes	35	0.057	0.714	0.229
	No	227	0.088	0.546	0.366
	z-value		-0.6148	1.8683*	-1.5853

Note: *,**,*** denotes statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7. Ordered Probit Results: Model Incorporating Log Sample Size

	MODEL 1			MODEL 2		
	Unweighted			Weighted		
Variable	Coefficient (b)	SE	b/SE	Coefficient (b)	SE	b/SE
IMPFACTOR	0.3284	0.1566	2.10**	0.2149	0.1661	1.29
YRPUB	-0.0145	0.0329	-0.44	0.0372	0.0402	0.93
DBEGIN	-0.1301	0.0332	-3.91***	-0.1016	0.0440	-2.31**
DEND	0.1121	0.0385	2.91**	0.0334	0.0510	0.66
SAMPSIZE	0.1142	0.2570	0.44	-0.0335	0.2538	-0.13
IND	-0.8307	0.4251	-1.95*	-0.6970	0.5187	-1.34
COUNTRY	-0.3259	0.3322	-0.98	-0.2052	0.3108	-0.66
OLS	-0.2315	0.2275	-1.02	-0.1490	0.2664	-0.56
GROWTH	-0.0841	0.2099	-0.4	0.0573	0.3861	0.15
EARN	-0.0927	0.2101	-0.44	-0.2455	0.3226	-0.76
TRAD	0.3924	0.3417	1.15	0.9142	0.3740	2.44**
MGTEXP	0.6223	0.3121	1.99**	1.0456	0.5632	1.86*
INDEXP	0.7406	0.4368	1.70*	1.4883	0.4962	3.00**
OWNENTEXP	0.5192	0.3061	1.70*	0.3506	0.5494	0.64
RELACTEXP	0.7647	0.3201	2.39**	0.7483	0.4472	1.67*
STARTEXP	0.5887	0.3210	1.83*	0.1254	0.4868	0.26
n			257			235
#of iterations			3			3
LogL			-195.3401			-198.1119
chi-square			70.57			39.49
df			16			16
p			0.0000			0.0009
	P(Y=0)	P(Y=1)	P(Y=2)	P(Y=0)	P(Y=1)	P(Y=2)
IMPFACTOR	-0.0354	-0.0840	0.1194	-0.0339	-0.0432	0.0772
YRPUB	0.0016	0.0037	-0.0053	-0.0059	-0.0075	0.0134
DBEGIN	0.0140	0.0333	-0.0473	0.0160	0.0204	-0.0365
DEND	-0.0121	-0.0287	0.0407	-0.0053	-0.0067	0.0120
SAMPSIZE	-0.0123	-0.0292	0.0415	0.0053	0.0067	-0.0120
IND	0.1240	0.1437	-0.2677	0.1440	0.0760	-0.2200
COUNTRY	0.0385	0.0767	-0.1152	0.0326	0.0409	-0.0735
OLS	0.0249	0.0592	-0.0841	0.0246	0.0280	-0.0526
GROWTH	0.0095	0.0207	-0.0302	-0.0088	-0.0120	0.0208
EARN	0.0104	0.0230	-0.0334	0.0397	0.0476	-0.0873
TRAD	-0.0341	-0.1150	0.1490	-0.1108	-0.2318	0.3426
MGTEXP	-0.0487	-0.1897	0.2384	-0.0918	-0.3070	0.3988
INDEXP	-0.0482	-0.2389	0.2871	-0.1146	-0.4260	0.5406
OWNENTEXP	-0.0424	-0.1560	0.1985	-0.0444	-0.0887	0.1331
RELACTEXP	-0.0534	-0.2412	0.2946	-0.0820	-0.2047	0.2867
STARTEXP	-0.0454	-0.1809	0.2263	-0.0184	-0.0277	0.0461

Note: *,**,*** denotes statistical significance at the 10%, 5%, and 1% levels, respectively

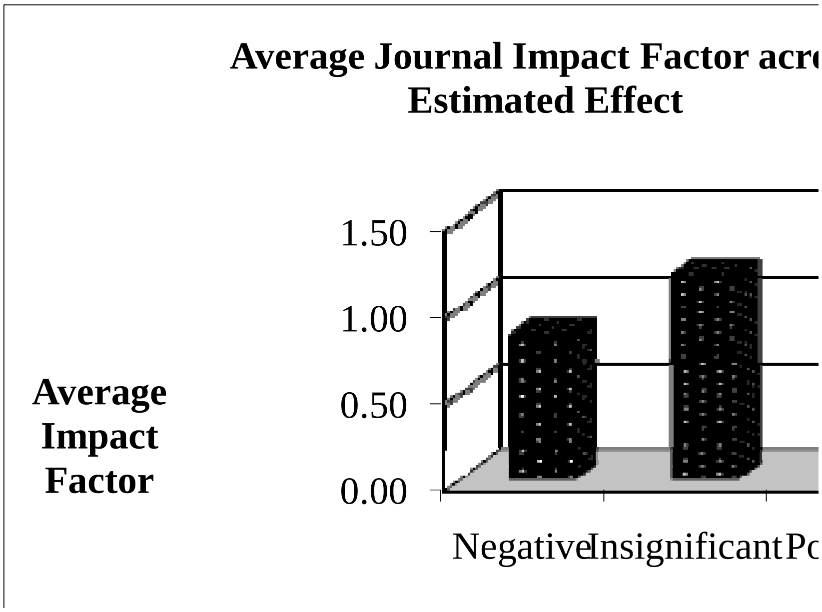

Figure 1. Average Impact Factor across Estimated Effect

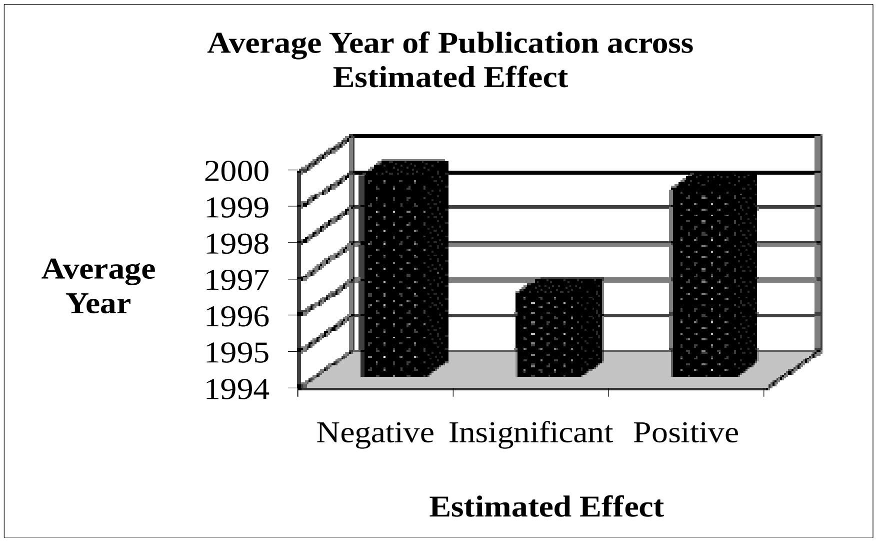

Figure 2. Average Year of Publication across Estimated Effect Category

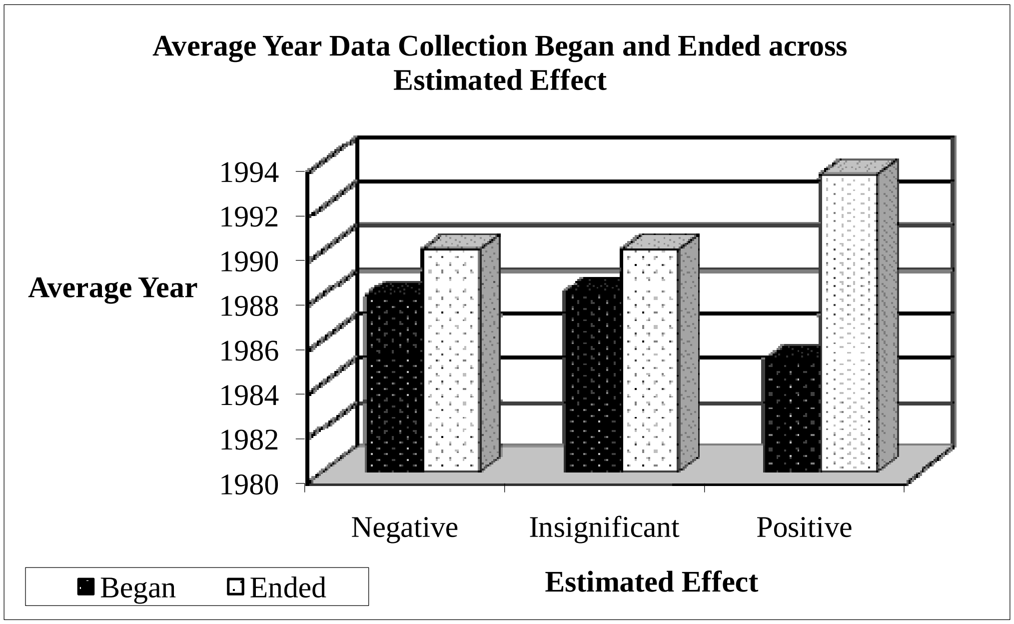

Figure 3. Average Starting and Ending Year for Data across Estimated Effect