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Do the Self-Employed More Likely Emerge From Sequential or Parallel Work Experience in Business-Related Functions?

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Recent theory suggests generalists are more likely than specialists to become self-employed. However, little research examines whether different career paths of generalists are equally effective. I argue those experiencing business-related functions in parallel rather than sequentially more likely become self-employed—as a career proceeds over years—because "connections" detected across domains during parallel work experience are particularly valuable in discovery of future opportunities. Yet, positive effects of experiencing domains sequentially are more strongly amplified when individuals are analytically disposed. Analyzing careers of scientists and engineers, SESTAT data broadly support the hypotheses but mostly for male, incorporated, and/or nonacademic entrepreneurial self-employment.

Introduction

Recent research suggests that the self-employed entrepreneur tends to be drawn from the pool of business generalists (Lazear, 2005). Specialists, in contrast, are simply more valuable when directed or coordinated by managers. Although additional studies indicate that the generalist orientation is useful (e.g., Backes-Gellner, Tuor, & Wettstein, 2010; Wagner, 2006), little is known about the different career paths taken by those who acquire diverse knowledge and become entrepreneurial generalists. We also know little about the vocational tendencies that support those career trajectories, or the resulting outcomes.

Investigating the different career paths taken by entrepreneurial generalists is important because there are opposing, mutually exclusive schools of thought regarding how prospective self-employed entrepreneurs can best acquire important knowledge (see most notably Bechard & Gregoire, 2005). On one hand, some scholars advocate interdisciplinarity where functional subjects could be taught in a generalist fashion (i.e., via job rotation) merely with entrepreneurship as a context (e.g., Ray, 1990). In contrast, other

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scholars support a more specialized transdisciplinarity (Heinonen & Poikkijoki, 2006), whereby business functions would be experienced more directly in the context of one another in entrepreneurial career development (i.e., via apprenticeship). In this study, I ask: Do entrepreneurial generalists tend to emerge from experiencing work domains sequentially or in parallel? And what moderates the effectiveness of these two modes?

Building on learning theory (e.g., Brown, Collins, & Duguid, 1989), this article argues that there is a difference in the effects of experiencing knowledge domains sequentially versus in parallel. Those who experience knowledge domains in parallel are more likely to become self-employed than those who experience them sequentially, since the results of important connections across domains can be revealed spontaneously via trial-and-error, even if the (nature of the) connections themselves are not revealed. Under sequential (work) experience, only the results of those connections among decisions and choices within a domain are spontaneously identified or generated. Although it might take time, parallel work experiences are, thus, more likely to lead to self-employment. Of course, there still remain other common situations where sequential experience can trump parallel experience. Specifically, the effects of extended sequential experience are more positively and strongly amplified when individuals are shown to be *analytically disposed* as indicated by years of extensive formal scientific training. Better-formed connections *across* domains could then be "pieced together" across these periods, leading to the perception of valuable knowledge combinations. In contrast, the indirect or specific connections encountered under parallel experience are at risk of becoming too unwieldy to analyze.

The article proceeds as follows. In the next section, I present theory accompanied by anecdotal evidence. Then, using SESTAT survey administrations, I empirically examine the educational and sociological backgrounds of scientists and engineers, including the business functions they experience over time during their career. The SESTAT database, in particular, is valuable in addressing this particular research because it can capture the parallelism of experience across years, for thousands of respondents. Results, limitations, and future research directions are presented before some concluding remarks.

Theory and Hypotheses

Examples abound in the popular press about individuals who chose self-employment after acquiring broad business-related knowledge. Consider Karen Maguire. In the late 1970s, she obtained a master's degree in comparative literature that benefited her understanding of the communications domain. She served briefly as a professor, and then in the mid-1980s she joined an investment management firm in a sales role, then moving up to director of marketing for the Bank of Boston. Finally in 1994 she founded Satuit Technologies, a private company that provides enterprise and hosted customer relationship management (Chang, 2005). Sharon Beasley, also self-employed, recalls making fresh homemade cookies at home growing up. After getting her business degree from the University of Toronto and 12 years' worth of stints in corporate lending and strategic planning, she started the now-famous Canadian company called Mrs. Beasley's Cookies (Colman, 2003). Or we might profile Warren M. Thompson. After getting an MBA from the University of Virginia, he rose through the ranks over 9 years to become a regional vice president of Host International, directing operations for that food service subsidiary of Marriott Corp. Finally in 1990 he decided to form Thompson Hospitality LP, which by 1993 had revenues of $34.4 million (Hayes, 1994). In a separate case, Marc Benioff by age 26 was vice president at Oracle—making $300,000 a year—directing not only sales at Oracle, but marketing and product development as well. He founded Salesforce.com a few years later (Adler, 2003).

Broad Business Knowledge and Acquiring Different Work Experiences in Parallel

How might individuals acquire the broad knowledge that leads them to self-employed entrepreneurship? On one hand, they may experience multiple domains sequentially, one at a time. College students may take accounting classes one semester and then separately take marketing classes the next semester, or company engineers may rotate from a manufacturing department to a marketing one. On the other hand, individuals may have experienced multiple domains together on the road to self-employment. Chief operating officers (COOs) are often in charge of making basic decisions that transcend various functional departments, such as accounting, marketing, finance, and operations. Either case offers a prototypical template linking the experience of multiple business domains to entry into entrepreneurial self-employment.

In general, acquiring knowledge within any one domain begins with processing information encountered within the domain. Information from any of these functionally oriented domains is interpreted, organized, and stored by cognitive or knowledge structures, defined as "mental templates that individuals impose on an environment to give it form and meaning" (Walsh, 1995). Knowledge structures in turn are acquired and shaped from either repeated experience, or acceptance of available theory (e.g., Finke, Ward, & Smith, 1996). Acquiring a knowledge structure typically requires relating it to other knowledge structures the individual already possesses (Brown et al., 1989). A knowledge structure may be acquired by connecting it or making a one-to-one match to a direct, exclusive collection of more basic concepts, in the form of a definition. Or it may be acquired by making connections to a wide variety of other concepts. For example, an individual may be exposed to milling machines in the context of assembly plants, thus shaping his knowledge structure of milling machines in a way that relates to assembly plants. As a result, he might say that "milling machines are devices that should be far away from adhesion machines when placed in an assembly plant because the milling debris can compromise the quality of adhesion processes." He may even understand this before being exposed to what a milling machine looks like or does. As knowledge structures are acquired and developed, they also begin to form as the basis of choices and decisions (Barsalou, 1983).

Experiencing Different Business Functions in Parallel, and Self-Employment Likelihood

How knowledge structures underlying choices and decisions are shaped differs depending on whether exposure to domains comes sequentially or in parallel. Research in situated cognition argues that "knowledge is situated, being in part a product of the activity, context, and culture in which it is developed and used" (Brown et al., 1989, p. 32). Thus, "a concept . . . will continually evolve with each new occasion of use, because new situations, negotiations, and activities inevitably recast it in a new, more densely textured form" (Brown et al., p. 33). Furthermore "situated cognition resides in the duality—the recursive interaction—between *how attributes of a situation evoke and shape particular schemas* and how schemas make particular attributes of the situation salient" (Elsbach, Barr, & Hargadon, 2005, p. 424, emphasis added).

When domains are acquired in parallel, individuals like Thompson and Benioff are processing information from multiple domains at the same time, acquiring the knowledge structures underlying choices and decisions corresponding to one domain potentially "from scratch" in association with or in the context of relatively unrelated knowledge structures corresponding to other distinctly different domains. An individual experiencing domain C and domain D at the same time may be exposed for the first time to certain knowledge structures and, thus, the effects of choices C_{1a} and C_{1b} available to decision C_1 and other choices D_{1a} and D_{1b} available to a decision D_1. The individual's own understanding of how to make decisions and choices in domain C is in the context of—if not fundamentally based on—decisions and choices in domain D. (The general effect of choice C_{1a} is not learned but rather only its specific effect in the context of D_{1a}.)

For example, a design engineer might enter a firm, begin a divisional management rotation program which exposes him or her to *unfamiliar* manufacturing and marketing information and knowledge structures simultaneously. Due to the principle of situated cognition described earlier, prototypes are incomplete (see Baron & Ensley, 2006, p. 1341). Because the knowledge structures acquired are so systematically underdeveloped, the decisions and choices experienced among the different manufacturing and marketing domains are not well understood, and thus cannot be readily related or connected via a straightforward series of principles (Arthur, 2007). Analysis or theorizing is unlikely to help in identifying such specific, indirect connections given different vaguely understood choices experienced in specific contexts under parallel work experiences (for related discussion see Hayek, 1945, pp. 521–522).[1]

However, such connections may still be readily seen and confirmed between seemingly unrelated decisions or choices across domains by combining trial-and-error and learning-by-doing. While decisions and choices across domains are likely unrelated or unconnected in any direct manner they may be connected to one another through more indirect means: information unique to specific markets, times, or places make available situations that can reveal the existence of connections between the decisions and choices in domain C and the decisions and choices in domain D. Due to the context specificity of experiential learning, connections are at risk of becoming developed into oversimplified generalized theories, even "naïve" ones (see Murphy & Medin, 1985), which are incorporated into the actor's cognitive map. Nevertheless, in future periods when those connected decisions or choices are encountered together, the actor's cognitive map reveals that connections exist among these decisions and choices, and sets of valuable decisions and choices can still be transferred and applied later in other contexts (see Thorndike, 1932).[2]

Generally speaking, in acquiring knowledge domains in parallel, people are likely to shape their knowledge structures in the context of unrelated information but the next moment may also shape them in the context of related information. Extending the earlier example, a person experiencing manufacturing and marketing at the same time may begin shaping from scratch her understanding of the manufacturing term "concurrent engineering" in the context of its effects on product launch timing and consumer purchasing behaviors. This alone does not bestow upon this person a significant understanding of the term "concurrent engineering." The next moment, the individual might understand more generally that "concurrent engineering" is prescribed whenever the underlying manufacturing process specifications are severely interdependent. Thus, one moment this

1. I use the terms "simultaneous" and "in parallel" interchangeably.

2. While trial-and-error could also be used during sequential work experience, at any given time individuals are processing information from multiple domains separately, and thus any trial-and-error is used strictly to acquire knowledge structures and identify or make connections associated with (sets of) decisions and choices within any one domain, not across domains.

individual is shaping her knowledge structure of "concurrent engineering" in the context of an unrelated domain of marketing, the next moment in the context of the related domain of manufacturing. The important upshot is that parallel experiences introduce the additional possibility that knowledge structures are acquired in incomplete manners.

Consider alternatively the two-period case where an individual experiences domains sequentially, as did Maguire and Beasley. For instance, a college student learns about the effects of marketing decisions in a marketing class during one semester, and learns about the effects of finance decisions in a finance class the next semester.[3] Under such a situation, at any given time, representations of knowledge in memory relate to dispositions culturally shaped by highly related other bits of knowledge and information (see Goodnow, 1990). More generally, the individual acquires and develops knowledge structures underlying decisions and choices in domain A in one period, then acquires knowledge structures underlying decisions and choices in domain B the next period. In the first period, he may be taught the effects of an A_1 decision but only in relation to other decisions highly typical for domain A. In the next period, he would experience the effects of a B_1 decision but only in relation to other decisions highly typical for domain B. When domains are acquired separately, the individual's understanding of decisions and choices in one domain is not based on decisions from other unrelated domains, as he is *shielding* himself from processing information from those domains. The individual's own understanding of how to make a decision or choice in one domain is captured only in relation to other highly related decisions and choices typical of the same domain, and at any given time the effects of a set of highly related decisions and choices are being understood. Due to the acquisition of highly typical associations, not only are knowledge structures and prototypes underlying decisions and choices acquired more completely (see Rosch & Mervis, 1975)—and thus the general effects of choices and decisions experienced—but the existing connections relating choices or decisions within a domain are likely more direct, straightforward, and explicit in nature. In future periods, individuals may encounter a collection of decisions (and associated choices) that spans domains. However, in contrast to the case where different domain experience takes place in parallel, trial-and-error over decisions and choices is not available here: trial-and-error across domains is not inherently supported by that process where domains are acquired sequentially. Connections among choices and decisions across domains are thus not immediately identified or seen in real time, and the value-creating sets of decisions and choices spanning across domains remain relatively undiscovered.

Opportunity discovery, according to scholars such as Baron and Ensley (2006), involves "connecting the dots" between seemingly unrelated situations or trends in identifying patterns. In developmental psychology, researchers call the ability to discern meaningful patterns within otherwise unconnected information "relational reasoning" (for a review, see Dumas, Alexander, & Grossnickle, 2013). Recent research shows that simultaneous observation is particularly beneficial to relational learning of concepts. In a study on children, Son, Smith, and Goldstone (2011) find evidence that simultaneous viewing strengthens connections between multiple instances by giving children more time to link instances, whereas during sequential experience those connections are weaker or incomplete. They also argue that sequential viewing requires more working memory because children need to hold both instances in mind to compare them, whereas presenting instances all at once frees up working memory resources for attending to the relational structure.

3. One may inquire whether a student who takes multiple classes in one semester is experiencing domains sequentially or in parallel. Unless there is one class where concepts from these classes are taught together, this article's theory holds that this represents sequential (or more accurately here, "separated") experience.

Studies by Loewenstein and Gentner (2001) and Namy, Smith, and Gershkoff-Stowe (1997) also support this empirical finding. In citing Sweller (1994), Son et al. re-assert that "sequential viewing may present an extrinsic load, needing to remember instances, that is superfluous to the task of learning relations [while] simultaneous training presents a germane load helpful for learning schema-like patterns without needing to deploy additional resources for remembering the items." Finally, in their seminal work on whole-task versus part-task training, Naylor and Briggs (1963) find that unpredictable, highly integrated tasks (such as those prototypically entrepreneurial) benefit more from whole-task training than the accumulation of part-task training.

Project-based or problem-based learning (PBL) offers another conceptual framework for my first hypothesis. PBL is based on a "driving question" crafted in such a way to lead students to explore, encounter, and investigate the central concepts and principles of multiple disciplines, in solving an ill-structured problem. Empirical research shows that project-based education trumps discipline-based teaching when it comes to improving "problem formulation" skills (Gallagher, Stepien, & Rosenthal, 1992) and utilizing diversity of knowledge for subsequent problem solving (see Stepien, Gallagher, & Workman, 1993), both typical of entrepreneurship.

Hypothesis 1: Acquiring different work experiences in parallel (vs. sequentially) increases the likelihood of self-employment.

The Moderating Effect of Analytical Disposition. Of course, there still remain general situations where sequential work experience can trump parallel work experience. Specifically, those who are analytically disposed are less likely to benefit from simultaneity of experience than those who are less analytically disposed, where analytical disposition is defined here as the inherent or acquired cognitive tendency to use reason and step-by-step analysis (or make inferences, e.g., Messick, 1984).

When individuals spend time acquiring domains in parallel, they are understanding a set of knowledge structures, decisions, and choices in the context of other relatively unrelated knowledge structures, decisions, and choices (see Brown et al., 1989). Decisions and choices are not understood in the general sense, and generalizable connections between decisions and choices across domains are not easily found. Instead seeing connections requires the consideration of specialized markets, times, or places. Connections among choices or decisions are, thus, highly specific, indirect, and difficult to express, thus at risk of eventually becoming only tacitly understood. The prevailing tendency to rely on sets of rules, principles, or logic—that is, analytical disposition—is simply less valuable to the efforts of combining connections and discovering valuable knowledge combinations when the knowledge underlying connections cannot even be expressed.

However, as analytical disposition increases, the relative benefit of sequential experience increases, insofar that connections can be derived. Under sequential experience, at any given time individuals are acquiring and shaping knowledge structures in the context of other highly typically related knowledge structures. Individuals then have a simpler, fuller, and more general understanding of all decisions and choices based on those fully developed knowledge structures (Walsh, 1995). Even though connections do not spontaneously *emerge* across domains when they are acquired separately, disposition to use and even rely on one's faculties for analytical ability better helps to *derive* explicit connections between these fuller knowledge structures across domains.

Research in educational psychology and occupational training—conceptual and empirical—support this perspective. Riding and Sadler-Smith (1997) differentiate between wholist versus analytic dimensions in cognitive style while Antonietti and colleagues distinguish analysis from intuition (Antonietti, 1991; Iannello, Antonietti, & Betsch, 2011). Pask and Scott (1972) differentiate between "holists," versus "serialists," and find that holists and serialists learn best when their teaching materials are designed to match with their learning style. Seidel and England (1999) extract the subsample of 64 out of 100 students showing a clear preference for a single cognitive style, and find that a sequential processing preference was significantly associated with a preference for structured nonintegrated informational environments (also see Cavanagh & Coffin, 1994).

Hypothesis 2: Increases in analytical disposition diminish the positive effect of additional parallelism of work experiences, in determining future self-employment.

Thus, by combining both hypotheses, it is presented here that one mode is not necessarily better than the other. Connections across domains can take place in both cases, either under sequential or parallel work experience. What determines the more effective mode is the degree to which individuals are prone to relying on cognitive analysis instead of past experience. Those relying on past experiences need not rely on cognitive analysis, for they can simply import or bring to bear, and apply, knowledge from those experiences to current situations. Those relying on cognitive analysis need not rely on that breadth of rich experience. Instead, they simply need a deep understanding and grasp of a set of concepts, which they can combine together.

Data

Following Elfenbein, Hamilton, and Zenger (2010), data used to analyze the hypotheses come from NSF's private SESTAT panel database. SESTAT is a comprehensive and integrated set of three NSF-sponsored survey-based data sets recording the demographic, educational, and employment characteristics of scientists and engineers in the United States. The SESTAT database begins with a random sample of the U.S. population in 1993 with at least a bachelor's degree who either work in or are educated in science or engineering.[4] Respondents are asked for information about what degrees they have, what fields those degrees are in, employment history (self-employed vs. paid-employed), salary data, demographic and family data, and the types of work activities or domains acquired at their present job. Between 1993 and 1999, every 2 years, respondents are resurveyed (with some survey attrition), and new respondents are added. In all, precisely 50,800 respondents are common across these four waves, but after dropping those listed as unemployed in 1999 and keeping both paid-employed and self-employed individuals, my sample size starts with 42,725 respondents.[5]

Of course, an ideal data set exploring possible antecedents of self-employment would contain rich information covering decades and a large sample (see Schmitt-Rodermund, 2004). Still, the SESTAT data set trades off richness of data per individual (i.e., frequency of data collection, and extent of information provided by the data) for the breadth of

4. Much of the theory covered here (especially regarding project-based learning) has been validated precisely predominantly in the fields of science and engineering (from medicine to accounting to information science).
5. The survey was indeed administered to the unemployed, and while recent research examines the transition from unemployment to self-employment (Thurik, Carree, Van Stel, & Audretsch, 2008), the survey did not allow the unemployed to address the nature of any (current) functional work experience.

coverage across individuals. However, the breadth of knowledge required to support entrepreneurial endeavors generally takes place across months or years, not days. Furthermore, it is not unreasonable to expect that paid employees do not change tasks day by day at work. Instead, major shifts in their work activities only take place on an annual basis. Thus, this SESTAT data set can be a useful one for studying the effects of work activities (especially their simultaneity) on the likelihood of future self-employment.

Dependent Variable

Following Elfenbein et al. (2010), a dummy variable in 1999 is assigned the value of 1 if the respondent declared s/he was self-employed in the 1999 survey and 0 otherwise. While the survey does ask respondents whether they work full time versus part time, it does not offer respondents a way to indicate hybrid entrepreneurship status.

Explanatory Variables

Measuring Total Number of Domains. Respondents were asked to indicate which of 14 work activities (e.g., domains) occupied a "significant amount of their time during a typical work week at their job." The domains listed were accounting, applied research, basic research, computer applications, design, development, employee relations, management and administration (Haber & Reicheil, 2007), operations (Bhave, 1994), professional services, quality management, sales, mentoring, and "other." I take a total unweighted count of the different domains an individual acquired in 1993 and 1995 and 1997, representing the diversity of an individual's knowledge.

Note that the empirical analysis is thus considering the experience of relating business functions given products to be commercialized or services to be delivered. Thus, the article is not examining exploration across multiple technological knowledge domains or search for links between technology and market (Gruber, Macmillan, & Thompson, 2008). Very possibly, people can come up with new ideas based on combinations of disparate technological domains, and yet not exploit the idea and follow through to become self-employed. I argue that they would not become entrepreneurially self-employed because they do not know enough about the important business functions. Even a simple incorporated gardening operation must involve reasonable effectiveness in combining business functions, and not all MBAs or managers can effectively become self-employed partially precisely because they do not possess this knowledge or capacity to understand.

Measuring Extent of Domain Experience, Acquired Sequentially Versus in Parallel. Deriving this measure is not straightforward. For example what happens if domains X, Y, and Z are acquired in 1993 and then domains W and Z acquired in 1995? Should W be coded as a sequentially acquired domain since it is acquired separately from X and Y, or coded as parallel since it was acquired with Z? To resolve this issue, instead of counting domains, I count pairs of domains. One could create a variable that measures the extent to which domain experience is parallel in terms of the number of unique *pairs* of domains that are acquired concurrently. A positive coefficient on such a variable would indicate that an individual who experiences more domains in parallel—holding fixed the number of domains experienced—is more likely to choose self-employment. Yet the identification of connections between domains requires multiple experiential periods to begin approaching the expertise required to make connections (e.g., Chase & Simon, 1973; Gagne & Glaser, 1987). More repetitions in associating information from one domain to other information from another domain engrains the association in the mind, and is more likely to lead to (cued) recall, where awareness of one of the pieces of information leads to the retrieval of the associated other piece of information. After all, the ability to evaluate and utilize outside knowledge is largely a function of the level of prior related knowledge (Cohen & Levinthal, 1989; also see Lechmann & Schnabel, 2014). Thus, parallelism is measured as the number of pairs experienced at the same time, throughout two of the three survey episodes ("Pairs twice"; e.g., experiencing accounting and quality management in 1993 and 1995), or in all three survey episodes ("Pairs thrice"). A positive and statistically significant coefficient would indicate that experiencing domains in parallel is more impactful than experiencing domains sequentially.[6,7]

Measuring the Extent to Which Analytical Disposition Interacts With Domains Experienced Sequentially. Disposition to use reasoning (e.g., make inferences) is proxied here via one's level of formal education. Past scholars have suggested the relationship, in the context of entrepreneurship. Notably, Shane (2003, p. 69), in citing Casson (1982), states that "education improves entrepreneurial judgment by providing people with analytic ability and an understanding of the entrepreneurial process." Consider the following. After college, people can choose to pursue further formal education, or accumulate experiences in the workforce. Those who pursue formal education after a bachelor's degree instead of jumping into the workforce likely associate with at least one of two possible scenarios. On one hand, at the margin they likely prefer being trained about principles and theory ahead of acquiring experience, thus indicating their preferred cognition. Such preference for reasoning is used to solve unfamiliar problems, especially ones that require connecting decisions and choices across domains (Wenke, Frensch, & Funke, 2005). Unfamiliar problems are precisely the types of problems chosen by individuals as they write theses to complete advanced graduate degrees (see Mayer, 2000). And an individual's capacity to reason is not only linked to the likelihood that s/he attends graduate school but also graduates with such degrees (Mayer). Alternatively, according to more economically oriented theory one can argue that analytical disposition is developed as a result of the sunk investment in training about analytical processes or tolerating reliance on analytical thought during formal education. I do not make claims about which rationale applies, but rather only that educational attainment proxies for the preferred cognitive tendency.[8] Regardless, Kolb (1984, p. 63, also ch. 7) argues that aspects of our cognitive style together represent a "stable state" in individuals shaped by the extent of schooling, and professional careers, where "the transition from education to work involves for many a transition from a reflective learning orientation to an active one" (p. 88).

The theoretical arguments for a positive relationship between educational level and analytical disposition have been repeatedly evidenced in the educational sciences literature. Giancarlo and Facione (2001) find significant positive relationships between

6. Due to interest in the analysis of the number of knowledge domains acquired, I exclude respondents who left these fields blank throughout any of the employment spells (roughly 7.9% of the total sample).
7. One may argue that I am only measuring the number of pairs experienced in parallel, and neglecting the number of pairs experienced sequentially in my empirical analysis. Introducing both of these variables ends up leading to collinearity issues, since the sum of these two variables represents a (geometric) function of the number of total domains experienced. I choose to measure the number of pairs experienced twice because the data show significant multicollinearity between a "pairs once" variable and the number of total domains experienced.
8. See Silva (2007) for further discussion and analysis on the relationship between innate talent and Lazear's jack-of-all-trades theory.

analytical disposition and level of undergraduate education, across the 4 years of university curriculum. King, Wood, and Mines (1990) examined whether the critical thinking scores of college and graduate students would differ by educational level, and found significant main effects for educational level on each of the three types of critical thinking tests that they implemented; specifically, graduate students regularly scored higher than undergraduate seniors. Finally, Kitchener and King (1990) analyzed data from almost 1,000 individuals who had been tested on the Reflective Judgement Interview, one of the best-known measures of analytical disposition, and found a consistent upward trend according to educational level, from high school graduates all the way to advanced doctoral students.

At first blush, there is at least one potential objection to measuring analytical disposition via educational attainment. One might object that higher levels of education indicate deep specialization in a single field which potentially hinders the discovery of connections across *technological fields*. While that may be the case, I examine the discovery of connections across *business fields* or functions; the drastic difference between the knowledge found in technological fields versus business functions better allows for the use of educational attainment in technological fields as an indicator of analytical disposition as it applies to business fields.

Educational attainment is measured by whether individuals obtained master's or doctorate degrees. The master's degree typically requires individuals to develop the capability to more deeply analyze a domain, and the PhD degree typically requires individuals to draw from a variety of domains or (subdomains) to reason and solve a universally novel theoretical or practical problem. The education variable equates to 2 for those with any master's degree but not PhD, 3 for PhD degree holders, and 1 otherwise. This variable is multiplied by the parallelism variable to obtain the interaction. A negative coefficient for this interaction would support hypothesis 2, since the effects of sequentiality in experience is presumed strengthened in the presence of analytical disposition.[9,10] I also include an additional variable indicating whether a respondent specifically possesses an MBA degree.

Control Variables

Age. Age is associated with both intelligence (Horn & Cattell, 1967) and resources. Notably, age is expected to positively relate to self-employment insofar that social and financial capital accumulates over time. Early retirees may opt for self-employment if they decide to return to the labor market. Furthermore, Levesque and Minniti (2006) hypothesize and show that younger people are more likely to bear the slower, less immediate rate of return often characteristic of start-ups. To isolate any spuriousness, I control for age. I also add the square of Age into the regression to account for any nonlinearities in the relationship.[11]

To ensure that I capture appropriately the effects of analytical disposition as proxied by education, and minimize the explanatory effect of analytical predisposition before

9. The educational attainment variable is not then multiplied by a sequentiality oriented "complement" to the parallelism interaction to form another interaction variable, else severe multicollinearity with the Total-Domains variable results.
10. Unfortunately, the SESTAT database offers no data regarding majors, subjects studied, or university grades.
11. Both Age and the square of Age are taken from the 1997 survey.

education can serve as its signal, I focus on respondents that are likely done with schooling by the beginning of the first survey episode. Thus, because a PhD takes 5–6 years on average, a respondent going straight to obtain a PhD should be roughly 28 years old by the time of graduation. Since a respondent should be this age by the time of the first survey episode, I eliminate all respondents that are not at least 32 years of age by 1997.[12]

Level of Education. Educational attainment shows up repeatedly in studies as a variable explaining self-employment entry, sometimes evaluated as insignificant (e.g., Evans & Jovanovic, 1989), sometimes significant (e.g., Aronson, 1991). Following Lazear (2005), I expect that greater specialization in human capital investments mainly improves specialist income—and indicator of opportunity cost—and thus itself leads to a lesser likelihood of self-employment. Including education as a control variable here tests for this alternative possibility, in the face of investigating hypothesis 2.[13] Education has also been found in some research to have a U-shaped relationship with the likelihood of entry into self-employment (see Blanchflower, 2000, p. 488), and so the squared term is included as well.[14]

Historical Ability. Studies vary in showing that self-employed entrepreneurs tend to be drawn from high performers or low performers (Hamilton, 2000). Those high in "entrepreneurial ability" are often better candidates for starting a new venture, even if they generally face greater opportunity costs (Amit, Muller, & Cockburn, 1995). At the same time, those with high ability manifest a greater capacity or willingness to multitask (Colom, Martinez-Molina, Shih, & Santacreu, 2010). To account for ability, I include (the natural log of) the individual's stated salary in 1997 (see Hamilton, pp. 623–624). Roughly 2.7% of respondents of the total sample gave no salary data, so they are dropped from the regression analyses.[15]

Furthermore, to eliminate confounds between total pay with choices about working part time versus full time, and to avoid potential ambiguity regarding one's time spent moonlighting in self-employment, I eliminate all individuals who report working less than full time during the year (i.e., working less than 52 weeks per year, and less than 40 hours per week) for both 1995 and 1997 (such data were not collected in 1993).

Exposure to Varied Business Environments. People are naturally exposed to different sets of skills as they transition to different firms or job positions (Lepak & Snell, 1999). Additionally, they would broaden their access to networks and social capital, which alone could influence the likelihood of involvement in new venture creation. To account for the confound, job change indicators for 1995 and 1997 are included. The indicator equals 1 if the respondent has had the same employer and the same job position throughout the previous 2 years, it equals 2 if either the employer or job position has changed, and it equals 3 if both the employer and the job position have changed.

12. Results of the empirical analysis do not change significantly in magnitude or statistical significance, due to this adjustment.
13. See Spector and Brannick (2011, p. 297) for a discussion of the use of controls as "alternative hypothesis tests."
14. Notably, Blanchflower (2000) looks at those who leave school before the age of 15, versus those who leave after 22 years of age. Within this range, there was a U-shaped relationship between age and self-employment likelihood. Given that those leaving school before the age of 15 probably cannot signal their ability, the squared education term here might be capturing the difference between necessity-based versus opportunity-based entrepreneurship.
15. No statistically significant differences exist between kept and dropped observations.

Firm Size. The responsibilities of individuals that acquire multiple domains may differ depending on the size of the firm. More generally, people may attempt to expose themselves to more skills (and more multitasking) in anticipating a future career decision to become an entrepreneur (Elfenbein et al., 2010). Those who anticipate this will be more likely to choose to work in small firms instead of large firms where intra-firm mobility will be more costly. To more generally account for the "small firm effect," where previous episodes in small firms tend to foreshadow or lead to such "spawning," I also account for the size of firms in a respondent's employment history (in both 1995 and 1997).

Risk Perception. Those worried about loss of paid employment will hold that attitude especially if finding another comparable job is unlikely. If they are worried about finding a comparable job, they will not want to leave their current job to start a new venture, especially since that is likely to be at least as risky as staying in current paid employment. At the same time, those worried about loss of employment are bound to diversify their knowledge investments to hedge against it (Hsieh, Parker, & Van Praag, 2012; Kihlstrom & Laffont, 1979). To capture an individual's perception of risk in light of possible future entrepreneurial self-employment, I use two categorical measures: individual self-reports of the amount of concern for job loss, as well as the job loss of somebody else in the household. The data codes "very concerned" as a 1, "somewhat concerned" as a 2, and "not very concerned" as a 3. No other categories were used when this data was collected, only in the 1997 version of the questionnaire.[16]

The final step in the data selection is to only analyze first entry into self-employment within the 6-year period (1993–1999) covered by the data. In other words, I retained only those respondents who were paid employees from 1993 to 1997, with the intention of analyzing the choice of becoming self-employed in 1999.

Summary Statistics

Table 1 shows summary statistics of the data set subject to empirical analysis. Educational level and the mode of experience (i.e., sequential vs. simultaneous) are not highly correlated. An individual characteristic does not appear to underlie and explain both this mode and self-employment likelihood simultaneously.

Results

Table 2 shows logit regressions of self-employment entry in 1999, capturing what determines the first self-employment episode across the 6-year time frame. According to Model 1, capable employees with recent experience in smaller companies and exposure to different business environments are more likely to choose self-employment. Model 2 added the MBA variable with no substantive effect to the regression. Models 3 and 4 added the "TotalDomains" variables, also with no effect. According to Model 5, the more domain pairs experienced simultaneously over an extended period of 3–4 years, the greater the likelihood of self-employment, and the education-concomitance interaction negatively influences that relationship. Model 6 looks at the effects when domain pairs are experienced simultaneously over a period of 5–6 years, and shows no effect. When

16. Race and gender are also measured by the data set, but are excluded as controls because these variables do not particularly distort the theoretical relationship between the dependent and key explanatory variables in any way (see Spector & Brannick, 2011). Regardless, inclusion of these two variables do not qualitatively affect the results.

Table 1

Summary Statistics Underlying Data Used in Regression Analysis

						Simple correlation coefficients									
Variable	Obs	Mean	Std.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) SE99	13,057	.020	.141	0	1										
(2) Age	13,057	45.853	8.059	32	74	.0136									
(3) Age sq	13,057	2,167.471	763.074	1,024	5,476	.0136	.9948*								
(4) Gender†	13,057	.788	.408	0	1	.0043	.1553*	.1527*							
(5) Education	13,057	1.912	.855	1	3	−.0138	.2479*	.2412*	.0269*						
(6) Education sq	13,057	4.387	3.420	1	9	−.0133	.2501*	.2436*	.0292*	.9917*					
(7) MBA	13,057	.059	.236	0	1	.0099	−.0186*	−.0178*	.0278*	.0356*	−.0160				
(8) Log of salary1997	13,057	11.072	.445	4,043	13.816	.0192*	.2161*	.2098*	.1928*	.3016*	.3039*	.0564*			
(9) Job change1995	13,057	1.301	.588	1	3	.0238*	−.1513*	−.1477*	−.0478*	−.0325*	−.0376*	.0603*	−.0395*		
(10) Job change1997	13,057	1.292	.572	1	3	.0447*	−.1694*	−.1644*	−.0218*	−.0519*	−.0590*	.0618*	−.0068	.1707*	
(11) Employer size1995	13,057	3,077.288	2,266.174	5	5,000	−.0697*	.0643*	.0596*	−.002	.1494*	.1530*	−.0077	.0762*	−.0902*	−.0478*
(12) Employer size1997	13,057	2,950.949	2,280.935	5	5,000	−.0817*	.0578*	.0541*	.0187*	.1528*	.1607*	−.0037	.1257*	−.0776*	−.0909*
(13) Spousal job concern	13,057	2.738	.541	1	3	.0078	−.0031	.0004	.0622*	.0380*	.0370*	.0204*	.0968*	.0065	.0015
(14) Self job concern	13,057	2.699	.568	1	3	−.0066	−.0251*	−.0189*	.0005	.0481*	.0497*	−.0121	.0730*	−.0107	−.0207*
(15) Tenure/instructor†	13,057	.122	.328	0	1	−.0423*	.1487*	.1481*	−.0608*	.2968*	.3067*	−.0657*	−.0324*	−.0561*	−.0873*
(16) TotalDomains	13,057	6.305	2.261	1	14	.0211*	−.0335*	−.0354*	.0280*	−.0665*	−.0742*	.0330*	.0479*	.0885*	.0914*
(17) TotalDomains sq	13,057	44.858	30.263	1	196	.0215*	−.0315*	−.0331*	.0176*	−.0775*	−.0846*	.0301*	.0305*	.0875*	.0858*
(18) Domain pairs twice, trained	13,057	4.010	4.632	0	46	.0137	.0008	−.0023	.0306*	.0023	−.0033	.0318*	.0780*	.0314*	.0329*
(19) Pairs twice × Edu interaction	13,057	7.678	9.956	0	105	−.0015	.0869*	.0810*	.0271*	.3360*	.3279*	.0412*	.1724*	.0194*	.0059
(20) Domain pairs thrice, trained	13,057	2.179	3.278	0	36	−.0049	.0479*	.0431*	.0452*	.1048*	.1073*	.0086	.1705*	−.0408*	−.0519*
(21) Pairs thrice × Edu interaction	13,057	4.460	7.464	0	84	−.0082	.1050*	.0990*	.0429*	.3499*	.3530*	.0064	.2239*	−.0451*	−.0643*

Variable	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(12) Employer size1997	.6869*									
(13) Spousal job concern	.0103	.0076								

Table 1

Continued

Variable	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(14) Self job concern	.0315*	.0233*	.3925*							
(15) Tenure/instructor†	.1171*	.0676*	.0043	.0665*						
(16) TotalDomains	−.0623*	−.0700*	−.0403*	−.0452*	−.0206*					
(17) TotalDomains sq	−.0684*	−.0767*	−.0472*	−.0503*	−.0205*	.9764*				
(18) Domain pairs twice, trained	−.0535*	−.0462*	−.0454*	−.0369*	.0162	.6295*	.6533*			
(19) Pairs twice × Edu interaction	.0024	.009	−.0272*	−.0115	.1172*	.5173*	.5281*	.8613*		
(20) Domain pairs thrice, trained	−.0615*	−.0325*	−.0016	−.0017	.0630*	.4000*	.4077*	.3728*	.3541*	
(21) Pairs thrice × Edu interaction	−.0127	.0128	.0109	.0129	.1425*	.3195*	.3196*	.3008*	.4254*	.8890*

*Indicates statistical significance at the $p < .05$ level.
†This variable is used in regressions involving subsamples.

Table 2

Logit Regressions Testing Hypotheses 1 and 2 (N = 13,057)

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age	.0608 (.0761)	.0617 (.0760)	.0589 (.0761)	.0591 (.0761)	.0646 (.0764)	.0637 (.0762)	.0692 (.0764)
Age sq	−.000421 (.0008)	−.000429 (.0008)	−.000399 (.0008)	−.000401 (.0008)	−.000458 (.0008)	−.00045 (.0008)	−.000507 (.0008)
Education	−.644 (.5760)	−.965 (.6530)	−.986 (.6530)	−.984 (.6530)	−.744 (.6640)	−1.016 (.6540)	−.77 (.6640)
Education sq	.133 (.1450)	.213 (.1640)	.22 (.1650)	.219 (.1650)	.201 (.1650)	.233 (.1650)	.205 (.1660)
MBA		.313 (.2700)	.313 (.2700)	.313 (.2700)	.317 (.2700)	.325 (.2700)	.328 (.2700)
Log of salary1997	.419*** (.1450)	.408*** (.1450)	.396*** (.1450)	.397*** (.1460)	.409*** (.1470)	.441*** (.1470)	.453*** (.1490)
Job change1995	.144 (.0967)	.139 (.0968)	.132 (.0971)	.132 (.0971)	.134 (.0972)	.117 (.0974)	.12 (.0974)
Job change1997	.394*** (.0923)	.391*** (.0923)	.384*** (.0926)	.384*** (.0926)	.379*** (.0928)	.366*** (.0931)	.363*** (.0932)
Employer size1995	−.0000794** (.0000)	−.0000786** (.0000)	−.0000782** (.0000)	−.0000782** (.0000)	−.0000779** (.0000)	−.0000838** (.0000)	−.0000831** (.0000)
Employer size1997	−.000204*** (.0000)	−.000205*** (.0000)	−.000204*** (.0000)	−.000204*** (.0000)	−.000206*** (.0000)	−.000204*** (.0000)	−.000205*** (.0000)
Spousal job concern	.137 (.1330)	.133 (.1330)	.136 (.1330)	.136 (.1330)	.134 (.1330)	.138 (.1330)	.134 (.1330)
Self job concern	−.0903 (.1150)	−.0874 (.1160)	−.0843 (.1160)	−.0842 (.1160)	−.0823 (.1160)	−.0839 (.1160)	−.0798 (.1160)
TotalDomains			.0302 (.0275)	.0113 (.1300)	.0358 (.1320)	.0159 (.1300)	.0419 (.1320)
TotalDomains sq				.0014 (.0094)	−.000054 (.0097)	.0029 (.0094)	.000854 (.0097)
Domain pairs twice, trained					.0646** (.0310)		.0777** (.0327)
Pairs twice × Edu interaction					−.0401** (.0166)		−.0444** (.0174)
Domain pairs thrice, trained						−.0364 (.0503)	−.0789 (.0544)
Pairs thrice × Edu interaction						−.00394 (.0237)	.0176 (.0250)
Constant	−9.967*** (2.3860)	−9.615*** (2.4070)	−9.595*** (2.4070)	−9.557*** (2.4200)	−10.25*** (2.4460)	−10.11*** (2.4370)	−10.77*** (2.4650)

* p<.1, ** p<.05, *** p<.01

the PairsTwice and PairsThrice variables are all included in Model 7, it appears that experiencing more domain pairs simultaneously over a period of 3–4 years still has a robust positive effect on the likelihood of future self-employment. Both hypothesis 1 and hypothesis 2 can be supported.

Table 3 refines the analysis, by re-running regressions for male versus female respondents. Gender is introduced to account for any differences between male and female career progressions (e.g., DeMartino & Barbato, 2003). The empirical results are startling. While the hypotheses hold up for men, the hypotheses are not supported for women. This potentially makes sense given the recent literature on the relative importance of emotion to women entrepreneurs in the entrepreneurial entry decision (Armstrong, 2011). Another pair of regressions was run separately for nonacademic versus academic respondents, given that academic entrepreneurship emerges from very different conditions compared to nonacademic entrepreneurship.[17] Finally, separate regressions are run for incorporated self-employed versus nonincorporated self-employed, given that informal entrepreneurship (Williams & Nadin, 2010) ranging from babysitting to drug dealing simply does not require combining the same levels of business knowledge as incorporated ventures, which typically require formalized processes such as submitting business planning documents or annual accounting statements to Chambers of Commerce. Hypotheses 1 and 2 are particularly supported in the context of entrepreneurship involving males, nonacademic, and/or incorporating entrepreneurs. Again, however, the effect of experiencing pairs together apparently begins to diminish after roughly 4 years.

Table 4 illustrates the impact of the interaction effect on probabilities of self-employment given different numbers of total domains, simultaneity, formal education, and historical ability. As level of education increases, the effects of simultaneity first relate positively to probability of self-employment and then negatively. Thus, the negative interaction effect actually overcomes the positive main effect of simultaneity of experiences. This pattern holds for any given level of TotalDomains and over the entire range of simultaneity. The data thus appear to suggest that further formal education should not necessarily be the focus of small-business-oriented policy makers unless programs encouraging sequential work experiences are subsequently implemented. In contrast, the data suggest that those contemplating additional parallel work experiences should first consider their level of analytical disposition, as reflected by their chosen level of formal educational attainment. The upshot is that those interested in maximizing or fostering future self-employment should first consider both their work activity profiles and their (expected) level of formal educational attainment. The top half and bottom half of Table 4 also highlight the sizes of the effects of parallel work experiences, relative to differences in historical ability. The rationale underlying the $65k salary in the top half is that this amount is almost equivalent to the average salary represented in the sample.

Are individuals who acquire knowledge domains sequentially more likely than others to become self-employed at a given moment if their analytical disposition is high enough? This generally does not appear to be the case. For all of Table 4, the highest possible probability for master's degree holders is still lower than the lowest likelihoods for bachelor's degree holders. Additional formal education seems to associate with a decrease in likelihood of self-employment, across the board.

In addition to illustrating the effects of the interaction, I also calculate the marginal effect of a variable on probabilities of self-employment. Instead of calculating the partial

17. Academic entrepreneurs were identified as those who declared themselves as types of instructors ("tenured," "tenure-track," or "nontenure-track") anytime between 1993 and 1999.

Table 3

Logit Regressions Testing Subsamples

Model	(8) Female	(9) Male	(10) Academic	(11) Nonacademic	(12) Non-incorp	(13) Incorporated	(14) Male, non-acad, incorporated	(15) Male, non-acad, incorporated
Age	.0145	.0705	−.028	.0725	.148	.0394	.0821	.0835
	(.1720)	(.0861)	(.4100)	(.0791)	(.1150)	(.1050)	(.1200)	(.1200)
Age sq	.000207	−.000537	.00095	−.000529	−.00109	−.000384	−.000825	−.000839
	(.0018)	(.0009)	(.0040)	(.0008)	(.0012)	(.0011)	(.0013)	(.0013)
Education	−3.422**	−.135	–	−.756	−.875	−.564	−.495	−.517
	(1.7140)	(.7260)	–	(.6710)	(.9790)	(.8960)	(.9990)	(.9990)
Education sq	.864**	.0506	–	.23	.232	.152	.165	.175
	(.4290)	(.1800)	–	(.1670)	(.2430)	(.2230)	(.2490)	(.2490)
MBA	1.402**	.0732	–	.298	.356	.282	.188	.195
	(.6060)	(.3060)	–	(.2710)	(.3990)	(.3620)	(.4010)	(.4010)
Log of salary1997	.138	.488***	−.122	.338**	.362*	.457**	.485**	.511**
	(.3080)	(.1690)	(.8860)	(.1510)	(.2150)	(.1980)	(.2280)	(.2290)
Job change1995	.0642	.136	.577	.117	.0666	.178	.148	.139
	(.2140)	(.1100)	(.5740)	(.0989)	(.1520)	(.1250)	(.1420)	(.1420)
Job change1997	.561***	.326***	1.416***	.316***	.345**	.397***	.279**	.269*
	(.2040)	(.1050)	(.4640)	(.0953)	(.1410)	(.1220)	(.1390)	(.1390)
Employer size1995	−.0000942	−.0000672	−.000031	−.0000679*	−.000034	−.000112**	−.0000854	−.0000895
	(.0001)	(.0000)	(.0002)	(.0000)	(.0001)	(.0001)	(.0001)	(.0001)
Employer size1997	−.0000596	−.000251***	−.000243	−.000207***	−.000227***	−.000191***	−.000247***	−.000247***
	(.0001)	(.0000)	(.0002)	(.0000)	(.0001)	(.0001)	(.0001)	(.0001)
Spousal job concern	.173	.127	.439	.116	.0514	.215	.235	.238
	(.2780)	(.1520)	(1.0360)	(.1340)	(.1840)	(.1900)	(.2190)	(.2200)
Self job concern	.0501	−.112	.282	−.0544	−.229	.0616	.0524	.0525
	(.2750)	(.1280)	(1.0060)	(.1170)	(.1600)	(.1660)	(.1820)	(.1820)
TotalDomains	−.276	.152	−.184	.0411	−.0734	.166	.212	.22
	(.2330)	(.1610)	(.7310)	(.1340)	(.1870)	(.1860)	(.2160)	(.2170)
TotalDomains sq	.0297*	−.0106	.00591	−.000113	.00548	−.00722	−.0167	−.0164
	(.0169)	(.0119)	(.0560)	(.0099)	(.0143)	(.0134)	(.0160)	(.0161)
Domain pairs twice, trained	−.0534	.0923***	.0476	.0673**	.0187	.0907**	.134***	.135***
	(.0779)	(.0345)	(.1020)	(.0315)	(.0513)	(.0395)	(.0428)	(.0450)

Table 3

Continued

Model	(8) Female	(9) Male	(10) Academic	(11) Nonacademic	(12) Non-incorp	(13) Incorporated	(14) Male, non-acad, incorporated	(15) Male, non-acad, incorporated
Pairs twice ×	.000308	−.0501***	–	−.0426**	−.019	−.0538**	−.0657**	−.0654**
Edu interaction	(.0363)	(.0190)	–	(.0171)	(.0245)	(.0230)	(.0256)	(.0267)
Domain pairs								−.0169
thrice, trained								(.0694)
Pairs thrice ×								−.00526
Edu interaction								(.0360)
Constant	−4.36	−11.79***	−8.552	−9.631***	−11.71***	−11.71***	−12.81***	−13.13***
	(5.2740)	(2.8070)	(13.5600)	(2.5140)	(3.6830)	(3.3170)	(3.8030)	(3.8200)
N	2,762	10,295	1,597	11,460	12,911	12,937	9,056	9,056
R-sq	.052	.063	.155	.049	.046	.061	.063	.063

* $p<.1$, ** $p<.05$, *** $p<.01$

Table 4

Predicted Probabilities of Entrepreneurial Entry in 1999 Illustrating the Interaction Effect Among TotalDomains, Simultaneity, and Education, by 1997s Salary (Using Model 5)

SALARY 1997 = $65,000

		TotalDomains=4 Education					*TotalDomains=6* Education		
		1	2	3			1	2	3
	1	2.31%	1.46%	.93%		3	2.59%	1.52%	.89%
	2	2.36%	1.44%	.88%		6	2.79%	1.46%	.76%
Pairs twice	3	2.42%	1.42%	.83%	Pairs twice	9	2.99%	1.39%	.64%
	4	2.48%	1.40%	.79%		12	3.22%	1.33%	.54%
	5	2.54%	1.38%	.74%		15	3.46%	1.27%	.46%
	6	2.60%	1.36%	.71%					

		TotalDomains=8 Education					*TotalDomains=10* Education		
		1	2	3			1	2	3
	7	3.05%	1.54%	.77%		15	3.94%	1.46%	.53%
	11	3.36%	1.45%	.62%		20	4.44%	1.35%	.40%
Pairs twice	15	3.69%	1.36%	.49%	Pairs twice	25	5.00%	1.25%	.31%
	19	4.06%	1.28%	.40%		30	5.62%	1.16%	.23%
	23	4.47%	1.21%	.32%		35	6.31%	1.08%	.18%
	27	4.91%	1.14%	.26%		40	7.08%	1.00%	.13%
						45	7.94%	.93%	.10%

SALARY 1997 = $150,000

		TotalDomains=4 Education					*TotalDomains=6* Education		
		1	2	3			1	2	3
	1	3.24%	2.07%	1.31%		3	3.64%	2.15%	1.26%
	2	3.32%	2.04%	1.24%		6	3.91%	2.06%	1.07%
Pairs twice	3	3.40%	2.01%	1.18%	Pairs twice	9	4.20%	1.97%	.91%
	4	3.49%	1.98%	1.11%		12	4.51%	1.88%	.77%
	5	3.57%	1.95%	1.06%		15	4.84%	1.80%	.65%
	6	3.66%	1.92%	1.00%					

		TotalDomains=8 Education					*TotalDomains=10* Education		
		1	2	3			1	2	3
	7	4.28%	2.17%	1.09%		15	5.51%	2.06%	.75%
	11	4.71%	2.04%	.87%		20	6.19%	1.91%	.57%
Pairs twice	15	5.17%	1.92%	.70%	Pairs twice	25	6.95%	1.77%	.43%
	19	5.68%	1.81%	.56%		30	7.80%	1.64%	.33%
	23	6.23%	1.71%	.45%		35	8.73%	1.53%	.25%
	27	6.83%	1.61%	.36%		40	9.77%	1.42%	.19%
						45	10.91%	1.31%	.14%

Note that the probability of self-employment increases with simultaneity of experience for those with solely bachelor's degrees, but that the probability decreases for those who complete the master's or PhD. Besides the total number of domains, simultaneity, education, and the interaction, all other variables used in Model 5 are held at their population means (aside from the obvious adjustments to the squared terms and the interaction variable).

change in y^* as a result of changes in x, I calculate the more intuitive discrete change in $\Pr(y=1 \mid x)$. More specifically, I focus on the centered discrete change suggested by Kaufman (1996). Following Hoetker (2007) and Long (1997), I choose to compute the discrete changes based on averaging over all observations:

$$\frac{\Delta \Pr(y=1|x)}{\Delta x_k} = \frac{1}{N}\sum_{i}^{N}\left[\Pr\left(y_i=1|x, x_k+\frac{1}{2}\right)-\Pr\left(y_i=1|x, x_k-\frac{1}{2}\right)\right] \tag{1}$$

Based on equation 1, the discrete change was found in the two statistically significant experience-oriented independent variables listed in Model 14. Thus, for example, an additional pair experienced sequentially (in parallel) over the long term leads to a .16% increase (decrease) in self-employment likelihood for master's graduates and a .32% increase (decrease) for PhD graduates. Furthermore, averaged across the population, an increase in the product of concomitance and education of 5 units would yield a .40% decrease in future self-employment likelihood.

Yet the marginal effect of a change in both interacted variables (education and concomitance) is not necessarily merely equal to the marginal effect of changing just the interaction term. In fact even in the absence of an explicit interaction variable, the effect of a variable on the probability of the latent dependent variable is dependent on the values of the other independent variables. In response, I calculated the marginal effects of a change in both interacted variables, which corrects for the effect not captured in the interaction term (see Norton, Wang, & Ai, 2004). Analysis (available on request) shows that the correction has no meaningful effect.[18]

Discussion

Theory and empirical results from this study can be positioned within the literature in a couple of major ways. First, as noted by Sorenson and Fassiotto (2011, p. 1322) the literature has focused on (1) turnover events from the perspective of the organization, without looking at why some people leave to become entrepreneurs and others leave for other jobs; and (2) the dispositional or biographical features of those most likely to launch new ventures. Instead of neglecting potentially interactive effects between organizations and those who leave those organizations, the current article argues that the nature of past experiences (sequential vs. parallel) has a direct effect on likelihood of entrepreneurial entry, and that the depth of formal education—reflecting analytical tendency (e.g., Giancarlo & Facione, 2001)—has a moderating effect. Individuals who experience domains sequentially benefit relatively more from an analytical disposition. Traits and

18. To test whether the rational expectations model fit my data, and to examine entrepreneurial performance, following Hamilton (2000) I regressed all year-1999 entrepreneurs' salaries on education, the squared education term, marriage status, and race, and then added my domain-related variables. Interestingly, while the pairsthrice variables do not affect entry, they appear to have an effect on entrepreneurial performance. The more pairs are experienced in parallel over a span of 5+ years, the higher the subsequent entrepreneurial performance. Analytical disposition furthermore has the expected interaction effect when accounting for entrepreneurial salary instead of entrepreneurial entry likelihood. However, ultimately it is difficult to confirm these finding, insofar that the SESTAT data do not account for whether the entrepreneurs are treating profits as salary or as retained earnings. Moreover, empirical research continues to investigate whether an entrepreneurship career is chosen for nonpecuniary reasons (Benz, 2009; Hamilton, 2000).

training interact in a way that may help to reconcile puzzling anecdotes, such as why some college dropouts or dyslexics enter the self-employment sector and succeed so well at entrepreneurship while others with a doctorate fail or avoid entering the self-employment sector altogether (e.g., Sze, 2002).

Second, this study suggests that if managers want to groom subordinates into management while not risking their departure into entrepreneurship, it is safer to offer them experiences in varieties of domains sequentially, and not in parallel. Studies find that job rotation is valuable for employees in increasing value and motivation within the company (e.g., Campion, Cheraskin, & Stevens, 1994), perhaps via the increase in task variety. While job rotation may indeed lead to job satisfaction, the risk remains that workers like Beasley will still leave to become entrepreneurially self-employed.

Aside from managerial policy, educational institutions and policy makers can also glean some lessons learned from this study's findings. Educational institutions looking to develop successful entrepreneurship students should consider running freshmen students through a battery of cognitive tests and directing them through two types of entrepreneurship curriculum tracks, just as master's programs have thesis versus coursework-only tracks. Finally, apprenticeships have been a big focus recently by policy makers. Policy should look into focusing on offering apprenticeships to those who prefer using intuition over analytical reasoning.

Third, the study helps to reconcile debate on whether business schools should continue engaging students in experiential learning as a part of entrepreneurship education curricula (Souitaris, Zerbinati, & Al-Laham, 2007). Perhaps entrepreneurial skills cannot be taught in textbooks or the classroom and instead a transdisciplinary training model should be adopted (Klein, 2004). Some scholars emphasize that major components of entrepreneurial ability can be taught or stimulated in the classroom (Bechard & Toulouse, 1998), even to the extent that students would be successful in predicting the consequences of their own decisions (Fiet, 2001). Empirical results presented in this article suggest that sequential training of business function skills can be effective, more so for those with higher analytical disposition.

At a broader level, this research addresses, to varying degrees, the crossroads of three similar yet independent conversations in the literature: project-based learning in learning theory, interdisciplinarity in education, and apprenticeship in occupational training. Project-based learning was described earlier in the theory development section. Interdisciplinarity is defined as the combination of multiple domains or disciplines into one activity, with multidisciplinarity and transdisciplinarity at the ends. Unlike research on PBL, virtually all empirical interdisciplinarity research has avoided comparing the outcomes of different kinds of interdisciplinary treatments (Spelt, Biemans, Tobi, Luning, & Mulder, 2009). Apprenticeship, in contrast to didactic learning, embeds the learning of complex skills and knowledge within activities in the social and functional context of their use. If a problem at work involves combining knowledge from multiple domains, apprenticeship-driven learning can be applied in future related contexts (Collins, Brown, & Newman, 1989).

Of course, this study has its limitations. First, the data used here to test the hypotheses are useful at a macro level while compromising analysis at more micro levels. What naturally leads to entrepreneurial self-employment is likely a process spanning multiple years, where prior knowledge evolves over many years in terms of both content and structure (aside from entrepreneurship by necessity) (Harvey & Evans, 1995). Unfortunately, it is logistically difficult (and perhaps vocationally unacceptable to employers) to follow hundreds or dozens of employees and ask them precisely what work activities they covered, every day for multiple years. Instead I offer an analysis at the level of the week, i.e., asking thousands of respondents what activities took up "significant amounts of their time in a given workweek." That said, while there is one remote possibility that employees are always splitting part of their workweek (say, Monday and Tuesday) to work on activity A, and devoting the other part of their workweek (say, Wednesday through Friday) to work on activity B, the level of concomitance of that experience is still greater than if an employee reports working on activity A during a week, and then working on activity B during another week a full 2 years later. Second, in this article entire career progressions are unavailable, and only 8 years' worth is captured by the data. To capture the amount of knowledge acquired beyond the 8-year period covered in the data, age is used as a variable. Barring the collection of data on knowledge acquired since grade school, this methodological shortcoming is arguably irremediable. Third, some of the seemingly high probabilities of self-employment may relate to the nature of the data, which only examines scientists and engineers. The coefficients and marginal effects of the variables might be different if nonscientists and nonengineers were included. Fourth, as stated earlier, this study does not include data that allows distinguishing between analytical disposition derived via genetics from that derived from sunk cost in educational attainment. Fifth, although recent work has investigated the effects of social contagion on entrepreneurial entry (Kacperczyk, 2013; see also Dobrev & Barnett, 2005), my data is silent about the existence, identity, or background of peers (i.e., co-workers or classmates). Future work although likely smaller in sample should take a look at the effects of experience heterogeneity and experiential ordering together with local social networks and the career progressions of those members.

Finally, there is limited to no information about type and size of businesses, type of occupation, and economic sector. Type of business is very vague, only distinguishing among industry sectors. Size of firm is vague (grouping all firms with less than 10 employees as a single category) and does not distinguish between singleton entrepreneurs and entrepreneur–employers. Type of occupation is not mentioned and economic sector only distinguishes among educational institutions, government institution, business/industry.

To investigate Lazear's theory, this article focused on investigating experiential order in business domains at work, instead of training involving technological knowledge domain, hobbies, or other extracurricular interests. Future research should consider examining the effects of experiencing *technological* domains sequentially versus experiencing them in parallel, perhaps from a creativity perspective (Ward, 2004). Certainly, human capital plays an important role in the complex process of technological or cultural venture creation, at both the individual and team levels (Shane, 2000). Just as long-term buildup of business-oriented knowledge has been shown here to affect self-employment likelihood, luck aside, opportunities typically emerge through the continuous shaping, development, or speciation of cultural hobbies, ideas, or technologies that are acted on (Garnsey, Lorenzoni, & Ferriani, 2008). However, my data set does not cover these. Furthermore, whereas business-oriented domains likely connect to one another to similar degrees, some technological knowledge domains combine dramatically more readily than others. For example the textile industry is likely to be combined more readily with the furniture industry than with the food condiment industry. Measures of distance between knowledge domains or measures of the rarity of finding any two knowledge domains within the same individual would be helpful. Similarly, I examined parallel work experience versus sequential work experience in business functions particularly because most if not all businesses need these functional skills to some extent, across all technological domains. It is arguably more difficult to draw conclusions if examining the effects of sequential versus parallel training within particular industry contexts. After all, perhaps some fields with better-defined concepts are better to experience sequentially, versus other fields which are best experienced in parallel (see Summers, Williamson, & Read, 2004).

Conclusion

This article seeked to examine why some but not others choose to become self-employed entrepreneurs. Specifically, it examines the interaction between business knowledge and cognitive disposition. Extending Lazear's work, the empirical results indicate that different modes by which a broad collection of business-related knowledge domains are acquired have differential effects on the likelihood of self-employment, particularly for self-employed entrepreneurship involving male, nonacademic, and/or incorporating entrepreneurs. In these contexts, experiencing domains in parallel increases the likelihood that connections are made between knowledge structures, choices, and decisions across multiple domains brought to bear in future periods to help in creating value, and interaction between experiential order and one's analytical disposition precedes entry (or re-entry) into self-employment. Specifically, increases in analytical disposition negatively influence the positive effect of additional simultaneity of experience, in determining self-employment. In other words, my results modify the standard jack-of-all-trades theory. Learning a large number of skills may not be so important. What's instead important is experiencing (or "learning") multiple skills together, or at least learning them in a way that complements one's (acquired) taste for processing information (i.e., analytical disposition).

REFERENCES

Adler, C. (2003). The fresh prince of software. *FSB: Fortune Small Business*, *13*(2), 42.

Amit, R., Muller, E., & Cockburn, I. (1995). Opportunity costs and entrepreneurial activity. *Journal of Business Venturing*, *10*(2), 95–106.

Antonietti, A. (1991). Why does mental visualization facilitate problem solving? In R. H. Logie & M. Denis (Eds.), *Mental images in human cognition* (p. 211–227). Amsterdam: Elsevier.

Armstrong, C.E. (2011). Thinking and slacking or doing and feeling? Gender and the interplay of cognition and affect in new venture planning. *Journal of Developmental Entrepreneurship*, *16*(2), 213–226.

Aronson, R.L. (1991). *Self-employment: A labor market perspective*. Ithaca, NY: ILR Press.

Arthur, W.B. (2007). The structure of invention. *Research Policy*, *36*, 274–287.

Backes-Gellner, U., Tuor, S.N., & Wettstein, D. (2010). Differences between entrepreneurs and employees in their educational paths. *Empirical Research in Vocational Education and Training*, *2*(2), 83–105.

Baron, R.A. & Ensley, M.D. (2006). Opportunity recognition as the detection of meaningful patterns: Evidence from comparisons of novice and experienced entrepreneurs. *Management Science*, *52*(9), 1331–1344.

Barsalou, L.W. (1983). Ad hoc categories. *Memory & Cognition*, *11*, 211–227.

Bechard, J.P. & Gregoire, D. (2005). Entrepreneurship education research revisited: The case of higher education. *Academy of Management Learning & Education*, *4*(1), 22–43.

Bechard, J.P. & Toulouse, J. (1998). Validation of a didactic model for the analysis of training objectives in entrepreneurship. *Journal of Business Venturing*, *13*(4), 317–332.

Benz, M. (2009). Entrepreneurship as a non-profit-seeking activity. *International Entrepreneurship and Management Journal*, *5*(1), 23–44.

Bhave, M.P. (1994). A process model of entrepreneurial venture creation. *Journal of Business Venturing*, *9*(3), 223–242.

Blanchflower, D.G. (2000). Self-employment in OECD countries. *Labour Economics*, *7*, 471–505.

Brown, J.S., Collins, A., & Duguid, P. (1989). Situated cognition and the culture of learning. *Educational Researcher*, *18*(1), 32–42.

Campion, M.A., Cheraskin, L., & Stevens, M.J. (1994). Career-related antecedents and outcomes of job rotation. *Academy of Management Journal*, *37*(6), 1518–1542.

Casson, M. (1982). *The entrepreneur*. Totowa, NJ: Barnes & Noble Books.

Cavanagh, S.J. & Coffin, D.A. (1994). Matching instructional preference and teaching styles: A review of the literature. *Nurse Education Today*, *14*, 106–110.

Chang, J. (2005). Career path. *Sales and Marketing Management*, *157*(5), 60.

Chase, W.G. & Simon, H.A. (1973). Perception in chess. *Cognitive Psychology*, *4*, 55–81.

Cohen, W.M. & Levinthal, D.A. (1989). Innovation and learning: The two faces of R&D. *The Economic Journal*, *99*, 569–596.

Collins, A., Brown, J.S., & Newman, S. (1989). Cognitive apprenticeship: Teaching the crafts of reading, writing, and mathematics. In L. B. Resnick (Ed.), *Knowing, learning, and instruction* (pp. 453–494). Hillsdale, NJ: Erlbaum.

Colman, R. (2003). Sweet success. *CMA Management*, *76*(10), 40–42.

Colom, R., Martinez-Molina, A., Shih, P.C., & Santacreu, J. (2010). Intelligence, working memory, and multitasking performance. *Intelligence*, *38*(6), 543–551.

DeMartino, R. & Barbato, R. (2003). Differences between women and men MBA entrepreneurs: Exploring family flexibility and wealth creation as career motivators. *Journal of Business Venturing*, *18*(6), 815–832.

Dobrev, S.D. & Barnett, W.P. (2005). Organizational roles and the transition to entrepreneurship. *Academy of Management Journal*, *48*(3), 433–449.

Dumas, D., Alexander, P.A., & Grossnickle, E.M. (2013). Relational reasoning and its manifestations in the educational context: A systematic review of the literature. *Educational Psychology Review*, *25*(3), 391–427.

Elfenbein, D.W., Hamilton, B.H., & Zenger, T.R. (2010). The small firm effect and the entrepreneurial spawning of scientists and engineers. *Management Science*, *56*(4), 659–681.

Elsbach, K.D., Barr, P.S., & Hargadon, A.B. (2005). Identifying situated cognition in organizations. *Organization Science*, *16*(4), 422–433.

Evans, D. & Jovanovic, B. (1989). An estimated model of entrepreneurial choice under liquidity constraints. *Journal of Political Economy*, *97*, 808–827.

Fiet, J.O. (2001). The theoretical side of teaching entrepreneurship. *Journal of Business Venturing*, *16*(1), 1–24.

Finke, R.A., Ward, T.B., & Smith, S.M. (1996). *Creative cognition: Theory, research, and applications*. Cambridge, MA: MIT Press.

Gagne, R.M. & Glaser, R. (1987). Foundations in learning research. In R. M. Gagne (Ed.), *Instructional technology: Foundations* (pp. 49–84). Hillsdale, NJ: Lawrence Erlbaum.

Gallagher, S., Stepien, W., & Rosenthal, H. (1992). The effects of problem-based learning on problem solving. *Gifted Child Quarterly*, *36*, 195–200.

Garnsey, E., Lorenzoni, G., & Ferriani, S. (2008). Speciation through entrepreneurial spin-off: The acorn-ARM story. *Research Policy*, *37*(2), 210–224.

Giancarlo, C.A. & Facione, P.A. (2001). A look across four years at the disposition toward critical thinking among undergraduate students. *The Journal of General Education*, *50*(1), 29–55.

Goodnow, J. (1990). The socialisation of cognition: What's involved? In J. Stigler, R. Shweder, & G. Herdt (Eds.), *Cultural psychology* (pp. 259–286). Cambridge: Cambridge University Press.

Gruber, M., Macmillan, I.C., & Thompson, J.D. (2008). Look before you leap: Market opportunity identification in emerging technology firms. *Management Science*, *54*(9), 1652–1665.

Haber, S. & Reicheil, A. (2007). The cumulative nature of the entrepreneurial process: The contribution of human capital, planning, and environment resources to small venture performance. *Journal of Business Venturing*, *22*(1), 119–145.

Hamilton, B.H. (2000). Does entrepreneurship pay? An empirical analysis of the returns to self-employment. *Journal of Political Economy*, *108*, 604–631.

Harvey, M. & Evans, R. (1995). Strategic windows in the entrepreneurial process. *Journal of Business Venturing*, *10*(5), 331–347.

Hayek, F. (1945). The use of knowledge in society. *American Economic Review*, *35*, 519–530.

Hayes, C. (1994). The freshman class of '94. *Black Enterprise*, *24*(11), 132–135.

Heinonen, J. & Poikkijoki, S.A. (2006). An entrepreneurial-directed approach to entrepreneurship education: Mission impossible? *Journal of Management Development*, *25*(1), 80–94.

Hoetker, G. (2007). The use of logit and probit models in strategic management research: Critical issues. *Strategic Management Journal*, *28*, 331–343.

Horn, J.L. & Cattell, R.B. (1967). Age differences in fluid and crystallized intelligence. *Acta Psychologica*, *26*, 107–129.

Hsieh, C., Parker, S.C., & Van Praag, M. (2012). Risk, balanced skills, and entrepreneurship. *Academy of Management Best Paper Proceedings*.

Iannello, P., Antonietti, A., & Betsch, C. (2011). Intuition in teaching. In M. Sinclair (Ed.), *Handbook of intuition research* (pp. 168–182). Cheltenham, U.K.: Edward Elgar.

Kacperczyk, A.J. (2013). Social influence and entrepreneurship: The effect of university peers on entrepreneurial entry. *Organization Science*, *24*(3), 664–683.

Kaufman, R.L. (1996). Comparing effects in dichotomous logistic regression: A variety of standardized coefficients. *Social Science Research*, *77*, 90–109.

Kihlstrom, R.E. & Laffont, J. (1979). A general equilibrium entrepreneurial theory of firm formation based on risk aversion. *Journal of Political Economy*, *87*, 719–748.

King, P.M., Wood, P.K., & Mines, R.A. (1990). Critical thinking among college and graduate students. *The Review of Higher Education*, *13*(2), 167–186.

Kitchener, K.S. & King, P.M. (1990). The reflective judgement model: Ten years of research. In M. L. Commons, C. Armon, L. Kohlberg, F. A. Richards, T. A. Grotzer, & J. D. Sinnott (Eds.), *Adult development, Vol. 2: Models and methods in the study of adolescent and adult thought* (pp. 63–78). New York: Praeger Publishers.

Klein, J.T. (2004). Prospects for transdisciplinarity. *Future*, *36*(4), 515–526.

Kolb, D. (1984). *Experiential learning: Experience as the source of learning and development*. Englewood Cliffs, NJ: Prentice Hall.

Lazear, E. (2005). Entrepreneurship. *Journal of Labor Economics*, *23*, 649–680.

Lechmann, D.S.J. & Schnabel, C. (2014). Are the self-employed really jacks-of-all-trades? Testing the assumptions and implications of Lazear's theory of entrepreneurship with German data. *Small Business Economics*, *42*, 59–76.

Lepak, D.P. & Snell, S.A. (1999). The human resource architecture: Toward a theory of human capital allocation and development. *Academy of Management Review*, *24*, 31–48.

Levesque, M. & Minniti, M. (2006). The effect of aging on entrepreneurial behavior. *Journal of Business Venturing*, *21*(2), 177–194.

Loewenstein, J. & Gentner, D. (2001). Spatial mapping in preschoolers: Close comparisons facilitate far mappings. *Journal of Cognition and Development*, *2*(2), 189–219.

Long, J. (1997). *Modeling frequency and count data*. Oxford: Oxford University Press.

Mayer, R. (2000). Intelligence and education. In R. J. Sternberg (Ed.), *Handbook of intelligence* (pp. 519–533). Cambridge: Cambridge University Press.

Messick, S. (1984). The nature of cognitive styles: Problems and promise in educational practice. *Educational Psychologist*, *19*, 59–74.

Murphy, G.L. & Medin, D.L. (1985). The role of theories in conceptual coherence. *Psychological Review*, *92*(3), 289–316.

Namy, L.L., Smith, L.B., & Gershkoff-Stowe, L. (1997). Young children's discovery of spatial classification. *Cognitive Development*, *12*, 163–184.

Naylor, J.C. & Briggs, G.E. (1963). Effects of task complexity and task organization on the relative efficiency of part and whole training methods. *Journal of Experimental Psychology*, *65*(3), 217–224.

Norton, E.C., Wang, H., & Ai, C. (2004). Computing interaction effects and standard errors in logit and probit models. *The Stata Journal*, *4*(2), 154–167.

Pask, G. & Scott, B.C.E. (1972). Learning strategies and individual competence. *International Journal for Man-Machine Studies*, *4*, 217–253.

Ray, D. (1990). Liberal arts for entrepreneurs. *Entrepreneurship Theory and Practice*, *15*(2), 79–93.

Riding, R.J. & Sadler-Smith, E. (1997). Cognitive style and learning strategies: Some implications for training design. *International Journal of Training and Development*, *1*(3), 199–208.

Rosch, E. & Mervis, C.B. (1975). Family resemblances: Studies in the internal structure of categories. *Cognitive Psychology*, *7*, 573–605.

Schmitt-Rodermund, E. (2004). Pathways to successful entrepreneurship: Parenting, personality, early entrepreneurial competence, and interests. *Journal of Vocational Behavior*, *65*, 498–518.

Seidel, L. & England, E. (1999). Gregorc's cognitive styles: College students' preferences for teaching methods and testing techniques. *Perceptual and Motor Skills*, *88*(3), 859–875.

Shane, S. (2000). Prior knowledge and the discovery of entrepreneurial opportunities. *Organization Science*, *11*(4), 448–469.

Shane, S. (2003). *A general theory of entrepreneurship*. Cheltenham, U.K.: Edward Elgar.

Silva, O. (2007). The jack-of-all-trades entrepreneur: Innate talent or acquired skill? *Economics Letters*, *97*, 118–123.

Son, J.Y., Smith, L.B., & Goldstone, R.L. (2011). Connecting instances to promote children's relational reasoning. *Journal of Experimental Child Psychology*, *108*(2), 260–277.

Sorenson, J.B. & Fassiotto, M.A. (2011). Organizations as fonts of entrepreneurship. *Organization Science*, *22*(5), 1322–1331.

Souitaris, V., Zerbinati, S., & Al-Laham, A. (2007). Do entrepreneurship programmes raise entrepreneurial intention of science and engineering students? The effect of learning, inspiration and resources. *Journal of Business Venturing*, *22*(4), 566–591.

Spector, P.E. & Brannick, M.T. (2011). Methodological urban legends: The misuse of statistical control variables. *Organizational Research Methods*, *14*, 287–305.

Spelt, E.J.H., Biemans, H.J.A., Tobi, H., Luning, P.A., & Mulder, M. (2009). Teaching and learning in interdisciplinary higher education: A systematic review. *Educational Psychology Review*, *21*(4), 365–378.

Stepien, W., Gallagher, S., & Workman, D. (1993). Problem-based learning for traditional and interdisciplinary classrooms. *Journal for the Education of the Gifted*, *16*, 338–357.

Summers, B., Williamson, T., & Read, D. (2004). Does method of acquisition affect the quality of expert judgment? A comparison of education with on-the-job learning. *Journal of Occupational and Organizational Psychology*, *77*, 237–258.

Sweller, J. (1994). Cognitive load theory, learning difficulty, and instructional design. *Learning and Instruction*, *4*, 295–312.

Sze, J. (2002). You can't keep a good man down. *Malaysian Business*, *58*.

Thorndike, E. (1932). *The fundamentals of learning*. New York: Teachers College Press.

Thurik, A.R., Carree, M.A., Van Stel, A.J., & Audretsch, D.B. (2008). Does self-employment reduce unemployment? *Journal of Business Venturing*, *23*, 673–686.

Wagner, J. (2006). Are nascent entrepreneurs "jacks-of-all-trades"? A test of Lazear's theory of entrepreneurship with German data. *Applied Economics*, *38*, 2415–2419.

Walsh, J.P. (1995). Managerial and organizational cognition: Notes from a trip down memory lane. *Organization Science*, *6*(3), 280–321.

Ward, T.B. (2004). Cognition, creativity, and entrepreneurship. *Journal of Business Venturing*, *19*(2), 173–188.

Wenke, D., Frensch, P.A., & Funke, J. (2005). Complex problem solving and intelligence: Empirical relation and causal direction. In R. J. Sternberg & J. E. Pretz (Eds.), *Cognition & intelligence: Identifying the mechanisms of the mind*. Cambridge: Cambridge University Press.

Williams, C.C. & Nadin, S. (2010). Entrepreneurship and the informal economy: An overview. *Journal of Developmental Entrepreneurship*, *15*(4), 361–378.

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