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Creative Productivity: A Predictive and Explanatory Model of Career Trajectories and Landmarks

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The author developed a model that explains and predicts both longitudinal and cross-sectional variation in the output of major and minor creative products. The model first yields a mathematical equation that accounts for the empirical age curves, including contrasts across creative domains in the expected career trajectories. The model is then extended to account for individual differences in career trajectories, such as the longitudinal stability of cross-sectional variation and the differential placement of career landmarks (the ages at first, best, and last contribution). The theory is parsimonious in that it requires only two individual-difference parameters (initial creative potential and age at career onset) and two information-processing parameters (ideation and elaboration rates), plus a single principle (the equal-odds rule), to derive several precise predictions that cannot be generated by any alternative theory.

Albert Einstein had around 248 publications to his credit, Charles Darwin had 119, and Sigmund Freud had 330, while Thomas Edison held 1,093 patents—still the record granted to any one person by the U.S. Patent Office. Similarly, Pablo Picasso executed more than 20,000 paintings, drawings, and pieces of sculpture, while Johann Sebastian Bach composed over 1,000 works, enough to require a lifetime of 40-hr weeks for a copyist just to write out the parts by hand. One might conclude from facts like these that exceptional productivity is a hallmark of outstanding creative individuals. And yet this induction may be contradicted by some curious exceptions and complications. Gregor Mendel managed to secure an enduring reputation on the basis of only seven scientific papers—considerably less than the 883 items claimed by the far more obscure naturalist John Edward Gray. Also, not all of the products that emerge from illustrious creators contribute credit to their names. Ludwig van Beethoven produced many compositions that only embarrass his admirers, just as William Shakespeare could write "problem plays" that are rarely performed today. Even Edison invented useless contraptions: The developmental costs for one failed device alone equaled all the profits he had earned from the electric light bulb!

Now turn to another facet of the phenomenon: how creative productivity is distributed across the life span. Wolfgang Goethe began writing poetry in his teens, wrote a best-selling novel in his mid-20s, composed a series of successful plays in his 30s and 40s, and completed Parts I and II of *Faust* at ages 59 and 83, respectively. Hence, perhaps creators have careers characterized by precocity and longevity. Not all creative individuals show this pattern, however. On the one hand, some creators may exhibit comparable precocious achievement only to burn out early. Pietro Mascagni became famous at age 26 with the production of his opera *Cavallieria Rusticana*, but his career thereafter underwent a precipitous decline. On the other hand, Anton Bruckner typifies the "late bloomer." He did not discover his mission as a symphonic composer until he was 39 years old and so produced his first genuine masterwork at age 50. He was still working on his last great symphony when death ended his labors at age 70.

These specific instances all suggest that creative careers are almost infinitely varied. There seem to be no secure regularities that describe how creative productivity varies across individuals or how it fluctuates within the life of a single individual. Nevertheless, this impression is quite mistaken. Behavioral scientists have been conducting empirical inquiries into this matter ever since Adolphe Quetelet's (1835/1968) pioneering work in 1835. The accumulated body of evidence shows that certain consistent relationships underlie what superficially appears to be a prohibitively complex phenomenon (Simonton, 1984b, 1988a). Indeed, the empirical data have inspired several behavioral scientists to propose theoretical explanations for the published observations. Some of these accounts focus on individual differences in creative productivity (e.g., Eysenck, 1995; Price, 1976; Shockley, 1957; Simon, 1955), whereas other interpretations concentrate on how creative productivity varies across the life span (e.g., Alpaugh & Birren, 1977; Beard, 1874; Cole, 1979; Diamond, 1984; Lehman, 1953; McCrae, Arenberg, & Costa, 1987). A few behavioral scientists have even offered explanations that simultaneously treat both cross-sectional and longitudinal variation (e.g., Allison, 1980; Allison, Long, & Krauze, 1982; Allison & Stewart, 1974).

For the past two decades I have been conducting empirical research on how creative productivity varies across and within careers. Furthermore, for most of this period I have been developing an integrative model that would explain the most robust empirical findings. The current article continues this long-term program by (a) reformulating, elaborating, and extending the proposed theoretical model so that its scientific utility becomes even more apparent and (b) providing new data analyses that

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lend even stronger empirical support to the theory. I begin with an overview of the broad theoretical framework that guides the model building. I then develop this perspective into two submodels, one covering longitudinal changes in output, the other treating cross-sectional variation in creative careers.

The General Theoretical Framework

I posit that the creative process is essentially Darwinian. That is, creativity entails some variation-selection process (or set of such processes) that generates and winnows out numerous conceptual combinations. Many notable psychologists have proposed that just such a process underlies creativity, including William James (1880), Donald Campbell (1960), and B. F. Skinner (1972; see also Epstein, 1990, 1991). In Campbell's (1960) "blind variation and selective retention" model, for instance, the creative intellect spontaneously constructs ideational combinations in a more or less unpredictable manner; a small proportion of these combinations is then selected for further elaboration and retention. Campbell showed that this Darwinian model was consistent with the introspective reports of creative individuals, such as those of the eminent French mathematician Poincaré (1921). Furthermore, this model is compatible with other Darwinian systems, like evolutionary epistemology and certain theories of sociocultural evolution (Campbell, 1965, 1974; Toulmin, 1972).

More importantly, others have elaborated Campbell's (1960) variation-selection model of creativity. I have developed this model into the "chance-configuration theory of creativity," with a special focus on scientific genius (Simonton, 1988b, 1988d, 1989b, 1993b, 1995b). This chance-configuration theory can account for several key aspects of scientific creativity, such as the phenomenon of multiple discovery and invention (Simonton, 1979, 1987b). Kantorovich (1993) has added several improvements to this theory, especially by extending it to the output of scientific communities (cf. Simonton, 1994b) and by documenting the crucial role played by serendipitous discoveries (see also Kantorovich & Ne'eman, 1989). Eysenck (1993, 1994, 1995) has connected the "Campbell–Simonton" model of creativity with a much broader theory of the creative personality that incorporates both experimental and correlational data (cf. Simonton, 1993a). Martindale (1990, 1994) has pushed the Darwinian perspective in a different direction by using it as a foundation for his evolutionary theory of stylistic change in the arts. The Darwinian framework has even inspired the development of computer programs that can emulate the creative process through "genetic algorithms" and "genetic programming" (Goldberg, 1989; Koza, 1992). These and related elaborations promise to help make variation-selection theory one of the most comprehensive and precise frameworks for understanding creative behavior in all of its complexity.

At present, however, I do not have to review these developments. Instead, I need only to lay down two assumptions that provide the basis for the model construction that follows:

1. The variation process is to some significant degree blind or haphazard. This means that at some crucial level the individual has no a priori way of foreseeing which ideational combinations will prove most fruitful (Simonton, 1995b). As a consequence, useful and useless variations are more or less randomly distributed both (a) across individual creators and (b) within individual careers. This is not tantamount to the claim that the creator does not employ some criteria or heuristics to restrict the initial range of the search (Simonton, in press-b). Nevertheless, for significant acts of creativity, a point is reached where the creator has minimal guidance from logic or past experience and thus must rely on an effectively nondirected search for new ideational variations among the population of relevant concepts (see also Stein & Lipton, 1989).[1] Indeed, a portion of this search may sometimes entail a quest for the most suitable heuristics that might narrow the scope of the problem.

2. This variation-selection process operates at multiple levels (Simonton, 1993b). At the intrapersonal or cognitive level, the creative mind is actively engaged in producing the ideational variations that can be selected, developed, published, exhibited, or otherwise disseminated according to the accepted procedures of a given creative enterprise. This product then becomes an entity that constitutes a disciplinary variation that must compete with other published variations coming from other creative minds. An article submitted to a technical journal or a poem submitted to a literary magazine is subjected to selection along with dozens if not hundreds of products of the same genre submitted by authors with comparable aspirations. Of the total submissions, only a subset survives the selection process operating at this interpersonal level. Nor does the selection process end here, but rather it shifts to even higher levels. Not all scientific articles have an impact on other scientists, as judged by citation indices or other criteria. Similarly, not all poems that appear in literary periodicals show up in anthologies that ensure a more lasting readership. Often only a tiny fraction of the total published products manage to run this gauntlet successfully among contemporaries, and fewer still survive for the consumption of posterity. These sociocultural levels are the most selective of all.

The second assumption is related to the first. Because the selection processes function at so many different levels, the variation procedure that happens at the cognitive level must be necessarily blind to the ultimate reception of any given conceptual combination. Even if a creator has a sound notion about what kind of product is most likely to get published or performed, he or she must be less confident about the long-term impact of that offering. As values shift, novel technologies emerge, or new facts appear—what was once a success may later become a failure, and what was once ignored may later become belatedly acclaimed. In the long run, creators must lack foresight regarding the sociocultural merits of their ideas. If it were otherwise, we would have to consider creators a special class of prophets.

The Longitudinal Submodel

Creative Productivity as a Function of Career Age

Suppose that each creative individual begins with a large set of concepts, ideas, images, techniques, or other cognitions that

[1] In making this assumption I am not denying the possibility of stylistic or content changes over the life span (see Arnheim, 1986; Lindauer, 1993a; Simonton, 1980b, 1983, 1989a) but only that the combinations are foresightful in any fashion. Any particular change in style or content may or may not constitute a good idea.

can be subjected to free variation. Of all the possible ideational combinations, only a subset exhibits enough promise to warrant additional development. Those ideational combinations thus selected then fill up the creator's sketchbooks, notebooks, or lab books. With sufficient time, these initial ideas can then be worked up into finished products and offered to the world. As some ideas are published, new ones are added to the inventory of works in progress. And so the process runs year after year throughout the career. If the creator is truly prolific, this twofold procedure of ideation and elaboration does not end until the person's death or incapacity.

To specify this process more formally, let N signify the total number of ideational combinations a creator is capable of conceiving in an unlimited life span.[2] However, only some very small fraction of this total count is perceived as publishable and thus worthy of selection for further elaboration. So, let m symbolize this smaller quantity (i.e., $m = sN$, where $0 < s < 1$). The quantity m is called the *initial creative potential* (Simonton, 1984a). This potential is transformed into actual products by a two-step process. First, workable ideas are obtained through some combinatory mechanism. Second, these ideas are developed into finished products. That implies that at any given time, t, the total quantity of potential ideas represented by m can be partitioned into three parts: (a) the amount of creative potential remaining, (b) the number of ideas that have already emerged that still await further development, and (c) the number of ideas that have become completed products. If these three variables are labeled as x, y, and z, respectively, the identity $m = x + y + z$ is obtained. Thus, at the onset of the career, at $t = 0$, $m = x$ and $y = z = 0$. But with each consecutive year ($t = 1, 2, 3$, etc.), the remaining potential x decreases while the number of ideational products z increases (whereas the intermediate quantity y first increases then decreases). I have thus introduced the assumption that the changes in x, y, and z are not a function of chronological age, but rather of *career age* (Simonton, 1984a, 1988a). Although career age correlates very highly with chronological age, the correlation is by no means perfect (Bayer & Dutton, 1977; Stephan & Levin, 1992). Furthermore, the distinction eventually has critical empirical and theoretical repercussions.

I now must describe how these changes take place over the course of the career. Let me first postulate that the rate at which creative potential is used up is directly proportional to the amount of creative potential that still remains. This assumption is analogous to the law of mass action in chemistry. Using the notation of calculus, I am assuming that $dx/dt = -ax$, where a is a proportionality constant ($0 < a < 1$). The negative sign simply indicates that the remaining creative potential is decreasing. This parameter is termed the *ideation rate.* At the output end of the two-step creative process, I make a parallel assumption, namely that the rate at which finished products emerge is directly proportional to the number of ideations still waiting development. For example, the more ideas that exist in the notebooks, the more projects can be going on simultaneously, and the more cross-talk across ideas, thereby stimulating a higher publication rate (see, e.g., Gruber, 1989; Hargens, 1978; Root-Bernstein, Bernstein, & Garnier, 1993). Accordingly, I can express this assumption as $dz/dt = by$, where b is another nonnegative proportionality constant that I shall term the *elaboration rate* ($0 < b < 1$). All that is left to do is to state how the intermediate quantity of the ideations, y, changes over time. The answer is simply the difference between the rate at which ideas are being added to the notebooks or sketchbooks and the rate at which ideas are becoming completed contributions, or $dy/dt = ax - by$.

I have just obtained a system of three first-order linear differential equations. With a few mathematical substitutions and manipulations, these equations can be converted into a single second-order differential equation (see Simonton, 1984a, for details). The solution to the later equation expresses z as a function of t. However, this equation is less interesting that its first derivative, which tells how the productivity rate changes as a function of t. In other words, what is sought is $dz/dt = p(t)$, or the number of products appearing in year t. The resulting equation is then $p(t) = c(e^{-at} - e^{-bt})$, where $c = abm/(b - a)$ and e is the exponential constant (2.718 . . .). A little algebra shows that this equation makes no assumptions about the relative sizes of the ideation and elaboration rates except to posit that they are not exactly equal. In the rare instance that $a = b$, the solution is modified only slightly, and with no theoretical consequences whatsoever. Specifically, $p(t) = a^2mte^{-at}$, with all the parameters defined the same as before (Simonton, 1988a).

Figure 1 shows the age curve predicted by this equation under a typical set of parameters ($a = .04$, $b = .05$, and $m = 305$). In addition, I have assumed that career age $t = 0$ at chronological age 20, meaning that this curve represents the trajectory of annual output for an individual who began the combinatory process at age 20. There are three features of this theoretical curve that must be stressed at once. First, it clearly indicates a single-peak function, the optimum appearing where $dp/dt = 0$. Specifically, this peak occurs at $t = (b - a)^{-1} \ln (b/a)$, or at about career age 22 in the present example. Second, the ascent to the point of maximum output is described by a concave downward (or decelerating) curve. Third, after a certain point the post-peak curve becomes concave upward and approaches the zero-output rate asymptotically. This inflection point appears where $d^2p/dt^2 = 0$, that is, at $t = (b - a)^{-1} \ln (b^2/a^2)$, or twice the career age at which the productive peak appears (i.e., about career age 45 in Figure 1). How well does this curve fit the observed data?

Methodological considerations. At first glance, this should be an easy question to answer because the relationship between age and creative productivity constitutes one of the oldest research topics in the behavioral sciences (Simonton, 1988a). The first empirical investigation was published by Quetelet (1835/1968), and a second systematic study appeared four decades

[2] Most of the core concepts, derivations, and findings in the section on the longitudinal submodel come from Simonton (1984a, 1988a, 1989a, 1991a). However, many new theoretical and empirical developments are also added here for the first time. Moreover, the longitudinal model has been reformulated in such as way as to change the meaning of Figures 1, 3, and 5 in the original publications. Where previously the vertical axis was said to refer to the output of products, it now indicates the production of ideas. This modification makes the differential equations more realistic and has the additional asset of permitting the introduction of the important concept of the least publishable unit as the link between molecular and molar acts of creativity.

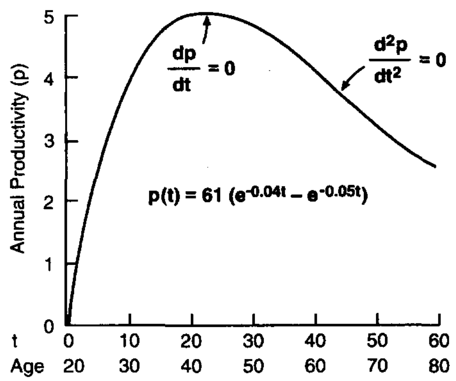

Figure 1. The predicted relation between career age, t, and annual production of creative ideas, $p(t)$, according to the longitudinal model, where e is the exponential constant, the ideation rate $a = .04$, the elaboration rate $b = .05$, and the initial creative potential $m = 305$, and hence $c = 61 = (.04)(.05)(305)/(.05 - .04)$. The relation is expressed as a function of career age t, where the career onset $t = 0$ occurs at age 20. The peak occurs where the first derivative $dp/dt = 0$ and the inflection point where the second derivative $d^2p/dt^2 = 0$. (Adapted from "Creative Productivity and Age: A Mathematical Model Based on a Two-Step Cognitive Process," by D. K. Simonton, 1984, *Developmental Review, 4,* p. 86. Copyright 1984 by the Academic Press. Adapted with permission.

later (Beard, 1874). Moreover, in the 20th century several psychologists devoted considerable attention to this issue, most notably Lehman (1953, 1962) and Dennis (1966). Nevertheless, before these data can be exploited, two main issues have to be addressed, one concerning measurement and the other statistical analysis.

1. In a strict sense, the equation that produced Figure 1 relates to only the generation of original combinations of ideas. Hence, to test the theory the number of ideational variations produced each consecutive period of a creator's career should be counted. In practice, this is rarely done. The only conceivable examples in the published literature are studies that counted the number or impact of melodies produced at different ages by classical composers (Simonton, 1977a, 1977b, 1980b, 1989d, 1991b). A single melody is a unit that can be said to be roughly equivalent to an individual ideational variation. Nonetheless, the overwhelming majority of investigations published since 1835 tabulate larger units, such as paintings, plays, patents, or publications. These units clearly contain multiple ideas rather than just one. In classical music, for example, a large form such as the symphony not only contains many different melodies, but in addition it may include new ideas regarding harmony, counterpoint, orchestration, formal structure, and a host of other attributes (Simonton, 1986a, 1995a). Accordingly, when the number of creative products per age period is tallied, clusters of ideational combinations are actually counted. Even so, this complication need not render empirical tests impossible so long as researchers are willing to make the following measurement assumption: For any given genre the number of original ideas composing a creative product does not change systematically with age.[3] For example, if researchers are counting scientific journal articles, they assume that each constitutes roughly the same unit of cognitive investment in terms of the number of ideational combinations contained. Under this assumption, the theoretical equation remains unaltered, except that instead of interpreting m as a measure of the total number of creative ideas an individual is capable of conceiving, m now represents the total number of creative products, say M, where $M = qm$ ($0 < q < 1$). All of the predictions generated by the theoretical model, both in its longitudinal and cross-sectional forms, will survive unscathed. In particular, if M is substituted for m in the theoretical equation, only the overall amplitude of the curve is reduced by the decimal fraction q. The general shape of the curve, including the specific location of the peak and the inflection point, is totally unaffected by this methodological adjustment.

Admittedly, sometimes an empirical inquiry may gauge productivity by contributions that include a great diversity of genres, where each genre has its own characteristic level of ideational richness. In classical music, for example, an opera probably contains more original ideas than a symphony, and a symphony more than a song. Fortunately, this does not cause any concern so long as the products tabulated are weighted appropriately (Simonton, 1990c). The main object of any weighting scheme is simply to make the tabulations conform to the amount of creative thought that actually went into each product (see, e.g., Eagly, 1974; Simonton, 1977a).

2. For this research domain, the matter of data analysis is much more complex than that of measurement. This is an area in the behavioral sciences where methodological artifacts are legion. The most irksome of these potential problems is the so-called *compositional fallacy* (Simonton, 1988a). This artifact is a variety of aggregation error that can arise whenever researchers try to make inferences about the typical age curves for individuals based on statistics that are averaged across many individuals. In particular, when researchers estimate the average productivity rates per time period across several careers, they may obtain a summary curve that does not accurately describe the career trajectories for any of the individuals that make up the sample. For example, suppose that the true age curve shows little or no post-peak decline. Researchers then collect a random sample of creative individuals and measure the number of products that emerged in consecutive age periods across all persons in the study. They likely discover that this aggregated curve exhibits an age decrement in productivity—notwithstanding the hypothesized lack of such a decline in any of the individuals composing the sample. This occurs because any random sample displays variation in life span. Because individuals who have died cannot possibly maintain their productivity, a progressive drop appears in the number of contributions that parallels the survival rate of the sampled individuals.

Naturally, this particular artifact is fairly easy to remedy. Quetelet (1835/1968) did so by making a simple arithmetic adjustment so that the productivity data were expressed on a per capita basis. Dennis (1966) overcame this problem by restricting the sample to creators who lived to become octogenarians. And I (Simonton 1977a) fit polynomial functions only for those periods in which my creators were actually alive.

[3] It is not necessary to assume that q stays constant across the life span if it is possible to posit that the secular trend is uncorrelated with the other parameters of the model.

Nonetheless, not all published analyses have taken these methodological precautions, which severely limit their utility for theory testing. Furthermore, some aggregation errors are not so readily corrected. May one illustration suffice.

According to the longitudinal model, creative productivity is a function of career age, not chronological age. Yet most of the published data performs the tabulations in terms of chronological age. That is, adulthood is subdivided into consecutive 10- or 5-year age intervals, and the number of contributions produced by the sample are then tallied into each period. This can easily produce a curve that contradicts the theoretical expectation portrayed in Figure 1 even when this same curve describes each individual's career trajectory perfectly. This artifact emerges because creators will vary in the age at which they launched their careers. It can be presumed, quite plausibly, that the age at which individuals begin their creative ruminations is normally distributed in the population of creators (Simonton, 1991b). If so, then the prepeak portion of the aggregated curve is concave upward rather than concave downward (Simonton, 1984a). This unfortunate result can only be fixed by tabulating the data according to career rather than chronological age (e.g., Lyons, 1968; Simonton, 1977a, 1984a).

Of course, one might wonder why researchers cannot avoid this compositional fallacy altogether by fitting the age curves to individual-level data. Although this is sometimes done (e.g., Simonton, 1980b, 1983, 1986b), this strategy is not optimal from a scientific perspective. The reason is the same as why most behavioral scientists do not test their hypotheses against single cases. Individual differences are always substantial. Researchers thus always need to identify relationships that transcend any personal idiosyncrasies. This desideratum is especially urgent in the case of longitudinal counts of productive output per consecutive age periods. There are dozens of external events that impinge on individuals during the course of their careers that serve to enhance or depress the level of output in a given year or decade. A partial list must include the birth of children (Hargens, McCann, & Reskin, 1978; McDowell, 1982), physical illness (Lehman, 1953; Simonton, 1977a), the proximity of death (Simonton, 1989d), administrative responsibilities (Garvey & Tomita, 1972; Horner, Murray, & Rushton, 1994; Roe, 1965, 1972), professional affiliations (Allison & Long, 1990; Blackburn, Behymer, & Hall, 1978; Simonton, 1992c), academic tenure (Bridgwater, Walsh, & Walkenbach, 1982), economic fluctuations (Schmookler, 1966), and military conflicts (Simonton, 1980a). To cope with these intrusive events and circumstances, the investigator can introduce appropriate statistical controls (see, e.g., Simonton, 1977a, 1985, 1986b). Unfortunately, this is not always possible for all relevant factors. Therefore, the researcher must assume that many of these influential conditions are randomly distributed across the life span, and hence averaging across many separate careers will yield a summary curve in which all the random factors have canceled out (Simonton, 1988a). In other words, if due provision is made for the compositional fallacy, the aggregate curves can be more reliable indicators of longitudinal trends than is any individual curve. It is especially important to aggregate the curves across many different cohorts in order to accommodate the impact of such big events as war (e.g., Simonton, 1977a, 1985). Individuals born at different times will have such external events fall on different points in their lives and thereby permit these intrusions to cancel out in any sample heterogeneous on year of birth.

It may seem that I have devoted a lot of space to methodological issues for an article that purports to present a theoretical model. Nevertheless, I am not able to discern the relative merits of alternative theories without close attention to these matters. Often rival explanations make very similar predictions concerning most aspects of a behavioral phenomenon, such that their comparative empirical plausibility can only be settled by attending closely to certain critical areas in which the alternative accounts make divergent predictions. Yet if those critical areas are subject to methodological artifacts, the desired critical tests may prove impossible to carry out.

Empirical comparisons. Ever since Quetelet (1835/1968), researchers have published age curves that look very similar to that depicted in Figure 1. In general, productivity starts somewhere in the 20s, reaches a peak somewhere in the late 30s or early 40s, and then undergoes a steady decline that often approaches the horizontal axis asymptotically (Simonton, 1988a). Although few researchers have actually tried to fit mathematical curves to their data, it is usually evident that an overall age trend accounts for a significant percentage of variance in the aggregated data. For example, a second- or third-order polynomial in age usually explains a substantial proportion of the total longitudinal variation (Simonton, 1988a). More importantly, when the published data have been directly compared to the productivity levels predicted by the current model, the outcome is always supportive. For instance, when theoretical predictions have been directly compared against data sets reported in Lehman (1953), Dennis (1966), and Zuckerman (1977), Pearson product–moment correlations are obtained that usually fall in the upper 90s, with a range of .820 to .999 and with a median correlation of .967 (Simonton, 1984a).

The theory-based curve gets not only the overall trend right, but the specific details besides (Simonton, 1988a). For example, the onset of the age curve does indeed seem to be concave downward once appropriate provision is made for possible artifacts (Simonton, 1984a). Likewise, in samples of long-lived creators, the terminal phase of the career is indeed described by a concave upward slope (provided that the creators are active in disciplines with sufficiently early peaks; Simonton, 1984a; see also Lehman, 1960). The theoretical trajectory is also justified in predicting a single-peaked function (Simonton, 1984a, 1989a). To be sure, several investigators have purported to find double-peaked functions, whether two roughly equal maxima around midcareer (e.g., Pelz & Andrews, 1966; Stern, 1978) or a main peak with a subsidiary peak toward the close of the career (e.g., Robert A. Davis, 1953; Haefele, 1962). However, further scrutiny undermines any claims of double-peak functions. The reasons are twofold:

1. Frequently the bimodal age distributions are direct repercussions of the compositional fallacy. As I show later, different creative disciplines exhibit distinct age functions. If two fields with peaks at very distinct locations are aggregated into a single longitudinal tabulation, a two-peaked summary curve will result as an artifact. For instance, counts of mathematical productivity have shown that applied mathematicians may normally peak later in their careers than do pure mathematicians (Simonton, 1988a). Aggregating them together into a single tabulation has

then suggested a double-peak function in the aggregate that does not reflect the career trajectories that characterize each subdiscipline (e.g., Cole, 1979; Dennis, 1966; Stern, 1978).

2. Tabulations that exhibit double-peaked curves are the exception rather than the rule, and even in those data that apparently display bimodal curves, the case is never strong. Specifically, the actual magnitude of the supposed dip is negligible relative to the total longitudinal variation. This conclusion is empirically demonstrated by fitting the fourth-order polynomial time function that is necessary to provide for two maxima (e.g., Bayer & Dutton, 1977). Tests conducted thus far on longitudinal data have never found that the fourth-order polynomial adds a significant increment to the amount of variance accounted for by a second- or third-order polynomial (Simonton, 1977a, 1984a, 1988a).[4] In the absence of statistical tests proving otherwise, I have no basis for concluding that any theoretical model should accommodate two or more peaks in the age curve.

Before I turn to the matter of domain differences, it should be pointed out that the longitudinal model can successfully predict the age curves for individuals. For example, the correlation is .87 between the predicted and observed number of patents put out by Thomas Edison in each career decade (Simonton, 1989a). When I consider all the external events and circumstances that probably intruded on Edison's output, this degree of correspondence is quite respectable. Yet it remains true that the agreement between observed and predicted output rate is almost invariably higher for aggregated than for individual data.

Interdisciplinary Contrasts

It was noted earlier that the expected career trajectories depend on the specific creative activity under consideration. Something of the range in possibilities may be discerned in Figure 2, which is based on data published in Dennis (1966). The age curves can vary according to the slope of the ascent, the location

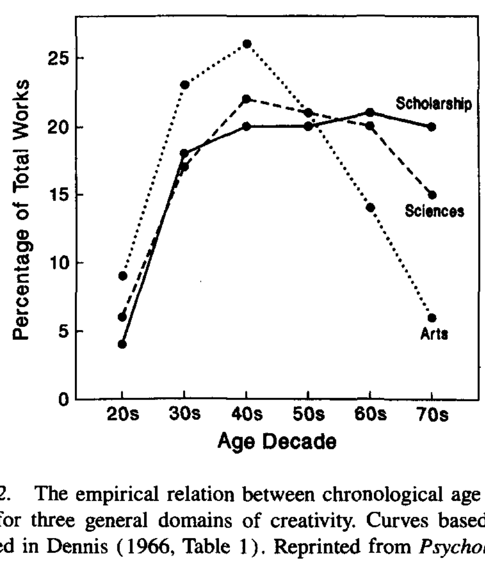

Figure 2. The empirical relation between chronological age and total output for three general domains of creativity. Curves based on data published in Dennis (1966, Table 1). Reprinted from *Psychology, Science, and History: An Introduction to Historiometry* (p. 120) by D. K. Simonton, 1990, New Haven, CT: Yale University Press. Copyright 1990 by the Yale University Press. Reprinted with permission.

of the productive peak, and the rate of the postpeak decline. In addition, these interdisciplinary contrasts in how creative output fluctuates across the career have been demonstrated in study after study, producing some of the most secure findings in the behavioral sciences (e.g., Dennis, 1966; Lehman, 1953, 1965). The contrasts among the diverse scientific disciplines are especially well documented (e.g., Adams, 1946; Diamond, 1986; Manniche & Falk, 1957; Moulin, 1955; Simonton, 1989a, 1991a; Stephan & Levin, 1992, 1993; Visher, 1947).

Fortunately, this tremendous variation is easily accommodated by the theoretical model. The shape of the predicted curve is not fixed, but rather it is dependent on the ideation and elaboration rates (i.e., a and b). In fact, whenever the theoretical curve is tested against longitudinal data, the ideation and elaboration rates are always considered free parameters (Simonton, 1984a, 1989a). Only in this way can the strong concordance between predicted and observed scores be obtained. Any "one-size-fits-all" age curve can be rejected on empirical grounds (Simonton, 1988a). Of course, in one sense the model's capacity to handle these contrasts is not a very impressive achievement. Polynomial age functions can do the same job about as well and with around the same number of free parameters. That is, a regression equation of the form $p(t) = B_0 + B_1 t + B_2 t^2 + B_3 t^3$ can be estimated, where the Bs are unstandardized regression coefficients and $B_0 = 0$ if t is measured in career age (Simonton, 1977a, 1988a, 1989b). Even so, the present model has two advantages over simply fitting polynomial trends.

First, polynomials are empirically awkward in that they usually provide unrealistic forecasts (a) when the predicted output is based on values of the independent variable that lie outside the range of the scores on which the parameters were estimated or (b) when most of the cases fall within a relatively narrow range on that independent variable. For example, it is not uncommon for second-order polynomials to predict negative output rates for octogenarians (who are too small in number to have a significant influence on the estimated parameters). Even worse, third-order polynomials usually predict that creators who live long enough eventually see their productivity explosively increase to impossible heights! This theoretical nonsense is avoided in the current equation where $p(t)$ always yields reasonable positive values and eventually descends to zero, even if career age approaches infinity.

Second, and most critically, only the estimated parameters of the present longitudinal model can claim to have psychological meaning. Unlike the regression coefficients for linear, quadratic, and cubic terms for a third-order polynomial, which lack substantive interpretations, the ideation and elaboration rates have theoretical content. Where a tells how fast ideational combinations are first emerging during the creative process, b tells how fast those combinations are then elaborated into presentable ideas. Therefore, when the theoretical curve is fit to actual data from diverse domains of creativity, parameter estimates should be obtained that are compatible with the nature of the concepts characterizing the field. It is for this reason, indeed, that a and

[4] The only unambiguous instances of fourth-order polynomial age functions involved cross-sectional rather than longitudinal data, which confound age effects with cohort effects (e.g., Bayer & Dutton, 1977; Blackburn et al., 1978).

b are termed "information-processing parameters" (Simonton, 1989a).

To illustrate, Dennis (1966) not only published tabulations for the broad domains of science, arts, and scholarship, as graphed in Figure 2, but also published the tabulations for subdomains within each of those areas. When a nonlinear estimation program is used to obtain the ideation and elaboration rates, intuitively plausible results are obtained (Simonton, 1989a). For instance, the typical career trajectory of poets implies estimates of a = .045 and b = .055, whereas that of novelists implies a = .034 and b = .040. In more concrete terms, the composition of poetry entails faster rates of ideation and elaboration than does novel writing. Similarly, where for mathematicians a = .032 and b = .044, the parameters for geologists are a = .026 and b = .034, suggesting that original ideas come slower and take longer to develop in the latter discipline. Both of these contrasts seem reasonable if the number and complexity of the concepts and techniques in the disciplines that have such divergent ideation and elaboration rates are compared (Simonton, 1989a).

It is important to recognize, however, that these two rates are independent of each other. Two disciplines may have identical ideation rates, but disparate elaboration rates, or vice versa. For example, judging from the productivity curves, the creative process in historians conforms to a = .018 and b = .034. Accordingly, historians apparently originate new ideational combinations about half as rapidly as do novelists, but take hardly longer to put those ideas in publishable form. In fact, when ideation and elaboration rates are correlated across 16 separate disciplines, the two parameters correlate only .097 (cf. Simonton, 1989a). Hence, a and b represent practically uncorrelated parameters.

It might appear at first that these differences may not amount to much. After all, researchers are invariably dealing with decimal fractions with zeroes in the first decimal space. Even so, tiny shifts in the parameters cause immense movements in the predicted peaks as well as in the magnitude of the postpeak declines. Something of this potential is illustrated in Figure 3, which shows how the theoretical curves change with only the smallest alterations of the ideation and elaboration rates. This point can be demonstrated more dramatically and empirically using the parameter estimates just given. In career-age equivalents, the peak productive periods fall in the following order: poets, 20.1; mathematicians, 26.5; novelists, 27.1; geologists, 34.8; and historians, 38.5 (Simonton, 1988a). An 18-year contrast between predicted peaks is by no means trivial.

Another way of demonstrating the implications of even small differences is to go back to the theoretical meaning of the ideation rate a, which in many respects represents the most important of these two information-processing parameters. This a indicates the speed at which the individual consumes the initial reservoir of creative potential (m). It can be easily shown that the reciprocal of the ideation rate multiplied by the natural logarithm of 2 gives the expected creative half-life of a particular creative domain. The half-life is the career age at which 50% of the initial creative potential already has been transformed into either works in progress or completed contributions (Simonton, 1984a, 1988a). Using the above parameter estimates, researchers can thus say that the half-life is 15.4 years for poets, 21.7 for mathematicians, 20.4 for novelists, 28.9 for geologists, and 39.7 for historians. Thus, it takes poets two fifths as long to exploit their creative potential as it does for historians.

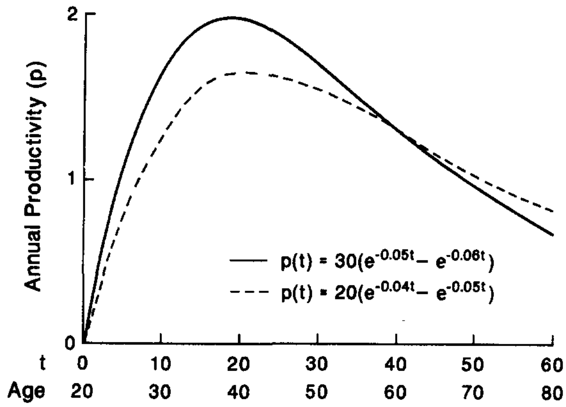

Figure 3. Predicted relation between the production of creative ideas, $p(t)$, and career age, t, for two disciplines that differ slightly in the rates of ideation (a) and elaboration (b), but with identical initial creative potential (m = 100) and age at career onset (t = 0 at age 20). As in Figure 1, e is the exponential constant. Reprinted from "Career Landmarks in Science: Individual Differences and Interdisciplinary Contrasts" by D. K. Simonton, 1991, *Developmental Psychology, 27,* p. 120. Copyright 1991 by the American Psychological Association.

This latter observation may help in appreciating why poets actually have shorter life spans than do other literary figures (Simonton, 1975). Because they burn themselves out so fast, relatively speaking, poets may die younger without leaving as much potential creativity "nipped in the bud." In contrast, novelists and historians who die unusually young will have seen far less of their potential creativity realized and thus may not yet have produced a sufficient quantity of outstanding work on which to hang a durable posthumous reputation. In making this statement I am not claiming that the faster information-processing rates causes poets to die young, but only that the short half-life permits them to die young while still having made sufficient impact on literature to attain distinction. The career trajectories for short- and long-lived poets will be the same, with early career peaks in both cases, but they will differ in where the curves are truncated in the postpeak career (see Lehman, 1953; Simonton, 1977a). This is analogous to the finding that precocious achievers within a single discipline tend to have lower life expectancies for a very simple reason: potential late bloomers who die before "blooming" will not even make it into samples of successful creators (see Simonton, 1977b; Zhao & Jiang, 1986). Notice that according to this explanation mathematicians should have shorter expected life spans than do geologists, given the contrast in their respective information-processing parameters. That is indeed the case (Simonton, 1991a).

The present theoretical model is the only one currently in existence that successfully predicts the age curves for the various creative disciplines and provides reasonable substantive interpretations for the parameters estimated using model-fitting procedures (Simonton, 1988a).

Quantity Versus Quality Within Careers

There exists a critical methodological issue that I have thus far ignored: What counts as a creative product? Some researchers, such as Lehman (1953), insisted on counting only those products that actually had an impact on a discipline. The resulting studies thus concerned the relation between age and quality of output. Other investigators, such as Dennis (1966), tabulated all products claimed by a particular creator, whether those products were influential or not. These studies then pertained to the relation between age and quantity of output. Both strategies have their assets and deficits. The measurement of quality, of course, presents the problem of determining how to separate the wheat from the chaff. Do researchers rely on the judgments of those who write the histories of the disciplines or do they depend on citation indicators that supposedly reveal the opinions of colleagues? Do researchers determine the success of artistic productions by performance frequencies or the number of published editions? The possible operational definitions are very numerous. In contrast, defining longitudinal output according to total productivity, regardless of quality, obviates the need for some evaluative technique. Moreover, counts of quantity, unlike those of quality, directly reflect individual behaviors. The generation of a discrete product constitutes an observable behavior that is not contingent on any subjective assessments. Hence, quantity measures can be said to be the most objective. On the other hand, if researchers are really interested in creative productivity, it would seem that measures of quantity fall short of their needs. Creativity is usually defined as the generation of ideas that are both original and adaptive. Neither of these attributes can be defined at the individual level alone, for both imply some kind of comparison with, or judgment by, other persons. Thus, quantity may measure productivity, but only quality may assess genuine creativity.

The reason why this matter is so crucial is that investigators often believed that the age curves for quantity measures differed substantially from those obtained for quality measures (Simonton, 1988a). Dennis (1966), for example, criticized Lehman's (1953) work for just this very reason, saying that the age decrements in output observed in the postpeak phase of the career resulted from Lehman's focus on history-making products. Dennis thought that by looking at total output without respect to impact, the decline in the later years would be much less substantial. Unfortunately, this debate was not addressed in the most convincing manner. Rather than making direct comparisons of age curves for quantity and quality drawn from the same sample of creative individuals and using the same data sources, comparisons were usually made using age curves that came from different persons and divergent data sources. Moreover, on theoretical grounds alone, I must predict an intimate connection between quantity and quality. According to the variation-selection model, the production of ideational combinations is in some fundamental sense "blind." Both good and bad ideas should appear throughout the career. Indeed, the odds of producing an influential or successful idea should be a positive function of the total number of ideas generated. Quality is then a probabilistic function of quantity (Simonton, 1984a, 1988a, 1988d).

The empirical research strongly endorses this theoretical expectation. In fact, the connection between quantity and quality was first demonstrated by Quetelet (1835/1968). After obtaining a list of French plays, Quetelet classified the works into three groups according to quality (i.e., first, second, and third order). He then tabulated the number of plays in each group into 11 consecutive 5-year age periods. Because correlation coefficients had not been invented yet, Quetelet could not make a definite statement about the degree of correspondence, but the data are there for anyone to make the calculation. The creation of first-order plays correlated .82 with the production of second-order plays and .84 with the output of third-order plays, while the agewise appearance of second-and third-order plays correlated .91. Not only are these figures statistically significant (all ps = .002 or smaller), but substantively significant besides. More recent data show comparable results (e.g., Over, 1989; Simonton, 1977a, 1984b, 1985; Weisberg, 1994). If total output is divided into minor and major works, the two tabulations exhibit very similar fluctuations over the course of the career. Those periods in which the most minor products appear tend to be the same periods in which the most major works appear. And it is not just the overall age curves that run parallel: Departures from the age trend also tend to go together (Simonton, 1977a, 1985, 1988a, 1989a). If the output of neglected works is higher (or lower) than would be predicted, the emergence of successful works is correspondingly higher (or lower). Moreover, the congruence between the longitudinal distributions of major and minor products is not contingent on the particular operational definition used for distinguishing major from minor work (Simonton, 1988a). Depending on the type of creativity involved, the distinction can be made according to performance frequencies, citation rates in professional journals, reference in standard histories, frequency of appearance in anthologies, and so forth, with the same results.[5]

Let me examine this longitudinal congruence differently. Rather than look at the longitudinal correlation between the output of major and minor works per unit of time, longitudinal changes in the *quality ratio,* which is defined for each time period as the number of major works divided by the total number of works produced (Simonton, 1988a), can be inspected. In other words, the success rate can be calculated as a ratio of hits to total shots, then determining whether this ratio changes systematically over the career. When this is done, the ratio is found to stay approximately constant across the life span (e.g., Oromaner, 1977; Over, 1988; Simonton, 1977a, 1984b, 1985; Weisberg, 1994). Those just launching their careers have about the same hit rate as those heading toward retirement, and both groups of persons display about the same quality ratio as those who are at their peak productive age. This consistent finding permits us to formulate the *equal-odds rule* (Simonton, 1994a, in press-a; formerly more awkwardly called the "constant-probability-of-success" principle, as in Simonton, 1988a). This rule says that the relationship between the number of hits and the total number of works produced in a given time period is positive, linear, stochastic, and stable. That is, if the number of hits

[5] Actually, some care must be exercised when employing citation measures because citations are only stable indicators of quality over the long term (Simonton, 1984c, 1992b). For some of the sources of instability, see Barnett, Fink, and Debus (1989), MacRae (1969), Price (1965), and Trimble (1986).

is regressed on the total number of attempts, a regression equation is obtained that has the following four properties: (a) the regression slope predicting the dependent variable using the independent variable will be positive (the slope always being a decimal fraction that indicates the hit rate); (b) the function will be linear insofar as the addition of quadratic and higher order functions will not appreciably increase the amount of variance explained; (c) the equation will be stochastic in the sense that a large proportion of the variance will remain unexplained; and (d) the regression slope will neither increase nor decrease with increases in career age, nor will it exhibit some other simple and consistent longitudinal trend (as determined by the introduction of the appropriate interaction terms).

This principle is found to be extremely useful in deriving several highly distinctive predictions, but right now what the rule is not asserting needs to be emphasized. First, the equal-odds rule does not claim that the quality ratio stays absolutely constant throughout the career in a deterministic fashion. On the contrary, owing to the capriciousness of the variation-selection processes, there may be good years, where all attempts become hits, and bad years, where all shots miss the mark. Second, the rule does not assert that either major or minor works comprise homogeneous groups, each consisting of works of equal merit. On the contrary, the very distinction between major and minor creations is largely arbitrary, since creative products can usually be arrayed along some continuous scale from the most minor to the most major. Often some decision has to be made about where to make the cut-off according to the selectivity of the criterion (e.g., a set number of citations, performances, exhibits, or reprintings). It is especially crucial to recognize that even among the major works, creations may vary substantially in impact or importance. *Hamlet, King Lear, Othello, Macbeth,* and *Romeo and Juliet* are all counted among the best plays of William Shakespeare, and yet the data show that substantial and reliable variation exists even among these plays in their relative magnitude of success—*Hamlet* standing head and shoulders above the rest (Simonton, 1986b). This fact becomes crucial to the final elaboration of the longitudinal model.

Interdisciplinary Contrasts in Career Landmarks

So far I have been characterizing a creative career in terms of productivity age curves, such as those seen in Figures 1–3. This is not the only way of describing the career's typical progression, however. Instead, I can describe the longitudinal placement of certain creative products that represent the highlights of any career. The appearance of these creative products can be styled *career landmarks* (Simonton, 1991a, 1991b; cf. Lehman, 1946; Raskin, 1936; Zhao & Jiang, 1986). There are three of them: the *age at first contribution,* the *age at best contribution,* and the *age at last contribution.* A contribution is simply a major work, however operationalized. It may entail a frequently cited journal article, a composition that entered the standard repertoire, a patent that resulted in a commercially successful product, and so on. The best contribution is that work that has the most impact by the same criterion, whether citation rate, performance frequency, or commercial success. This special status is almost invariably easy to determine because the distribution of impact across creative products for a particular individual exhibits the same elitist form as that observed in the distribution of creative output across individuals (see, e.g., Moles, 1958/1968; Simonton, 1986b, 1989c). Whatever the details, the three career landmarks obviously demarcate the onset, peak, and termination of the most influential portion of a creative career. Minor works will usually appear before, within, and after this interval, but all major works are by definition included within this period.

The final step in constructing the longitudinal model is to integrate discussion of the career landmarks with what is already known about the age curves. It is easiest to begin with the middle landmark. According to the equal-odds rule, the most major works will appear in those periods of the career in which the most total works appear. If the equal-odds rule is truly general in application, the single best work should then be suspected to appear most likely in those periods in which the most major works appear (for evidence see, e.g., Quetelet, 1835/1968; Simonton, 1980b, 1986a, 1991b). Consequently, the best contribution will have the highest likelihood of appearing when the most total works emerge. To be sure, because the longitudinal distribution of productivity is skewed right—placing more total output after the productive peak than before—the exact location of the best contribution may come somewhat after the absolute maximum (see, e.g., Simonton, 1991b). Nonetheless, the age at best contribution can be safely concluded usually to track fairly closely the age of maximum output rate.[6]

This conclusion can be immediately applied to what has been observed about interdisciplinary contrasts in career trajectories. Different domains of creativity tend to have productive maxima at distinct career ages. Therefore, the age at best contribution should likewise vary across disciplines and in the same manner. The age at best contribution should be youngest for fields with fast ideation and elaboration rates and oldest for fields with slow ideation and elaboration rates. That prediction is consistent with the empirical research published to date (Simonton, 1975, 1988a, 1991a). For example, poets do indeed publish their single best work at a younger age than do novelists, a discrepancy that has been shown to be cross-culturally and transhistorically invariant (Simonton, 1975).

What about the first and last career landmarks? Here pretty much the same logic applies. As is evident from inspecting Figures 2 and 3, disciplines vary in how fast total output is accumulated at the beginning of the career. That means that, all other factors held constant, those fields that exhibit steeper slopes in the initial part of the trajectories will be more likely to have the first contributions appear early, whereas those with more gradual slopes at the outset will be prone to have first contributions appear later. Likewise for the last contribution: Disciplines where the postpeak slopes are more gradual will have a higher probability of having the last contribution occur later, whereas those where the postpeak slopes are more precipitous will have a higher probability of having the last contribution

[6] The differential impact of distinct creative products is a curvilinear function of age even though the hit rate exhibits no such longitudinal trend, in line with the equal-odds rule. This occurs because impact exhibits a skewed distribution across products, the products with the most extreme scores then appearing where productivity peaks. This would not happen if impact were symmetrically distributed.

occur earlier in life. Hence, it is possible to discover substantial variation in the placement of first, best, and last contribution across any set of domains that differ substantially in career trajectories. Again, this is definitely the case (Simonton, 1988a, in press-a). Figure 4 offers one illustration drawn from a study of 2,026 scientists and inventors in nine different domains of creative productivity. The contrasts here seen are both statistically and substantively significant.

In order to derive predictions regarding the first and last career landmarks, I made two implicit assumptions that must now be made explicit. First, I tacitly assumed that the equal-odds rule applies to across-discipline comparisons. For example, if mathematics has a higher hit rate than found in the earth sciences, that alone could explain the discrepancy in the age of first contribution. Secondly, I have presumed that the factor q, which relates the number of ideas produced to the number of products that result (i.e., $q = M/m$), is also identical across all compared disciplines. In different terms, the size of the least publishable unit is assumed to be the same. Neither of these two assumptions is likely to be the case for all comparisons across disciplines.

Nonetheless, these complications do not imply that results like those reported in Figure 4 are irrelevant to the evaluation of the current longitudinal model. First of all, the validity of the two assumptions is not germane to the middle career landmark, which is located near the peak productive age no matter what the differences may be in hit rates and least publishable units. Furthermore, variation in these two factors cannot explain away the contrasts in the first and last landmarks except under special

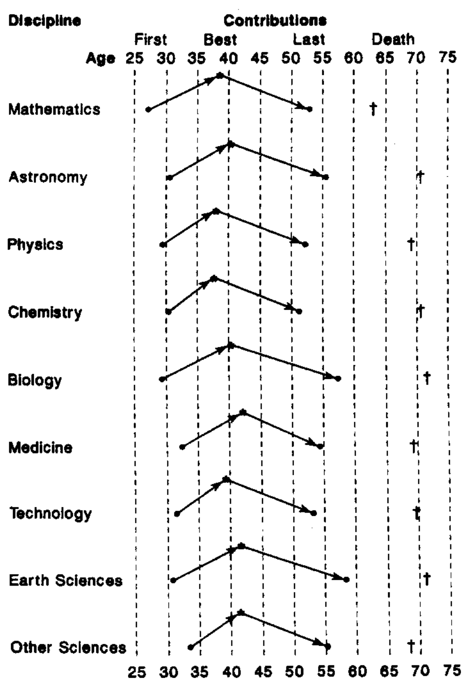

Figure 4. The location of the three career landmarks for 2,026 scientists and inventors in nine disciplines (Simonton, 1994a, Figure 7.3). Reprinted from *Greatness: Who Makes History and Why* (p. 188), by D. K. Simonton, 1994, New York: Guilford Press. Copyright 1994 by Guilford Press. Reprinted with permission.

circumstances. For example, if all disciplines had the same underlying age curves, but differed only in the success rates or the number of ideas per product, then spacing of the three career landmarks would be proportional across various disciplines. Those fields with earlier first contributions would automatically have later last contributions, and the distance from the best contribution would exhibit the same ratios. Simple inspection of Figure 4 reveals that this is not the case (or by calculating the ratios from the data in Simonton, 1991a). Moreover, the fact exists that whatever the ambiguities in the interpretation of results like these, there remains solid evidence that the age curves vary from discipline to discipline (Simonton, 1988a, 1989a). Accordingly, it seems plausible that these contrasts would have some observable repercussions on where the three career landmarks occur over the life span.

The Cross-Sectional Submodel

Cross-Sectional Distribution of Productivity

Individual differences in productivity are truly remarkable. For many behavioral and cognitive phenomena, cross-sectional distributions appear to be adequately described by the ubiquitous "bell-shaped" or "normal" curve. The distribution for lifetime productivity, in contrast, is extremely skewed right, with an exceptionally long upper tail (Simonton, 1984b). For instance, Dennis (1955) examined the total output of contributors to seven diverse domains, including music, linguistics, chemistry, and geology. An extreme disparity emerged between those in the upper end of the productivity distribution and those in the lower end. In particular, those in the upper 10% in terms of lifetime output tended to produce about 50% of all the contributions to the field. In stark contrast, those individuals whose total output placed them in the bottom half of the distribution could take credit for only about 15% of the work published in the field. Moreover, the mode of the productivity distribution is unity, meaning that the most typical creator is one who has only a single idea, as in the proverbial one-book author. Comparable findings have been found repeatedly in the research literature, making it one of the most robust facts in the behavioral sciences.

So well established is this phenomenon that it has provided the basis for two behavioral laws. First is the Lotka law, which states that the number of individuals who produce n contributions is inversely proportional to n^2 (Lotka, 1926). This yields a distribution with a long upper tail and with a mode at unity. The second is the Price law. This affirms that if k gives the number of people making contributions to a field, then the square root of k gives the number of those individuals who account for half of everything produced in the domain (Price, 1963). Although the exact formal connection between these two laws is a matter of debate (Allison, Price, Griffith, Moravcsik, & Stewart, 1976; Egghe, 1987), both have garnered considerable empirical support (Price, 1963; Simonton, 1988d). More importantly, both concur that a small percentage of the creators active in a given domain will make the lion's share of the contributions.

It deserves emphasis that the skewed distribution is not confined to total lifetime output. Even when brief intervals during the career course are considered, the same elitist distribution (e.g., Allison, 1980; Endler, Rushton, & Roediger, 1978; Shockley,

1957) is discovered. In any given year, most contributors produce at most a single contribution, whereas a mere handful of individuals are responsible for a dozen or more publications. To be sure, the frequency distribution over small intervals cannot be as extremely skewed as that obtaining over entire careers—even the most prolific creators are limited to 24-hr days. Still, the more diminutive inequalities found in annual output rates continue year after year, resulting in the awesome disparities at life's end. The crucial point here is that the cross-sectional distribution in lifetime productivity cannot be explained as a trivial consequence of an underlying skewed distribution of career lengths. The contrast between strong and weak producers appears early, at the very beginning of the career, and continues right through to the career's termination (Dennis, 1954b, 1956). Indeed, one of the best predictors of success in science is the number of publications a young scientist makes before earning a doctoral degree (Clemente, 1973; Segal, Busse, & Mansfield, 1980).

The present combinatory model provides one explanation for this unusual behavioral phenomenon (Simonton, 1988a, 1988d). Assume that the amount of material available for free variation is normally distributed in the population of creators in an enterprise. Clearly the number of ideational combinations that can be generated from this given supply is not a linear function of the number of elements available. According to combinatorial mathematics, the number of possible combinations grows at least exponentially as a function of the number of items undergoing permutations (see Barsalou & Prinz, in press). This indicates that the distribution of potential combinations (or N, in the notation introduced earlier), has a *lognormal distribution.* As a consequence, if creative potential remains proportional to the total number of available combinations (i.e., $m = sN$) and if the number of possible products remains proportional to the initial creative potential (i.e., $M = qm = qsN$), then the cross-sectional distribution of products will also be lognormal, whether counted over the entire career or within a given segment of the career. Lognormal distributions are extremely skewed right, with long upper tails. Those creators located at the tips of these tails, moreover, will never run out of ideas—even should they become centenarians.

Although a combinatory model can help explain the peculiar cross-sectional distribution of productivity, it is by no means the only conceivable explanation. Indeed, the literature is full of rival interpretations, some of which have been developed with impressive mathematical sophistication (e.g., Allison, 1980; Eysenck, 1995; Price, 1976; Shockley, 1957; Simon, 1955). Therefore, the present account can only be considered a weak explanation in the sense that it makes no predictions that allow it to be distinguished from alternative explanations. Nonetheless, it remains true that the distinctive pattern of individual differences is consistent with what would be expected from a combinatory model. Furthermore, none of the explanatory models that have been offered to date can be considered mutually exclusive. Consequently, it is perfectly possible that all models collaborate to produce the elitist distributions repeatedly identified in the research on individual differences in creative productivity.

Quantity Versus Quality Across Careers

Often scholars are quite wary of calculations of total output (e.g., Rubin, 1978). Such tabulations frequently are considered mere bean counting that places too much emphasis on quantity rather than quality. Perhaps the productive elite contains mere mass producers, whereas the perfectionists are those who should receive credit for the true masterpieces in a given creative domain. Yet this potential objection does not receive any support from the facts. For example, the same skewed distribution that appears in total lifetime output also emerges when attention is confined to that subset of works that actually have an impact (e.g., J. Cole & S. Cole, 1972; Green, 1981; Oromaner, 1985). To illustrate, the Price law can be applied to the cross-sectional distribution of works contributed by various composers to the classical repertoire. According to one survey (Moles, 1958/1968), approximately 250 composers have at least one work regularly performed, which implies that around 16 should be responsible for half the pieces so honored. That is indeed true (Simonton, 1984b).

On theoretical grounds, of course, this agreement should not be a surprise. If the Darwinian framework is basically sound, then the equal-odds rule should apply to individual differences in productivity, not just to longitudinal changes in output. As a consequence, quality and quantity must be closely related. Those individuals who produce the most major works should also produce the most minor works, on the average. An abundance of empirical studies has shown this to be the case (Dennis, 1954a, 1954c; Helmreich, Spence, Beane, Lucker, & Matthews, 1980; Segal et al., 1980). In the sciences, for example, a scientist's total output is the single best predictor of the total number of citations he or she receives in the technical literature (S. Cole & J. R. Cole, 1973; Crandall, 1978; Richard A. Davis, 1987; Gaston, 1973; Helmreich et al., 1980; Over, 1990; Rushton, 1984; Simonton, 1992b). Indeed, even when attention is restricted to the citations received by a scientist's best work, that count is still a positive function of total output. For instance, in a sample of physicists the correlation was .72 between the total number of articles published and the number of citations that were received by the three most-cited articles (S. Cole & J. R. Cole, 1973).

Furthermore, the connection between quantity and quality holds even if quality is judged by some criterion other than citation counts, such as the awards and honors received or the person's contemporary or posthumous reputation (Dennis, 1954a, 1954b; S. Cole & J. R. Cole, 1973; Simonton, 1984c, 1992c). The total number of contributions is not only the best predictor of eminence (Albert, 1975; Dennis, 1954a, 1954c; Feist, 1993; Simonton, 1977b, 1991a, 1991b, 1992b), but in addition productivity probably plays the major role in explaining the stability of a creator's reputation across generations (Over, 1982b; Rosengren, 1985; Simonton, 1991c). Individuals who have produced a large and diverse body of products have higher odds of having at least one work survive that ensures their long-term eminence.

It is essential to note that the relationship between quantity and quality is by no means perfect. Notwithstanding the high correlations normally seen (between around .50 and .75), the amount of variance explained is not enough to remove a considerable amount of scatter around the regression line. This scatter means that there indeed exist numerous residual errors of prediction, residuals that may be either positive or negative in sign. On the one hand, some produce more influential works than might be predicted from the statistical regression and thus count as so-called perfectionists who boast excellent quality ratios. On the other hand, some generate much fewer successful products than would be predicted from the regression equation and thereby be considered so-called mass producers whose hit rates are dismal. Nevertheless, the existence of these residual cases does not contradict two generalizations. First, the vast majority of individuals in any creative discipline have scores that fall on or fairly close to the regression line. The more total products, the more successful products—and the more unsuccessful products. Second, the quality ratio, while variable, does not vary in any systematic fashion across individuals, so that mass producers and perfectionists do not appear to be distinguishable from individuals with equivalent productivity rates (see, e.g., Richard A. Davis, 1987; Simonton, 1985). In short, the equal-odds rule seems to apply to cross-sectional data as well as to longitudinal data, a conclusion that is essential to the predictions that are derived in the next section.[7]

Longitudinal Location of Career Landmarks

Both the cross-sectional distribution and the quantity–quality correlation have been shown to be consistent with the theoretical model here under development. Predictions that set this model apart from all others have not yet been deduced, however. That deficiency can be rectified now, starting with an extremely important empirical result: To predict how productive a creator is going to be in a particular career interval, knowing who the person is far more useful than knowing how old the person is (Over, 1982a, 1982c; Simonton, 1977a, 1991a, 1992b; Stephan & Levin, 1992). That differential predictive power ensues from the fact that the amount of variance attributable to age is much less than the amount of variance resulting for individual differences. For instance, an octogenarian with high creative potential can display more creative output than a younger colleague at the career peak who has appreciably less creative potential (Simonton, 1990b). This cross-sectional variation has immediate consequences for predicting the longitudinal placement of the career landmarks. The dispersion surrounding the mean ages at first, best, and last work is always substantial (Lehman, 1946; Raskin, 1936; Simonton, 1977b, 1991a, 1991b, 1992b). An illustration is found in the data underlying the results depicted in Figure 4 (Simonton, 1991a). The standard deviations for these career landmarks range between 7.2 and 15.3 years. The maximum and minimum scores offer an even more dramatic story: The first landmark may occur between 11 and 73 years of age, the middle between 17 and 81, and the last between 20 and 102. How can individual differences of this magnitude be accommodated?

It so happens that the longitudinal model has two features that make just the provisions required. To simplify the discussion, but without any loss in ultimate generality, assume that a group of individuals who are all active in the same creative endeavor are to be considered. That means that the ideation and elaboration rates (a and b) can be held constant. Given that assumption, career trajectories can still vary across creators in two ways.

First, individuals can differ in *initial creative potential*. Presumably, m would have some distribution in the population compatible with the Lotka and Price laws. Variation in initial creative potential affects the expected age curve in a very precise manner. Because the two information-processing parameters are fixed, only the constant c in the theoretical formula is permitted to vary. So, factor c becomes directly proportional to m (i.e., $c = fm$, where $f = ab/(b - a)$. That is, the initial creative potential determines the height of the curve, or the overall level of productivity throughout the career, from first idea to last idea. Even when products are counted rather than ideas, the same conclusion holds. The predicted output per unit of time is only decreased by the factor q. According to the model, then, individuals who differ only in creative output, but who otherwise contribute to the same domain, have extremely similar career trajectories, with identical productive peaks and with pre- and postpeak slopes that are proportional to the contrast in respective output rates (see, e.g., Christensen & Jacomb, 1992; Horner, Rushton, & Vernon, 1986; Lehman, 1953).

Second, individuals can vary in their age at career onset (i.e., the chronological age at which career age $t = 0$). Theoretically, the career begins when the creator begins the process of generating ideational combinations within a specific domain of creativity. Methodologically, this may be operationalized any of a number of ways, including the age of highest degree, the age of first publication, and the age at first composition (e.g., Lyons, 1968; Simonton, 1991b). The specific operational definition depends on the nature of the domain. The critical fact is that individuals may range from "early bloomers," who launch their careers at exceptionally precocious ages, and late bloomers, who get an unusually late start.

No theoretical grounds exist for supposing that initial creative potential should be correlated positively or negatively with age at career onset. On the contrary, there are both theoretical and empirical reasons for believing that these two individual-differences variables should be uncorrelated with each other. The two factors should have, and do have, rather distinct developmental determinants, for example (Simonton, 1992a, 1996a). Thus, on the one hand, age at career onset is largely determined by the age when an individual began acquiring the necessary expertise in a domain. Because it normally requires about a decade of intense study and practice to acquire the skills and knowledge needed to support the combinatory process, age at career onset must be placed accordingly (Ericsson & Charness, 1994; Ericsson, Krampe, & Tesch-Römer, 1993; Hayes, 1989; Simonton, 1991b). On the other hand, initial creative potential is determined by the total number of domain-relevant ideas that are acquired as well as the richness of the interconnections among them (Eysenck, 1995; Martindale, 1995; Simonton, 1988d, 1996a). This associative richness is itself a complex function of a whole host of genetic, familial, and educational variables (Eysenck, 1995; Simonton, 1987a, 1992a, 1994a, 1996a). Hence, in all subsequent arguments the correlation between ini-

[7] More precisely, the cross-sectional version of the equal-odds rule would be expected to hold in the long run. In the short term, certain transient factors can operate to introduce disparities. For example, citation rates to scientists increase dramatically after they win the Nobel Prize, and a similar but not nearly so pronounced effect occurs upon election to the National Academy of Sciences (Inhaber & Przednowek, 1976). Thus acts of recognition allot instantaneous but temporary prestige value to even lesser work.

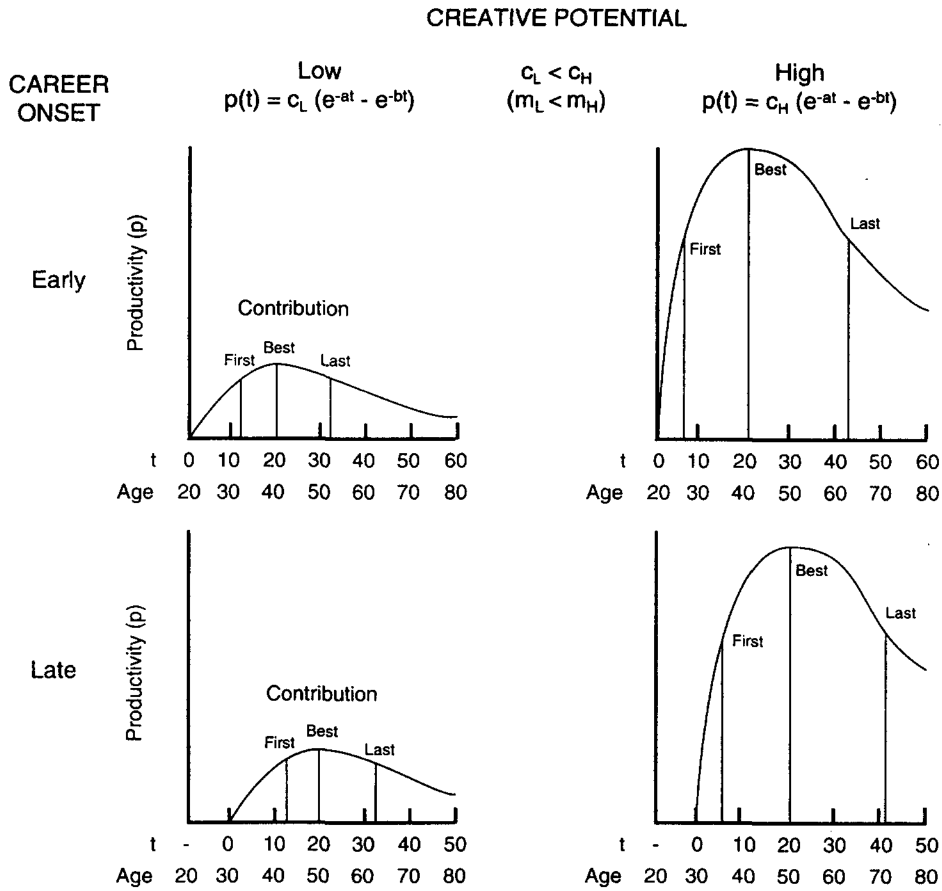

Figure 5. Typology of career trajectories according to early or late career onset ($t = 0$ at age 20 versus age 30) and low or high initial creative potential (m_L versus m_H, hence yielding different coefficients c_L versus c_H, respectively). As in Figure 1, a is the ideation rate, b is the elaboration rate, and e is the exponential constant. Adapted from "Career Landmarks in Science: Individual Differences and Interdisciplinary Contrasts" by D. K. Simonton, 1991, *Developmental Psychology, 27,* p. 121. Copyright 1991 by the American Psychological Association.

tial creative potential and age at career onset is assumed to be precisely zero. Fortunately, as I show later, this assumption can itself be tested by the empirical predictions that it generates.

To help visualize the arguments, these two uncorrelated individual-difference variables are used to construct a simple fourfold typology of career trajectories (Simonton, 1991a). Figure 5 gives a graphic representation of the four career types. On the left-hand side are the career trajectories for individuals who are low in initial creative potential, whereas on the right-hand side are the trajectories for individuals who are high in initial creative potential. In line with theory and research, the curves have the same form, but differ in amplitude. The term *amplitude* is used to mean that the productivity rate per annum differs according to the ratio of m_H/m_L. On the other hand, the curves presented at the top of the figure show the trajectories for individuals with an early age of career onset ($t = 0$ at chronological age 20), whereas the curves at the bottom show the trajectories for individuals with a late age of career onset ($t = 0$ at chronological age 30). In this case the curves are identical in amplitude, but differ in where the trajectory is terminated by death. Figure 5 can then be used to derive the first prediction regarding the longitudinal location of the three career landmarks.[8]

Prediction 1. Total lifetime productivity correlates negatively with the age of the first contribution and positively with the age of the last contribution (for empirical support, see Albert, 1975; Lehman, 1946; Simonton, 1977b, 1991a, 1991b, 1992b; Zhao & Jiang, 1986).

Here the left-hand curves are compared with the right-hand

[8] Some of the predictions that follow originate in an earlier development of the model, namely, Prediction 1 and Corollary 1A, the portions of Prediction 2 and Corollary 2A that deal with the correlations with age at the best contribution, Prediction 4, and the segment of Prediction 5 that refers to the effects of partialling out age at best work (cf. Hypotheses 3, 6, 7, and 8 in Simonton, 1991a). On the other hand, all of Corollary 1B, Prediction 3, Corollaries 3A and 4A, the part of Prediction 5 that deals with the effects of partialling out the age of maximum output rate, and all of Prediction 6 are new here. The documentation of the empirical support for these latter predictions, of course, is also introduced in this paper for the first time.

curves to contrast levels of creative potential. Clearly those creators who enjoy higher potential accumulate total products at a faster rate than those whose potential is lower. By applying the equal-odds rule, this means that those with higher creative potential should get a hit earlier than those with lower creative potential. The same straightforward logic holds for the age at last contribution. Those with higher creative potential are producing at a faster rate toward the end of the career, increasing the likelihood of a major work appearing at a later career age. It is essential to observe that Prediction 1 entails no hidden tautology (Simonton, 1988a). For example, suppose that the first and last landmarks merely track closely the onset and termination of the productive career. If O is lifetime output, then it is obvious that $O = R(L - P)$, where R is the mean annual rate of output, L is the age that productivity ended (longevity), and P is the age that productivity started (precocity). Mathematically, the three independent determinants of lifetime output may adopt a wide range of correlations without violating this identity. In the absence of a theory affirming the contrary, any one of the three independent determinants of lifetime output can be converted into the exclusive correlate of the dependent variable simply by constraining the other pair. For instance, the difference between P and L, which gives the career length, could be a constant (i.e., those who begin early end early), implying that total output would be a function solely of the mean output rate R and the prediction would not hold.[9]

Prediction 1 does not really depend on how lifetime productivity is measured. To the extent that the equal-odds rule holds, counts of total output should give the same results as do counts of only major works. Moreover, because lifetime productivity is the main correlate of professional reputation, the following subsidiary prediction:

Corollary 1A. Individual eminence correlates negatively with the age of the first contribution and positively with the age of the last contribution (for empirical support, see Albert, 1975; Lehman, 1958; Raskin, 1936; Simonton, 1977b, 1991a, 1991b, 1992b). Nor is this the sole corollary possible. Lifetime productivity is only one indicator of initial creative potential. The maximum output rate is another. Therefore, we obtain

Corollary 1B. Maximum output rate correlates negatively with the age of the first contribution and positively with the age of the last contribution (for direct empirical support, see Simonton, 1991b; indirect support in S. Cole & J. R. Cole, 1973; Dennis, 1954b; Lehman, 1958).

What about the middle career landmark? Unlike the first and last landmarks, the age at which the best contribution appears does not depend on initial creative potential. For individuals working in the same domain, m decides the height of the age curve but not the form of that curve. In particular, the age at maximum output does not vary with individual differences in total output or the maximum output rate. Now when the placement of the career landmarks according to discipline was discussed, it was concluded that the best work would be found at that career age in which the most total output appears. The same principle applies here. Accordingly, another prediction is arrived at with two corollaries.

Prediction 2. Lifetime productivity correlates zero with the age at the maximum output rate and zero with the age at the best contribution (for direct empirical support, see Lehman, 1958; Simonton, 1991b, 1992b; indirect support in Christensen & Jacomb, 1992; Zuckerman, 1977).

Corollary 2A. Individual eminence correlates zero with the age at the maximum output rate and zero with the age at the best contribution (for direct empirical support, see Raskin, 1936; Simonton, 1991b; indirect support in Lehman, 1958; Zusne, 1976).

Corollary 2B. Maximum output rate correlates zero with the age at the maximum output rate and zero with the age at the best contribution (for direct empirical support, see Simonton, 1991b; indirect support in Christensen & Jacomb, 1992; Horner et al., 1986; Lehman, 1958; Zuckerman, 1977).

Prediction 2 and its corollaries thus join to make a remarkable claim: The supremely prolific and distinguished elite who make numerous contributions to the domain tend to reach their career peak—as judged by their single best work or the maximum output rate—at the same career age as holds for the majority of their more obscure colleagues whose low productivity only allows them to claim one big hit.

The next set of predictions focus on the correlations among the ages of the three career landmarks. The first two of these predictions are superficially simple, but they have implications that are more profound.

Prediction 3. The age at the maximum output rate correlates positively both with the age at the first contribution and with the age at the last contribution (for empirical support, see Simonton, 1991b).

Prediction 4. The age of the best contribution correlates positively both with the age at the first contribution and with the age at the last contribution (for direct empirical support, see Simonton, 1991a, 1991b, 1992b; indirect support in Zusne, 1976).

Looking at Figure 5, the peak of the productivity curve always falls in the same career location relative to the first and last contributions. The same holds for the location of the best contribution. For the typical curves depicted in the figure, the career optimum is about midway between the first and last landmark, but a bit closer to the first. More specifically, the best work usually lies close to the harmonic mean between the first and last contribution (Zusne, 1976), and the peak productive age should be similarly placed. Thus, the ages at first and last contributions tell us where the career high point is most likely to be located, whether defined as the highest output rate or as the time when the single most important work appears. On first glance, Predictions 3 and 4 may seem necessarily true no matter what the theoretical explanation. After all, the middle landmark must be framed by the first and last landmarks, which provide the

[9] Just to show that Preposition 1 is not immediately obvious even to eminent psychologists who have studied creativity across the life span, Rudolf Arnheim's (1986) speculation that artists with shorter life spans (and hence more brief careers) may exhibit the same overall level of creative activity as long-lived artists by concentrating it in a shorter interval may be cited. He compared this phenomenon with the tendency for small mammals to breathe more rapidly and to have faster heart rates than large mammals, and hence the total number of breaths and heart beats are roughly the same despite the ample difference in life spans. This is tantamount to asserting that $R(L - P)$ equals some constant, contradicting Proposition 1.

lower and upper bounds. Nevertheless, one can conceive realistic scenarios in which the predicted correlations would not appear. For instance, imagine that the career peak is always placed at approximately the same chronological age, such as age 40. This placement may be caused by various exogenous circumstances, such as physiological, intellectual, or environmental factors. For example, scores on creativity tests often tend to attain a peak at around chronological age 40 (Simonton, 1990a; e.g., McCrae et al., 1987). Whatever the external cause, if the first contribution may appear anytime before age 40 and the last contribution anytime after 40, then both predictions would be disconfirmed, because the covariance of a variable with a constant is always zero. The same null result would appear if the career peak is randomly distributed around age 40. Thus, if these predictions hold, the middle landmark must be concluded to be dictated endogenously by career age rather than exogenously by chronological age. Furthermore, these predictions should hold even when individuals whose careers were long enough that the first and last landmarks place minimal constraints on the location of the middle landmark are examined exclusively (for evidence, see Simonton, 1991a).

Predictions 3 and 4 can be made more emphatic by realizing that the correlations are attenuated by individual differences in creative potential. Although the location of all three landmarks is a function of age at career onset, only the first and last career landmarks are a function of individual creative potential. Hence, the correlations among the three career landmarks should become more conspicuous once the variance introduced by any of our indirect indicators of initial creative potential is partialed out. The same argument applies to the correlations between the first and last career landmarks and the age of maximum output rate. We thereby obtain

Corollary 3A. The positive correlations between the age at the maximum output rate the ages at the first and the last contributions (as in Prediction 3) increase when either lifetime productivity or the maximum output rate is partialed out.

Corollary 4A. The positive correlations between the age of the best contribution and the ages of the first and last contributions (as in Prediction 4) increase when either lifetime productivity or the maximum output rate is partialed out.

A precautionary note should be inserted about these predictions that require partial correlations. In these corollaries lifetime productivity and maximum output rate are taken as indicators of underlying individual differences in initial creative potential (m). Yet it must be clear that the two alternative measures are by no means equivalent. The problem with lifetime productivity is that it is confounded with life span. Long-lived creators have more opportunity to realize their full creative potential than those creators whose lives where cut tragically short (Lindauer, 1993b; Simonton, 1975). Therefore, whenever lifetime productivity is used in partial correlations, either (a) the sample should be restricted to long-lived creators or (b) life span should be introduced as a control variable (Simonton, 1975, 1991a, 1991b, 1992b). The maximum output rate, in contrast, does not have this source of error, but it does have another: It generally constitutes a less reliable gauge of creative potential than lifetime productivity. The reliability of event tabulations (in this case counts of products) is a direct function of the size of the time intervals (Allison, 1977). Accordingly, a productivity measure based on a short time period tends to be less reliable than one based on a supremely long period, namely the length of an entire human life. To minimize measurement error, the maximum output rate should be calculated over an interval larger than a year, such as a 5-year or even 10-year period. For instance, the investigator can calculate the 5-year moving average for the tabulations of output across consecutive years and then take as the gauge of the maximum output rate the highest of these averages. The center of the "window" of that 5-year moving average would also provide us with a more stable measure of the age at maximum output rate (cf. Simonton, 1991b).

To say that the age at best contribution is positively correlated with the ages of first and last contribution is not the same as claiming that the first and last contributions are themselves positively correlated. In fact, this latter case is far more complicated, as is apparent by inspection of Figure 5. Here the two dimensions by which the four career trajectories are differentiated operate at cross-purposes. On the one hand, when creative potential is held constant and thus figures are only compared vertically, it is evident that an earlier career onset is positively associated with both a younger age for first contribution and a younger age for the last contribution. This implies a positive correlation between the first and last career landmarks. On the other hand, when career onset is kept constant and figures are only compared horizontally, the higher the initial creative potential, the younger the age for the first contribution and the older the age for the last contribution. This implies a negative correlation between the first and last career landmarks. Hence, the zero-order correlation between the ages of first and last contributions is a composite of two antithetical relationships. Even so, if an estimate of the career age independent of either first or last contribution is possessed, the chronological ages could be reset to the same career age. This recentering is accomplished by using either the age at the best contribution or the age at maximum output rate. According to theory, the chronological location of the career peak is dictated by age at career onset, not by individual differences in creative potential (for those working in the same discipline). Consequently, a prediction is obtained that cannot be derived from any theory that does not simultaneously acknowledge both individual differences in creative potential and the endogenous determination of the career peak.

Prediction 5. The first-order partial correlation between the ages of first and last contribution is negative after partialling out the age at the best contribution or the age at the maximum output rate (for empirical support, see Simonton, 1991a, 1991b).

The predictive power and uniqueness of this inference can be made more evident by deriving it mathematically rather than visually. If the theoretical model is valid, then covariance algebra can be applied to obtain the following partial correlation (see Appendix).

$$r_{SE.B} = \frac{r_{mS}r_{mE} + r_{AS}r_{AE}\,(1 - r_{AB}^2)}{(1 - r_{SB}^2)^{1/2}\,(1 - r_{BE}^2)^{1/2}}$$

Here the subscripts index initial creative potential (m) and the ages at career onset (A), first contribution (S), best contribution (B), and last contribution (E). All zero-order correlations are positive except r_{mS}, which is negative according to Prediction 1. In deriving this formula, it is assumed, according to theory, that the correlation between creative potential and age at career onset is zero (i.e., $r_{mA} = 0$). The probable sign of the partial correlation can be inferred from the inequalities $r_{AB} \gg r_{AS} \gtrsim r_{AE}$, which hold because the first correlation alone is determined solely by career onset (rather than initial creative potential), and the last two correlations are differentially constrained by life span. Under the assumption that the sample exhibits the full variance in creative potential, the term $r_{mS}r_{mE}$ can easily dominate the numerator, producing a negative partial (given that the denominator must always be positive). In contrast, if the age at the best contribution were determined by chronological age rather than by career age, $r_{AS} \gtrsim r_{AE} \gg r_{AB}$, and a positive partial correlation would become far more likely. In fact, when $r_{AB} = 0$, the partial correlation between the ages at first and last contribution, when controlling for the variance shared with the age of the best contribution, must exhibit the same sign as the zero-order correlation between the first and last career landmark, the only change being an increase in absolute magnitude. Using the same reasoning, it is possible to mathematically demonstrate that if the age at best contribution is influenced exclusively by the initial creative potential, then a negative correlation between the ages of first and last contribution is impossible except when $r_{mB} \cong 0$. The relevant numerator in this case becomes $r_{mS}r_{mE}(1 - r_{mB}^2) + r_{AS}r_{AE}$. Needless to say, the covariance algebra behind these conclusions is not altered if the age at maximum output rate is substituted for the age at best contribution.

The final prediction adopts a different strategy. In those instances where it is possible to obtain a measure of the age at career onset, it is possible to ask how long the creator must wait before obtaining the first contribution. In this case, the actual age at career onset is not a concern, but rather how the difference between the age at career onset and the age at first contribution varies according to initial creative potential. The answer is obvious from mere inspection of Figure 5. If the right-side figures are compared with the left-side figures, the time delay is clearly less for those with higher initial creative potential. High potential means a faster accumulation of total works, which, by the equal-odds rule, hastens the appearance of the first contribution. Now remembering how initial creative potential can be assessed two ways, the following is obtained (cf. Simonton, 1991b).

Prediction 6. The time interval between the age at career onset and the age at first contribution is negatively correlated with total lifetime productivity and the maximum output rate (for empirical support, see Simonton, 1991b).

Taken together, the previous theory-based derivations predict a configuration of zero-order and partial correlations that is extremely distinctive. So unique is this predicted pattern of covariances that the model is open to Popperian falsification. Just as important, every prediction has thus far survived empirical test in all investigations that contain the necessary statistical controls for birth year, life span, and discipline. The only exceptions are Corollaries 3A and 4A, which have not yet undergone direct empirical testing. Significantly, the model's predictions have been confirmed using data drawn from samples that varied greatly in creative domain, nationality, and historical period.[10] And the verifications have even held up under a variety of operational definitions of the central theoretical constructs. The empirical verification of these specific predictions would alone constitute substantial support for the theoretical model that generated them. Even so, the verifiable implications of the cross-sectional submodel have not yet been exhausted.

Longitudinal Stability of Cross-Sectional Variation in Productivity

Go back to the problem of counting productive output across a creator's career. For example, divide the career into decades and tabulate the number of works that came out in the 20s, 30s, 40s, 50s, 60s, and 70s. Furthermore, this can be done not just for a single creator, but for a whole sample of creators besides, all making contributions to the same discipline (and all living to age 79). As was learned earlier, the cross-sectional variation in output within each time period will be quite substantial. Within each decade a small proportion of contributors accounts for a hefty percentage of the total output. This fact leads researchers to ask if the individuals who are prolific in one decade are the same individuals who are prolific in the next decade. In other words, does the cross-sectional variation display stability across time?

The answer to this inquiry is clear: All the evidence to date shows that the individual differences in creative productivity display considerable stability during the course of the career (e.g., Christensen & Jacomb, 1992; Cole, 1979; Dennis, 1954b, 1956; Helmreich, Spence, & Thorbecke, 1981; Horner et al., 1986). Those who are the most prolific in the early part of the career are the most productive at the career peak as well as the most productive toward the end of life. Why?

One possible answer is that the continuity represents an autoregressive phenomenon. Productivity in the 30s is a function of productivity in the 20s, that in the 40s a function of that in the 30s, and so forth, up to the productivity exhibited in the 70s or later decades. This is the expectation provided by accumulative-advantage models of creative productivity (Allison et al., 1982; Allison & Stewart, 1974; Cole, 1979). These models see productivity as a behavior that responds to the reward structure of a discipline. Those individuals who are the most productive early in their careers receive the most incentives to maintain their productivity later in the career (e.g., through grants, awards, and upward mobility in professional affiliation). In a sense, the creator is like a pigeon in a Skinner box who is undergoing reinforcement for producing a superior cumulative record.

The current cross-sectional model offers a very different explanation. As is immediately apparent from Figure 5, the central factor underlying the productivity appearing across the career course is creative potential. Individuals with high initial creative potential are the most prolific in the first decade of their career, the most prolific at the peak of their career, and the most prolific in the last decade of their career—and the most productive in

[10] The only possible qualification on the generally confirmatory nature of the literature is that the model is not designed to explain the careers of the most obscure members of any discipline. The problem is that the lesser figures do not really exhibit careers but rather drop out of the competition early on (see, e.g., Allison & Stewart, 1974; Blackburn et al., 1978; Crane, 1965). In fact, all of the predictions regarding career landmarks only make sense for influential creators. If there is no impact, there can be no landmark.

all intervening periods as well. To be sure, a complication is introduced by individual differences in the age at career onset. Those creators who did not get their career off the ground until age 30 are not going to exhibit much productivity in the 20s no matter what their level of creative potential might be. Nevertheless, if variation in age at career onset is controlled in some way, it would be expected that the continuity in output would be substantial across consecutive age periods, whether decades, half decades, or years.

It may seem that the two rival explanations yield the same correlations, but that is far from true. The autoregressive model implies a highly distinctive correlation matrix known as the "simplex" (Loehlin, 1992). Correlations immediately adjacent to the diagonal are the largest, and then the correlations become dramatically smaller as they get more distant from that diagonal. The smallest correlation is between the two time periods farthest apart. In contrast, if the output observed in each time period is a function of a single underlying factor, initial creative potential, a correlation matrix should be obtained where the entries are much more similar. In the ideal case, in fact, they would all be exactly the same. Of course, the ideal in real data sets should not be expected. Variation in the age at career onset alone would attenuate the correlation between the output seen in the beginning of the career and that seen in later periods of the career. Moreover, the cross-sectional variance in productivity is higher in the middle units and much smaller at the career endpoints (especially at the career beginning). Such variance truncation unavoidably affects the correlations. Nonetheless, if the present model is correct, a single-factor model could be discovered to do an excellent job of reproducing the correlation matrix.

This prediction can be verified by applying latent-variable modeling techniques to data already published. Here are two concrete illustrations.

1. Dennis (1956) measured the productivity of 56 scientists who lived to become octogenarians, tabulating output in 6 consecutive decades from the 20s to the 70s. He then calculated the 15 correlations among these time series. The coefficients ranged from .33 between the 20s and 70s to .80 for the 40s and 50s. Nevertheless, the correlation matrix does not come close to showing a simplex structure. Not only is the correlation of .33 still substantial, but this correlation merely reflects the low reliability of productivity in the first decade, for reasons expressed above. Indeed, almost all of the small coefficients are those that involve output in the 20s. More importantly, a single-factor model does an excellent job reproducing the observed correlation matrix. Using the structural equation software EQS (Bentler & Wu, 1995) under generalized least-squares estimation, the latent-variable model yields a comparative fit index (CFI) of .994, a very impressive figure. Inspection of the residuals revealed that this model could be improved solely by adding a correlation between the disturbances for the first two decades. This modification gave a CFI of .996, a negligible increment. Obviously, the addition of this single parameter cannot threaten the generalization that the continuity in output across these careers can be almost entirely credited to a single unmeasured variable.[11]

2. Cole (1979) assessed the output of publications by 435 mathematicians. Because the participants were from roughly the same cohort (having received their doctorates between 1947 and 1950), the productivity could be tabulated in terms of years rather than ages. There were five consecutive 5-year periods, from 1950 to 1974. Across this 25-year interval, the correlation coefficients ranged from .61 between 1950–1954 and 1965–1969 to .79 between 1965–1969 and 1970–1974. Again, as expected, the first 5-year period was the one that showed the smallest overall correlations with the other periods. Otherwise the correlations making up the matrix ranged from .71 to .79, with no evidence for a simplex structure. This impression is confirmed again by using EQS to execute the same analysis as performed on the Dennis (1956) data. Not only did a single-factor model yield a CFI of .998, but there was no need to complicate the model by adding covariances among disturbances. The correlation matrix is adequately reproduced by a single latent variable. The only proviso is that the first half decade had a lower loading on this factor than did the subsequent time periods (.74 versus between .84 and .88).

The ultimate conclusion to draw from these two analyses is that a one-factor model can adequately explain longitudinal continuity in the cross-sectional variation in productivity. Given the other arguments and evidence, it seems reasonable to propose that this latent variable may reflect individual differences in initial creative potential. Indeed, this very factor may provide an alternative operational definition of m, a definition perhaps superior to either lifetime productivity or maximum output rate. At the very least such a latent-variable analysis would provide an index of the reliability of any measure of creative potential, as well as a substantively interesting gauge of the overall magnitude of longitudinal stability in a given sample of creative careers.

Discussion

The present theoretical model has been shown to lead to a host of specific and distinctive empirical predictions that have so far survived appreciable empirical scrutiny. The longitudinal submodel accounts for the career trajectories within individual creators, including such features as the contrasts between individuals active in different disciplines. The cross-sectional submodel offers even greater explanatory and predictive power. Most notable is its capacity to predict individual differences in the placement of the three career landmarks and to explain the longitudinal continuity in the cross-sectional variation in creative productivity. At present, there exists no alternative theoretical model that features a comparable capacity for explicating the phenomenon of creative productivity (for reviews, see Simonton, 1988a, 1996b). The only theories that even come close to handling the complexity of the phenomenon all originate in disciplines outside psychology, whether the accumulative-advantage models of sociology (e.g., Allison et al., 1982) or the human-capital models of economics (e.g., Diamond, 1984). These developments, while admirable in many respects, place all or most of the etiology in contextual circumstances outside the creative

[11] The possibility of correlated disturbances across time do not have to be excluded so long as a single-factor model explains most of the covariance between scores on consecutive time units. See Simonton (1991c) for a pertinent discussion of an analogous problem, namely the stability of reputation across time.

process. Thus, if creativity is believed to be at least to some extent a psychological phenomenon, the theory offered here represents the only current comprehensive psychological account.

To be sure, one can always offer interpretations for the diverse data on a piecemeal basis. One theory might be used to account for interdisciplinary differences in the age curves, another theory to handle the longitudinal stability of the cross-sectional variation in productivity, yet more theories to deal with the placement of each career landmark, and so on. The outcome would be an incoherent mix of often incompatible interpretations. Not only is the present account far more systematic than any such fragmented treatment, but additionally the model itself is far more elegant. All of the explanatory and predictive capacity is based on a small set of parameters and principles. The model requires only (a) the two individual-difference parameters, initial creative potential and age at career onset; (b) the two information-processing parameters, the ideation and elaboration rates, that characterize interdisciplinary contrasts in the origination and development of ideational combinations; and (c) the equal-odds rule, which establishes the covariances between quantity and quality of output for both longitudinal and cross-sectional tabulations. Given the parameters, plus the extraneous (but still personal) factor of life span, it is possible to differentiate an unlimited number of alternative career trajectories and thereby capture much of the richness that is witnessed in real creative lives. Moreover, underlying the entire model is a Darwinian variation-selection framework that has proven its scientific value explicating many other facets of creative behavior (e.g., Eysenck, 1995; Kantorovich, 1993; Martindale, 1990; Simonton, 1988d). If a good theory exhibits explanatory comprehensiveness, predictive precision, and conceptual parsimony, then the present model can be considered a good theory.

Despite the model's many assets, it remains open to criticism. Perhaps the most severe problem concerns the mathematical portion of the theory. As almost invariably happens in mathematical models, various simplifying assumptions had to be introduced in order to keep the mathematics tractable. Nevertheless, these assumptions can be relaxed various ways without altering the central predictions of the model (Simonton, 1984a, 1988a, 1996b, in press-a). For example, it is not necessary to assume that creative potential is always depleted but never replenished over the career course, for there are a variety of conditions under which this might happen without affecting the anticipated outcomes. Thus, it is possible to assume that the amount of recharge is always small in proportion to the amount extracted. This assumption is consistent with what is known about creators' careers (e.g., Dennis & Girden, 1954; Roe, 1972) and about the time commitment required to acquire and maintain expertise (e.g., Ericsson et al., 1993; McDowell, 1982). Similarly, the ideation and elaboration rates can be allowed to differ across individuals or to change across time so long as this variation is uncorrelated with initial creative potential and age at career onset (if otherwise, the resulting predictions would not fit the data anyway). Accordingly, the model would not be invalidated by the research showing that information-processing speed often decreases with age (Schaie, 1993; see, e.g., Christensen & Henderson, 1991). I lack the space to examine all the consequences of relinquishing every simplifying assumption. So may it suffice here to claim that the model is by no means at the mercy of its mathematical provisions.

Others may criticize the broader theoretical framework on which the model is based. Some may feel that Darwinian models place too much emphasis on chance and thereby downplay the role of goal-directed behavior (e.g., Gruber, 1989; Perkins, 1994). Others may maintain that such models understate the role of logical and conscious information processing, such as that stressed by cognitive scientists who study creativity from the standpoint of computational models of problem solving (e.g., Langley, Simon, Bradshaw, & Zythow, 1987; Weber, 1992; Weisberg, 1992). These and other possible complaints have been addressed elsewhere (e.g., Simonton, 1988c; 1993a; 1994a, 1995b; chap. 4; in press-b), so there is again no need to discuss the matter here (see also Kantorovich, 1993; Stein & Lipton, 1989). However, it should be pointed out that Darwinian models of the creative process may turn out to be far more compatible with various advances in the behavioral sciences. For instance, such models may prove more consistent with connectionist models of thought, which are acquiring greater importance in cognitive science (Martindale, 1995; Simonton, 1994b). More important, Darwinian models probably fit better what researchers are learning about the behavior genetic, psychometric, and developmental features of the creative personality (Eysenck, 1995; Simonton, 1988d, 1994a, 1996a).

Although many serious criticisms can be successfully addressed, the theoretical model still has many imperfections. The following four may need the most attention in future research.

1. The model is not just life span developmental, but it is perhaps prohibitively so besides. That is, the model treats the entire career from the age at career onset to the age at death (or at least until it is known for sure that the productive career has ended). After all, two of the three career landmarks—the ages at the best contribution and the last contribution—can only be operationally defined after it is known that no more works are forthcoming. As a consequence, all components of the model cannot be applied easily to creative individuals who are just beginning their careers, or even to those who are at midcareer. In particular, even though a measure of the age at career onset and a record of the domain of creative activity may be obtained, the level of initial creative potential cannot be known in advance. The best that can be done is to make tentative forecasts on the basis of the initial slope of the career trajectory in, say, the first career decade. For example, those individuals whose productivity rates rise most rapidly in the first decade are probably those who have higher creative potential. Yet such a measure in all likelihood is plagued with considerable measurement error, given how vulnerable creativity is to numerous extraneous influences, such as those enumerated earlier in this paper (Simonton, 1988a). Perhaps this deficiency can be remedied by isolating the early biographical antecedents of creative potential and then using these variables to enhance what predictive power is obtained from the early career trajectory alone (see, e.g., Simonton, in 1996a). If that goal is accomplished, the theory would become even more life span developmental in scope, because the adulthood career would then be linked with experiences in adolescence, childhood, and maybe even infancy (see, e.g., Simonton, 1991b). The outcome would be a theory that treats virtually the entire life of each creator.

2. Although the model does a very good job predicting and explaining the overall career trajectories of creative individuals, it is not designed to handle the fine structure of those trajectories. As already noted, the career of an individual creator is always subject to outside factors, some positive and others negative, which defect the observed performance from what would be predicted according to theory. While these random shocks can certainly be incorporated into the model on a post hoc basis, it is always inelegant to do so. This is especially true in the case of beneficial influences that excite a person to be more creative than theoretical expectation. Let one illustration suffice to indicate the nature of this problem. A curious feature of creative output in classical music is the frequent occurrence of the "swan-song phenomenon" (Simonton, 1989d). Composers facing the final years of their lives often exhibit a brief renaissance in creativity, a resurgence that yields works noticeably more successful than what had come immediately before. Although this effect apparently can be interpreted as a result of a brief upsurge in total output and thus can evoke the equal-odds rule to obtain the superior works, it is then necessary to explain how productivity can increase, however momentarily. One possibility is that the realization of the proximity of death serves to cancel out the influence of other factors that might serve to inhibit the level of output. For instance, composers might relinquish various professional and even personal responsibilities when they realize that their lives are quickly drawing to a close. This account may be true, but it also relies on considerations that lie outside the theory. And it certainly does not help matters that a totally different independent variable is involved in this phenomenon—years prior to death rather than years since career onset. Perhaps more adequate models have to introduce explicitly two time functions, one with time measured forward (for career age), the other with time measured backward (for anticipation of death).

3. Although the model is said to be cognitive in nature, it has no direct ties with the processes that are discussed by cognitive psychologists who investigate creativity (see, e.g., Smith, Ward, & Finke, 1995). To be more specific, even if the ideation and elaboration rates have been called information-processing parameters, they do not correspond to particular cognitive operations nor was the research on creative cognition used to define the differential equations that generated the longitudinal model. The only psychological specificity in the model is simply the assertion that the presumed two-step procedure is more consistent with some mental processes than it is with others (e.g., parallel rather than serial processing; see Martindale, 1995). This lack of specificity may be considered either an asset or a deficit, according to the psychologist's point of view. On the positive side, because the current conception is probably compatible with a fairly wide range of potential cognitive mechanisms, it is not vulnerable to the scientific fate of any one mechanism. For example, many rival theories exist about the nature of creative insight (Sternberg & Davidson, 1995), but the present model does not depend on just one of these actually being true. On the negative side, cognitive psychologists who hope that this model helps them pinpoint the precise processes that underlie creativity are going to be severely disappointed. The model simply does not provide sufficient constraints on the range of possibilities. It is my own hope that this deficiency is remedied as computational models of creativity become increasingly sophisticated. Eventually such models should simulate not just the output of single creative products, as is the current practice (Boden, 1991), but also replicate the generation of a whole corpus of works distributed across and within careers. By simulating creators and not just creations, such computer models might someday converge on formal representations not unlike those deduced in the present model. If that convergence happens, cognitive studies of creative productivity should merge with studies of individual differences and longitudinal changes in the same phenomenon.

4. A final theoretical deficiency concerns the connection between the longitudinal and cross-sectional submodels and the larger Darwinian framework to which they belong. Although some aspects of the theory bear a close relationship with the blind-variation and selective-retention thesis—the equal-odds rule being the best example—other aspects of the theory have a less tenuous association, or at least an association that needs additional development. To some extent this is a problem with the entire body of variation-selection theories, which may be said to form a loose set of models with a common theme or set of assumptions. Nonetheless, it would certainly benefit the current endeavor if it could be integrated more closely with other Darwinian-type theories, especially if those theories themselves could be made more intimately interrelated. For example, in Eysenck's (1995) recent theory, creative genius is associated with high scores on the Psychoticism scale, an attribute which itself is linked with certain cognitive dispositions (divergent thinking and remote associations) as well as certain cognitive quirks (negative priming and latent inhibition). How exactly do these mental operations articulate with individual differences and longitudinal changes in creative potential? Or, to give another illustration, in Martindale's (1990, 1994) evolutionary theory of stylistic change, artistic creation involves a two-step process very similar to that hypothesized here: Ideational variations are first generated via primordial cognition (i.e., primary process), and then certain of these are selected for further elaboration via conceptual cognition (i.e., secondary process). The comparative involvement of these two processes changes over historical time as a particular style emerges, develops, and becomes decadent. Does this imply that the ideation and elaboration rates in the current model change according to the developmental phase of a given artistic style? If the answer is affirmative, then we should predict changes in the predicted career trajectories for creators according to their contribution to the development of that aesthetic movement. To take this integration one step further, would the occurrence of shifts be predicted over historical time in the degree of Psychoticism exhibited by creators according to their particular historical place in stylistic evolution?

The assumption behind the above points is that the current model is basically correct and only needs more development. In the long run, of course, the opposite may prove to be true, as future investigators show it to be terribly mistaken. Maybe its conception of the creative process is flatly contradicted by forthcoming discoveries in cognitive science. Perhaps new predictions are derived from the model that are unambiguously inconsistent with existing data. Nonetheless, one would hope that the model is eventually replaced rather than ignored. The empirical literature on creative productivity contains a wealth of secure findings on individual differences and longitudinal changes. These rich results impose tight constraints on the range of possible explanations. So even if the present model ultimately fails, it should inspire other researchers to conceive more comprehensive, precise, and elegant scientific theories. Moreover, it is probably a safe bet that these superior theories would retain some core features of the present theoretical offering. Certainly some allowance would have to be made for interdisciplinary contrasts in the age curves, just as some provision would have to be made for cross-sectional variation in the age at career onset. In addition, there would have to be some accommodation for stable individual differences in underlying generative capacity, including the highly skewed cross-sectional distribution of that potential. No doubt career age has to replace chronological age as the central variable underlying longitudinal changes in creative output. And, finally, any model must make sense of the equal-odds rule, in both its longitudinal and cross-sectional applications. Whether such an alternative theory can be devised that can make the same empirical predictions under contrary theoretical explanations remains to be seen.

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Appendix

Derivation of Predictions

To derive this somewhat complicated-looking partial correlation, one first has to recognize that it is only necessary to be concerned with the numerator. This holds because the terms in the denominator are conventional for the first-order partial correlation between age at first contribution (*S*) and age at last contribution (*E*) controlling for age at best contribution (*B*). Concentrating on the numerator, then, begin with structural equations implied by the theoretical model.

$$S = r_{AS}A + r_{mS}m + e_S$$

$$B = r_{AB}A + e_B$$

$$E = r_{AE}A + r_{mE}m + e_E$$

$$r_{mA} = r_{mB} = 0$$

Here *S*, *B*, and *E* are defined as before, *m* is the initial creative potential, *A* the age at career onset, and the *e*s are the error terms for each equation. Without loss of generality, all variables except the error terms are assumed to be standardized *z* scores (i.e., $M = 0$ and $SD = 1$), so that all covariances between different variables will be identical to correlation coefficients. It is for this reason, too, that there are no intercepts in these equations (i.e., the intercepts are necessarily zero). The usual assumptions are made for recursive systems of equations, especially here that each error term is correlated only with its respective endogenous (or dependent) variable. Correlation coefficients are used instead of path coefficients for the standardized structural parameters because one of the equations is bivariate and the others each consist of two measured independent variables (*A* and *m*) that are uncorrelated according to the theory. Both of these conditions oblige the standardized parameters to be equivalent to *r*s between a given independent variable and its dependent variable.

Expressions for the three zero-order correlations in the numerator $r_{SE} - r_{SB}r_{BE}$ of the standard formula for this partial must be obtained. Each of these derived terms will entail a zero-order bivariate relationship between an empirically observable variable (one of the three career landmarks) and an underlying theoretical construct (either initial creative potential or age at career onset). There are several ways to proceed, including converting the system of equations into a path diagram and then using the tracing rule to decompose each of the three correlations in the term (Loehlin, 1992). An alternative is to use covariance algebra, which is what I will essentially do here from first principles. That is, for the benefit of those who do not know covariance algebra, I use only basic summation algebra and the definition of the Pearson product–moment correlation coefficient.

To obtain the correlation between *S* and *E* using the structural equations, the first equation for *S* is selected and both sides of the equation are multiplied by *E*. If this equation is valid, it holds for every single case in a given sample (any predictive inaccuracies being taken care of by the presence of e_S). The terms can be summed accordingly across all cases and divided by the sample size *n*. Remembering that the structural parameters are considered constants and that a constant can always be taken out of the summation (converting it into a factor of the summation), the new equation is obtained.

$$\tfrac{1}{n}\,\Sigma\, SE = r_{AS}\,\tfrac{1}{n}\,\Sigma\, AE + r_{mS}\,\tfrac{1}{n}\,\Sigma\, mE + \tfrac{1}{n}\,\Sigma\, e_S E.$$

Because the average cross-product of *z* scores (or standardized covariance) is nothing other than the product–moment correlation coefficient *r*, and given that e_S is uncorrelated with *E* (yielding a zero covariance), we thus obtain the expression

$$r_{SE} = r_{AS}r_{AE} + r_{mS}r_{mE}.$$

By multiplying the equation for *B* by *S* and following the same procedure, we also get

$$r_{SB} = r_{AS}r_{AB}.$$

Finally, multiplying the last equation for *E* by *B*, and noting that $r_{mB} = 0$, we obtain

$$r_{BE} = r_{AE}r_{AB}.$$

By substituting these values into the original expression for the numerator of the partial and rearranging the terms, the partial correlation predicted by the theory is obtained. By similar means the other partial correlations mentioned in the text are derived, such as that partialling out the age at maximum output.

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