Review of General Psychology
2008, Vol. 12, No. 1, 28–46

1089-2680/08/$12.00 DOI: 10.1037/1089-2680.12.1.28

Scientific Talent, Training, and Performance: Intellect, Personality, and Genetic Endowment

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Despite over a century of research, psychologists have still not established scientific talent as an empirically demonstrable phenomenon. To help solve this problem, a talent definition was first proposed that provided the basis for three quantitative estimators of *criterion heritability* that can be applied to meta-analytic and behavior genetic research concerning the intellectual and personality predictors of scientific training and performance. After specifying the ideal data requirements for the application of the three estimators, the procedures were applied to previously published results. Personality traits were illustrated with the use of the California Psychological Inventory and the Eysenck Personality Questionnaire with respect to two criteria (scientists versus nonscientists and creative scientists versus less creative scientists) and intellectual traits with the use of the Miller Analogies Test with respect to seven criteria (graduate grade-point average, faculty ratings, comprehensive examination scores, degree attainment, research productivity, etc.). The outcome provides approximate, lower-bound estimates of the genetic contribution to scientific training and performance. Subsequent discussion concerns what future research is necessary for a more complete understanding of scientific talent as an empirical phenomenon.

Keywords: scientific talent, intellect, personality, criterion heritability

Roger D. Kornberg received the 2006 Nobel Prize in Physiology or Medicine, an honor previously bestowed upon his father, Arthur Kornberg, in 1959. Not only has this father–son pairing occurred six times since the advent of the Nobel prizes in 1901, but this award has also been conferred on one mother–daughter pair, one brother–brother pair, and one uncle–nephew pair (Nobel Laureates Facts, n.d.). Moreover, only once out of these nine occasions was the prize received for the same achievement (viz., the father and son Braggs in 1915). Yet this prestigious honor has an extremely low base rate. The overwhelming majority of even the most distinguished scientists are never acknowledged with this premiere distinction. So the odds of two family members receiving the same prize would seem infinitely miniscule. Consequently, it seems reasonable to ask: To what extent are high-impact scientists born rather than made? What are the relative contributions of nature and nurture to the emergence of scientific achievement?

This issue was first addressed by Francis Galton in his 1869 *Hereditary Genius*. Galton showed that renowned scientists tended to have eminent biological relatives at a rate that far exceeded statistical expectation. Furthermore, the probability of a familial connection corresponded with the degree of kinship. Fathers, brothers, and sons are much more frequent than grandfathers, uncles, nephews, and grandsons, and the latter relations are in turn more frequent than great-grandfathers, great-uncles, first cous-

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This article is a substantial elaboration of a “think piece” presented at a meeting on Identifying and Developing Talent in Science, Technology, Engineering, and Mathematics held at the National Academy of the Sciences, Washington, DC, in 2006, and sponsored by the National Academies Center for Education, the American Psychological Association, the U.S. Department of Education, the National Institutes of Health, the National Science Foundation, and the National Commission on Teaching and America’s Future. I thank Tom Bouchard, Greg Feist, John Loehlin, and Michael Karson for facilitating my search for information required for the meta-analyses.

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ins, great-nephews, and great-grandsons.[1] On the basis of these and other pedigrees, Galton concluded that creative genius, scientific or otherwise, was determined at birth. Such a prestigious scientific pedigree even holds for Galton's own lineage. His blood relations included his grandfather Erasmus Darwin, his cousin Charles Darwin, and, more distantly, the latter's scientifically eminent sons, namely, Francis, the botanist, Leonard, the eugenist, and Sir George, the physicist—and, even more remotely, to the latter's son, the physicist Sir Charles Galton Darwin.

Galton's (1869) extreme biological determinism elicited criticism almost at once. The first major counterargument was presented by Alphonse de Candolle (1873), a scientist who, ironically, Galton had explicitly named as coming from a distinguished scientific family. Despite being the son of an illustrious scientist, Candolle showed that outstanding scientists are very much the product of specific political, economic, cultural, and educational environments. Candolle's research inspired Galton (1874) to examine some potential environmental factors in a survey of Fellows of the Royal Society of London (Hilts, 1975). The results were published in *English Men of Science: Their Nature and Nurture*. The subtitle implies that Galton had backed off a little from his extreme position, allowing some latitude for the input of various environmental influences. In line with this concession, he specifically examined the impact of family background, formal education, and geography on the emergence of prominent scientists.

Unfortunately, the empirical research since Galton's day has made little headway toward understanding the extent to which creative achievement in science has some foundation in natural endowment. Indeed, several psychologists have gone so far as to cast doubt on whether talent of any kind really exists (e.g., Ericsson, Roring, & Nandagopal, 2007; Howe, Davidson, & Sloboda, 1998). A prominent example is Howe's (1999) book *Genius Explained*. After devoting several chapters to scrutinizing the lives of such noted scientists as Michael Faraday, Charles Darwin, Albert Einstein, and other supposed scientific talents, Howe concluded with the chapter entitled "Born to be a genius?," in which he claimed that the answer to the question posed by the title is clearly negative. Similarly, Sawyer (2006), in his book *Explaining Creativity*, examined general creative talent and explicitly asserted "We can't look to genetics for the explanation of creativity" (p. 94). Furthermore, these negative conclusions are said to follow directly from relevant research in behavior genetics. For instance, Sawyer reviewed three investigations that allegedly disconfirm the role of genetic endowment in any form of creative achievement (viz., Barron, 1972; Reznikoff, Domino, Bridges, & Honeyman, 1973; Vandenberg, Stafford, & Brown, 1968).[2] Likewise, Ericsson, Roring, and Nandagopal (2007) cited two behavior genetic investigations in drawing the same conclusion about talent in general (viz., Bouchard & Lykken, 1999; Klissouras et al., 2001).

In fact, Ericsson, Roring, and Nandagopal (2007) went so far as to question whether behavior genetics can ever establish the case for talent in any domain of high-level achievement. After all, behavior geneticists rely heavily on the study of twins—especially monozygotic twins reared apart (MZA). That reliance ensues from the convention that the MZA intraclass correlation for any trait provides a direct estimate of the trait's heritability. Not only are MZAs relatively rare, but twins of any type may even be underrepresented among high-achieving adults (Goertzel, Goertzel, & Goertzel, 1978). If we add to the calculation the fact that only a small proportion of the population exhibits exceptional talent, then it would seem impossible to obtain MZA samples of sufficient size to support conclusive results. This argument certainly applies to scientific talent. For instance, a comprehensive longitudinal study of the mathematically precocious (Lubinski, Webb, Morelock, & Benbow, 2001) has extremely few twins in the sample (D. Lubinski, personal communication, March 15, 2007). Simonton's (1991a) study of 2,026 eminent sci-

[1] These terms are all for male relatives in part because few eminent female scientists existed in Galton's (1869) day. A notable exception was the astronomer Caroline Herschel, sister of astronomer Sir William Herschel and aunt of astronomer and physicist Sir John Herschel.

[2] More accurately, Sawyer (2006) cited "Vandenberg, 1968," the volume editor, rather than the single chapter in the volume that actually conducted the study (viz., Vandenberg, Stafford, & Brown, 1968).

entists contained only one twin (Auguste Picard). And, needless to say, there are no twins, monozygotic or dizygotic, among Nobel laureates in the sciences. Thus, not only may we lack direct evidence for scientific talent, but also it may never be possible to establish such substantiation with the use of standard behavior genetic methods.

Nevertheless, it is conceivable that indirect but still convincing support may be derived from two distinct sets of empirical findings. First, differential psychologists have shown that certain intellectual and personality variables tend to predict creative achievement, including achievement in the sciences (Feist, 1998; Simonton, 2004). Second, almost all individual-difference variables feature substantial heritabilities (e.g., Bouchard, 1994; Bouchard, Lykken, McGue, Segal, & Tellegen, 1990). To the degree that these two sets of variables overlap, a logical and empirical basis has been established for the existence of scientific talent. Specifically, if a genotypic trait provides some basis for a phenotypic trait, and if the latter trait predicts variation in scientific achievement, then the latter must have some genetic foundation. For example, Bouchard and Lykken (1999) demonstrated that the personality characteristics associated with scientific productivity display heritabilities ranging between .32 and .57, meaning that between 32% and 57% of the variance in those traits can be attributed to genetic endowment. Similarly, the Creativity Personality Scale (CPS) of the Adjective Check List (ACL) not only predicts scientific creativity (Gough, 1979) but also has a heritability of .54 (Bouchard & Lykken, 1999; Waller, Bouchard, Lykken, Tellegen, & Blacker, 1993). Hence, 54% of the variance in the CPS has a genetic contribution. Moreover, because predictive validities are known for this measure, we can draw a more powerful inference. For instance, CPS scores correlated .31 with the creativity ratings that expert judges assigned 57 mathematicians (Gough, 1979). This signifies that almost 10% of the variance in that criterion can be attributed to CPS (i.e., $.31^2 = .096$). Multiplying the squared criterion–trait correlation by the heritability coefficient then yields .052, which implies that over 5% of the variance in the rated creativity of these mathematicians might be ascribed to the genetic part of the CPS scores.

Naturally, matters can become more complicated when we have to take into consideration the full inventory of inheritable individual-difference variables that also correlate with some measure of scientific achievement. Accordingly, the principal goal of this article is to develop and illustrate objective and precise procedures for estimating the overall contribution of genetic endowment to scientific achievement. But before that task can begin it is first necessary to define exactly what we mean by talent.[3]

Talent Definition

An extensive literature has amply demonstrated that exceptional achievement depends on the acquisition of domain-specific expertise (Ericsson, Charness, Feltovich, & Hoffman, 2006). This mastery does not come immediately but rather must be the product of concentrated effort, such as *deliberate practice* (Ericsson, Krampe, & Tesch-Römer, 1993). One manifestation of this requirement is the *10-year rule* that asserts a full decade of intensive training and practice is usually required before an individual attains world-class mastery of a given domain of expertise (Ericsson, 1996). Too often, this dependence on an experiential factor is juxtaposed to the operation of innate talent or genius (e.g., Howe, 1999). Supposedly, the more achievement in science or other domains is contingent on accumulated domain-specific knowledge and skill, then the less important must be the role of natural endowment. Yet this conception of nature and nurture as being mutually exclusive is unnecessary and illogical.

[3] One anonymous referee also requested definitions of achievement, eminence, genius, and creativity because they sometimes seem to be used interchangeably. Here these constructs are considered to be overlapping but not identical. A person can achieve in almost any domain, such as scientific or artistic creativity, political or military leadership, individual or team sports, chess competition or musical performance, cooking or gardening. Truly exceptional achievement in a particular domain typically results in the attainment of eminence within that domain (e.g., Nobel laureate, an Olympic gold medalist, or a critically acclaimed violin virtuoso). However, the term *genius* is most often confined to eminence achieved within domains requiring either creativity or leadership (e.g., literary genius or military genius). And scientific genius is principally contingent on the demonstration of extraordinary creativity in science (i.e., the contribution of ideas recognized as both original and useful; see Simonton, 2000).

Rather than define talent as a mysterious phenomenon that operates independently of domain-specific expertise, talent is best conceived as a process that openly involves that expertise (Simonton, 1999, 2005). In different terms, scientific achievement is not a matter of either talent or training but rather a matter of talent operating in the context of that training. To be specific, scientific talent can be defined as any feature of natural endowment that has one or both of the following two effects.

First, talent enhances *training*. At the minimum level, training may be enhanced insofar as an individual has the personal characteristics required to engage in the arduous learning and practice necessary to reach mastery of a given scientific domain. For instance, a distinctive profile of personality, interests, and values may influence how much effort a student is willing to devote to doing exercises and problem sets in advanced physics courses. These traits may include high conscientiousness, extreme introversion, and an orientation toward "things" rather than "people" (Feist, 2006a). Yet enhanced training may also mean that a given individual (a) attains a higher level of domain-specific expertise for a given unit of training or (b) masters the requisite domain-specific knowledge and skill in less training time than average. The latter possibility is suggested by a key empirical finding with respect to creative achievement: Although the 10-year rule holds as a rough average, the generalization is qualified by considerable individual differences, some persons taking more time and other less (Simonton, 1996). Significantly, those individuals who take less than 10 years are more likely to display higher levels of creative productivity and more long-term impact than those who take more than 10 years (e.g., Simonton, 1991a, 1991b, 1992). Hence, some portion of this training enhancement may very likely reflect cross-sectional variation in native endowment.

Second, talent enhances *performance*. Enhanced performance indicates that an individual with a given amount of expertise will exhibit a higher level of scientific output or impact than other individuals with the same level of accumulated expertise. As a case in point, creative contributors to a particular discipline tend to display traits that differentiate them from those who solely exhibit domain-specific expertise in same discipline (Rostan, 1994). An example is Openness to Experience, a Big-Five factor that is positively associated with creativity (Harris, 2004; McCrae, 1987). Openness most likely makes direct contributions to the creative process underlying discovery and invention in the sciences. For instance, Openness is positively associated with both divergent thinking (McCrae, 1987) and reduced latent inhibition (Peterson & Carson, 2000; Peterson, Smith, & Carson, 2002). Divergent thinking enables the person to conceive alternative perspectives on a problem while reduced latent inhibition allows an individual to be sensitive to seemingly unrelated cues to the solution of a problem (Simonton, 2003). In fact, diminished cognitive filtering should facilitate the "opportunistic assimilation" of stimuli during the incubation period of the creative process (Seifert, Meyer, Davidson, Patalano, & Yaniv, 1995).

In general, training enhancement largely concerns the development of scientific talent in childhood through early adulthood, whereas the performance enhancement mostly concerns the manifestation of that talent through the course of the adulthood career. The former involves the acquisition of expertise, the latter the realization of that expertise in the form of recognized creative products. Three additional attributes of this twofold definition require special emphasis:

1. It is extremely unlikely that endowment constitutes a homogeneous psychological capacity. A person is certainly not born with a diffuse "gift" for science. Instead, the natural endowment most likely consists of a weighted composite of numerous and highly specific intellectual and personality characteristics (Simonton, 1999). Intellectual traits concern abilities and aptitudes, whereas personality traits concern tendencies, inclinations, interests, motives, and values. The former pertain to what persons *can do*, the latter to what persons *generally do* (Chamorro-Premuzic & Furnham, 2006). Thus, verbal reasoning is an intellectual trait, introversion a personality trait. Research going back as far as Cox (1926) has shown that personality traits can be every bit as important if not more important than intellectual traits in the prediction of high achievement (see also Cattell & Butcher, 1968; Feist & Barron, 2003). Cox was

also the first to demonstrate that a distinctive profile of traits are characteristic of each major domain of achievement (see also Raskin, 1936; Terman, 1954).

2. The endowed traits that enhance training need not be identical to those that enhance performance, albeit some overlap will likely exist between the two sets of traits. For example, general intelligence might make comparable contributions to both training and performance, whereas Openness to Experience might contribute much more to performance than to training. Indeed, Openness could even have a negative impact on training insofar as it distracts a student from specializing on a very narrow set of domain-specific knowledge and skills. One general repercussion of this differential impact is that the particular composition of a talent may shift over time, the traits affecting expertise acquisition differing somewhat from those that influence the realization of that expertise.

3. Natural endowment, whether intellectual or personality, may be either genetic or nongenetic. The genetic traits involve the direct transmission of genes from parents to offspring. As a consequence, such traits have nonzero heritability coefficients, where heritability is defined as the proportion of phenotypic variance in a population that can be attributed to genetic variance in that population (Falconer, 1989). Nongenetic endowment is any intellectual or personality trait present at birth that can be ascribed to some other developmental process. For instance, inborn characteristics that result from the intrauterine environment during pregnancy would be considered of this nature (McManus & Bryden, 1991). Specifically, to some undetermined extent talent in the mathematical sciences may be founded on nongenetic natural endowment (Benbow, 1987).

Although it is possible that nongenetic endowment can account for some features of scientific talent, this article will focus attention on genetic traits. The reason for focusing on genetic endowment is that it enables us to use research findings in behavior genetics to derive quantitative measures for gauging the magnitude of scientific talent.

Quantitative Measures

Suppose that a given criterion of scientific training or performance can be predicted with the use of a specific set of intellectual and personality traits, where k represents the number of predictive traits. The predictive value of these traits is indicated by a set of criterion–trait correlations or standardized partial regression coefficients. Let us also assume that each of these predictor variables has a corresponding heritability that specifies the proportion of the variance in that variable that can be attributed to genetic variance. From this information we want to create an estimate of the total heritability of the criterion. This can be called the *criterion heritability*, or h_c^2 ($0 \leq h_c \leq 1$). It turns out that it is possible to suggest at least three possible estimators. The first is defined by the following formula:

$$h_{c1}^2 = \Sigma r_{cj}^2 h_j^2, \tag{1}$$

where r_{cj}^2 is the square of the criterion–trait correlation for trait j, h_j^2 is the heritability of trait j, and the product of these two statistics is summed across all k traits. The rationale for this estimator is based on the fact that r_{cj}^2 indicates the proportion of variance in the criterion than can be explained by trait j. Because h_j^2 specifies the proportion of variance in trait j that can be explained by genetic endowment, then the product of the two gives the proportion of variance in the criterion that might be attributed to genetic variation. In effect, this was the formula used earlier in this article to estimate the genetic portion of the variance in the creativity ratings of mathematicians that can be attributed to CPS scores (where $k = 1$).

This first estimator makes an implicit assumption: The k predictor traits are all uncorrelated with each other. This condition would hold if the k traits were defined by principal components or by factor scores generated from an orthogonal rotation (using an algorithm that preserves factor orthogonality). Nonetheless, this assumption may often be too restrictive.

Even scales derived from orthogonal factor analyses will tend to be correlated (e.g., the dimensions making up the Big Five; Ilies, Gerhardt, & Le, 2004). Shared variance among the predictors implies that the squared criterion–trait correlation r_{cj}^2 will not represent the proportion of variance explained by the *j*th trait. Most commonly the statistic will be an overestimate, in which case h_{c1}^2 will also overestimate criterion heritability. One solution to this problem is to select only those criterion–trait correlates that are relatively orthogonal. By reducing the overlapping variance among the predictor traits h_{c1}^2 will become a less biased estimate.

Another solution would be to take advantage of multiple regression analyses that calculate the criterion-predictor associations for each item while partialling out the effects of the other items in the equation. Consistent with this tactic is the estimator that Ilies, Gerhardt, and Le (2004) suggested based on a simple path-analytic model, namely,

$$h_{c2}^2 = \Sigma \beta_{cj}^2 h_j^2, \qquad (2)$$

where (a) β_{cj} is the standardized partial regression coefficient obtained by regressing criterion *c* on the *k* predictor traits and (b) the summation is applied across *k* traits (i.e., $j = 1, 2, 3, ..., k$). The square of this coefficient is then multiplied by the corresponding heritability. Given that this coefficient is usually smaller than the correlation between the same two variables (i.e., $\beta_{cj}^2 < r_{cj}^2$), this estimator will be most often smaller than the first (i.e., $h_{c2}^2 < h_{c1}^2$). Hence, it will be less likely to have a positive bias.

The estimate given by Equation 2 does have one drawback, however, in that it has no upper bound. As a consequence, it is difficult to determine whether or not the genetic contribution is substantial, especially relative to the total predictability of the criterion. This disadvantage is the rationale for introducing a third estimator. This one is based on the squared multiple correlation R_c^2 between criterion *c* and the *k* predictor traits. This statistic indicates the proportion of variance in the criterion than can be explained by the *k* predictors, adjusting for the shared variance among those predictors. The squared multiple correlation is equal to the sum of the product of the criterion–trait correlations and the corresponding standardized partial regression coefficients; that is, $R_c^2 = r_{cj}\ \beta_{cj}$. As such, each term in the summation can be considered the increment that each trait *j* contributes to the total predicted variance. Therefore, each term can be multiplied by its respective heritability coefficient to estimate that portion of the explained variance that can be said to have a genetic basis. To be specific,

$$h_{c3}^2 = \Sigma\ r_{cj}\ \beta_{cj} h_j^2, \qquad (2)$$

where once more the sum is executed across *k* traits (i.e., $j = 1, 2, 3, ..., k$). It should be evident that this estimator has the squared multiple correlation as the upper bound (i.e., $h_{c3}^2 \leq R_c^2$). Hence, the ratio h_{c3}^2/R_c^2 provides an estimate of the proportion of the *explained* variance in the criterion that might be ascribed to genetic influence. This ratio can thus provide a useful evaluative statistic beyond the information provided by h_{c3}. In effect, h_{c3}^2/R_c^2 defines a weighted average of the heritabilities of the *k* traits that explain or predict the criterion *c*, the weights reflecting the contribution that each trait makes to that explanation or prediction.

The last two estimators, h_{c2}^2 and h_{c3}^2, are based on two critical assumptions. First, these estimators assume knowledge of the standardized partial regression coefficients. Without the β_{cj}s the investigator has no other recourse but to use the r_{cj}s in Equation 1. Yet this assumption is not problematic if the researcher knows the criterion–trait correlations and the intertrait correlations because these correlations suffice to obtain least-squares estimates. Most computer programs that execute multiple regression analysis will permit the input of these correlations in lieu of the raw data. Alternatively, the coefficients can be obtained by the direct mathematical manipulation of the correlations with the use of basic matrix algebra.[4]

The second assumption for the implementation of these estimators is that there are no "suppression effects" that undermine the interpretation of the terms in the two estimation equations (Maassen & Bakker, 2001). In the case of Equation 2, suppression can produce standardized partial regression coefficients that

[4] In formal terms, the estimator is $\boldsymbol{\beta} = \mathbf{r}_{cp}{}' \mathbf{R}_{pp}{}^{-1}$, where $\boldsymbol{\beta}$ is the vector of standardized partial regression coefficients, $\mathbf{r}_{cp}{}'$ is the transpose of the vector of criterion-trait correlations, and $\mathbf{R}_{pp}{}^{-1}$ is the inverse of the correlation matrix for the *k* traits that predict the criterion.

exceed unity (i.e., $\beta_{cj} > 1$ for some j), and hence the squared coefficient can also exceed unity (i.e., $\beta_{cj}^2 > 1$ for one or more traits). It is therefore technically conceivable that h_{c2}^2 might also surpass 1.0, an absurd outcome. Even if this does not happen, it does not seem reasonable to multiply the heritability h_j^2 by a number that exceeds unity and thereby render the trait's genetic contribution to criterion c greater than the genetic contribution to trait j itself. It must be manifest that any suppressor that yields this outcome cannot be incorporated into the equation that predictions criterion c, at least not if we seek a realistic estimate of h_{c2}^2.

For Equation 3 the problem is different, namely, that suppression can yield a standardized partial regression coefficient that has a different sign from the criterion–trait correlation coefficient on which it is based. When this happens, the product of the two will be negative (i.e., $r_{cj}\ \beta_{cj} < 0$ for some j), introducing a negative term in the equation (i.e., $r_{cj}\,\beta_{cj}\,h_j^2 < 0$ for some j). This prevents us from partitioning the explained variance into exclusively positive components. Because variances must always be positive, it makes no sense to have negative contributions to the summation.

In practice, these two repercussions of suppression are often connected. Specifically, a reversal in sign is often associated with enlarged rather than reduced standardized regression coefficients, including coefficients that are greater than one in absolute value. Therefore, the following strategy can be adopted to avoid both problems: Suppressor variables should be omitted until $r_{cj}\beta_{cj} > 0$ for every j. To avoid the deletion of too many predictive traits, the suppressors should be dropped sequentially, and then the β_{cj}s re-estimated after each deletion to determine if another suppressor must be left out. To the extent that suppression exists in the data, this procedure will yield conservative estimates of criterion heritability. That is, some unspecified amount of the genetic contribution is being ignored in order to partition the explained variance into positive components and to generate a plausible overall estimate.

This procedure's assumption that $r_{cj}\beta_{cj} > 0$ for all j can be justified on the basis of two separate considerations. First, the most likely expectation for a phenomenon of this type would be that r_{cj} and β_{cj} have the same sign. To find the contrary probably implies that the true sign of the association is given by β_{cj}, whereas the sign of r_{cj} reflects the impact of confounding factors that not only obscure the underlying association but actually reverse its direction (Maassen & Bakker, 2001). In different terms, the discrepant sign for r_{cj} is spurious. Second, suppression effects in psychometric data quite frequently arise when assessments of the k phenotypic traits share variance that should most properly belong to one or another measure (e.g., identical or similar items that are found in more than one scale because of item complexity). Accordingly, it can be argued that the assessments do not represent pure measures of the corresponding traits but rather they are contaminated by the common elements. For instance, the rather high correlations that observed among the scales of the California Psychological Inventory (Gough, 1987) can be partly attributed this problem (see, e.g., Horn, Plomin, & Rosenman, 1976).

It should be obvious that the three estimators given in Equations 1–3 are very closely related. In effect, they require a trait heritability to be multiplied by (a) a correlation coefficient squared, (b) a regression coefficient squared, or (c) the product of the former two coefficients (which still yields a second-degree term). When the trait predictors are uncorrelated, then $r_{cj} = \beta_{cj}$ for every trait j, and the three estimators become equivalent (i.e., $h_{c1}^2 = h_{c2}^2 = h_{c3}^2$).[5] Still, each estimator has unique assets and deficits. Equation 1 can be applied in the widest range of circumstances. It only requires knowledge of criterion–trait correlations and the parallel heritabilities. But to the extent that the trait measures are correlated, it will most likely yield a positively biased estimate of criterion heritability. Equations 2 and 3 solve this problem by using the standardized partial regression coefficients, which means that the latter information must be available, whether directly or indirectly. Yet they use this additional information in different ways. As a result, Equation 2 will

[5] The close relationship among the three estimators is becomes even more obvious when they are expressed in matrix algebra: $h_{c1}^2 = \mathbf{r}_{cp}{}'\,\mathbf{D}_h^2\,\mathbf{r}_{cp}$, $h_{c2}^2 = \boldsymbol{\beta}'\,\mathbf{D}_h^2\,\boldsymbol{\beta}$, and $h_{c3}^2 = \mathbf{r}_{cp}{}'\,\mathbf{D}_h^2\,\boldsymbol{\beta}$, where $\mathbf{r}_{cp}{}'$ and $\boldsymbol{\beta}$ are defined as in Footnote 4 and $\mathbf{D}_h^2$ is a diagonal matrix with the heritabilities along the diagonal and zero elements off the diagonal. Whenever $\mathbf{R}_{pp} = \mathbf{I}$, then $\mathbf{r}_{cp} = \boldsymbol{\beta}$, and the three expressions become identical.

normally yield a lower estimate than Equation 3 (because $\beta_{cj}^2 < r_{cj}^2$ once suppressors are omitted). Finally, because only Equation 3 produces an estimate that has a specifiable upper bound (viz., R_c^2), it may be the preferred estimator whenever it produces an estimate close to that of Equation 2 (i.e., $h_{c3}^2 \approx h_{c2}^2$).

The best approach to assessing the relative utility of the three quantitative measures is to apply them to actual data. Before doing so, it is first desirable to specify the nature of those data for an optimal evaluation.

Data Specifications

Ideally, relevant data for the application of the above estimators should satisfy the following six specifications.

First, the criterion variable or variables should be highly specific, and specific in two distinct ways. One, training criteria should be carefully distinguished from performance criteria. As noted earlier, the correlates of the former need not be identical to the correlates of the latter; the gift for learning science is not identical to the gift for creating science. In fact, different learning or performance criteria may require a divergent mix of personal traits. Two, the criteria should be confined to a particular scientific discipline and even subdiscipline. The reason for this stipulation is that the predictors of training or performance tend to be partly domain specific (Feist, 2006a; Simonton, 2004). The personal qualities needed for success vary across the physical, biological, and social sciences (Busse & Mansfield, 1984; Cattell & Drevdahl, 1955; Chambers, 1964). Even within a more delimited domain like physics it is necessary to distinguish between theoretical and experimental physicists (Roe, 1953).

Second, the predictive traits should encompass both (a) intellectual variables (e.g., general intelligence and more specialized abilities such as cognitive speed, verbal reasoning, and mathematical skills) and (b) personality variables (e.g., motives, attitudes, values, and vocational interests). It is especially important to include all correlates or predictors of scientific training or performance that are known to possess nontrivial heritabilities. To omit any such traits would have the unfortunate repercussion of underestimating h_c^2.

Third, all of the statistics should be calculated on the same samples or at least on samples drawn from the same well-defined population (see, e.g., Johnson, Vernon, Harris, & Jang, 2004). This requirement ensues from the fact that the absolute size of a correlation coefficient is contingent on the variances of the assessed variables. This contingency affects the criterion–trait correlations, the trait intercorrelations, and even the heritabilities (which are, after all, the squares of phenotype–genotype trait correlations). Given this information, one can calculate a value for h_c^2 that is representative of that same population. In contrast, if the various statistics come from different populations, then it would be more difficult to identify the population to which the estimated h_c^2 applies.

Fourth, whenever necessary and achievable, correlations and heritabilities should be corrected for attenuation due to measurement error (see, e.g., Ilies et al., 2004). For example, each bivariate correlation can be divided by the square root of the product of the reliability coefficients for the two variables (e.g., corresponding internal-consistency or test–retest reliabilities). For instance, each r_{cj} would become $r_{cj}\,(r_{cc}r_{jj})^{-1/2}$, where r_{cc} is the reliability coefficient for criterion c and r_{jj} is the reliability coefficient for the assessment of trait j. Likewise, each uncorrected heritability would be divided by the corresponding trait reliability (i.e., h_j^2/r_{jj}). Alternatively, all of the necessary parameters might be derived from confirmatory factor analyses or structural equation modeling with latent variables. The specific origin of the parameters matters less than the fact that the correction has been implemented. In the absence of the adjustment for measurement error both the criterion–trait relationships and the trait heritabilities can be underestimated, providing a negative bias in the estimation of h_c^2.

Fifth, correction for range restriction should also be implemented whenever possible and necessary. Truncated variance in one or both variables in a bivariate correlation must reduce the magnitude of the relationship (Hunter & Schmidt, 1990). Estimates of criterion–trait correlations or regression coefficients are especially susceptible to this problem. For instance, using an intelligence measure to predict training enhancement in graduate school must compensate for the fact that only the most intelligent applicants will even be admitted into graduate programs (see, e.g., Kuncel, Hezlett, & Ones, 2004).

Sixth and last, the h_j^2 for each trait j should be the broad- rather than narrow-sense heritability. A broad-sense heritability includes both additive and nonadditive effects (due to dominance and epistasis), whereas a narrow-sense heritability only includes the additive effects (Falconer, 1989). The concept of genetic endowment most consistent with the talent definition given earlier presupposes that all genetic effects are accounted for in the calculation of h_c^2. The narrow-sense heritabilities are restricted to the kind of familial inheritance presumed in Galton's (1869) *Hereditary Genius*. Although this may be of some interest in comprehending Galton's findings and the Nobel pedigrees mentioned at the outset of this article, the broad-based heritabilities have more extensive value. They can better account for eminent scientists who, like Isaac Newton, lacked any distinguished family lineage.

It may come as no surprise that it is absolutely impossible to satisfy all of these scientific desiderata given the current state of the empirical literature.[6] Even so, it is instructive to apply the estimators to the data that are available to obtain some rough estimates of criterion heritabilities.

Meta-Analytic Illustrations

To illustrate the relative utility of the three estimators, they will be applied to two distinct data sets. The illustration begins with personality traits and then turns to intellectual traits.[7]

Personality Traits

Feist (1998) compiled an exhaustive meta-analytic review of the personality traits associated with scientific and artistic creativity. He specifically examined the traits germane to three criteria: scientists versus nonscientists (SvNS; 26 studies of 4,852 participants), creative versus less creative scientists (CvLCS; 30 samples of 3,918 participants), and artists versus nonartists (39 studies of 4,397 participants). The SvNS criterion is relevant to scientific training, whereas the CvLCS is germane to scientific performance. Predicting the criteria were the scales of the California Psychological Inventory (CPI; Gough, 1987), the Eysenck Personality Questionnaire (EPQ; Eysenck & Eysenck, 1975), and the 16 Personality Factor Questionnaire (16PF; Cattell, Eber, & Tatsuoka, 1970). Although Feist attempted to consolidate the diverse results in terms of the Five Factor Model (e.g., Goldberg, 1993), he observed that these five factors did not adequately differentiate the three criteria, and so he also presented the findings in terms of the original scales of the CPI, EPQ, and 16PF. Because the meta-analytic and behavior genetic results are far more extensive for the CPI, I will focus on those findings to illustrate the analytical approach, and then more briefly treat the EPQ results. However, the 16PF meta-analytic findings must be ignored. Notwithstanding the availability of data for calculating both the criterion–trait correlations (Feist, 1998) and the trait intercorrelations (Cattell et al., 1970), suitable heritability estimates have not been published (cf. Loehlin, Horn, & Willerman, 1981). Happily, because the 16PF scales share considerable variance with the CPI scales (Campbell & Chun, 1977; Nerviano & Weitzel, 1977) it is unlikely that the following h_c^2 estimates will overlook much predictive genetic variance.

CPI estimates.

Feist (1998) presented the CPI effect sizes using Cohen's d. These values were converted into correlation coefficients for each phenotypic trait j using the formula $r_{cj} = d_j(d_j^2 + 4)^{-1/2}$ (cf. Hunter & Schmidt, 1990). The three vectors of criterion-trait correlations for the three compar-

[6] If all six of these conditions were met, and if no gene-environment interaction effects existed with respect to criterion c, then we would also obtain a new interpretation for the quotient h_{c3}^2/R_c^2. Not only will h_{c3}^2/R_c^2 provide an estimate of the proportion of explained variance in the criterion that is attributable to genetic variation, but also $(1 - h_c^2)/R_c^2$ offers an estimate of the proportion of explained criterion variance the can be ascribed to environmental variation. In short, the explained variance in the training or performance criterion can be uniquely partitioned into nature and nurture components.

[7] The focus of all analyses will be on calculating point estimates of h_c^2 because there is often insufficient information about the specific sample sizes that are required to calculate the standard error needed to obtain interval estimates (cf. Ilies, Gerhardt, & Le, 2004; Kuncel, Hezlett, & Ones, 2004). It will take much more applicable empirical research to get to the point that we can construct meaningful confidence intervals around the estimators.

isons are shown in Table 1. Following Feist, only those CPI criterion–trait correlations are considered for which $d_j \geq 0.49$ (i.e., at least "medium" effects). It is noteworthy that each criterion involves a very distinct set of traits. The variables that distinguish scientists from nonscientists (SvNS) are not identical to those that distinguish creative scientists from less creative scientists (CvLCS). Accordingly, the underlying genotypes must also be distinctive. This complies with Simonton's (1999, 2005) postulate that talent is defined in terms of separate profiles with respect to partially inheritable individual-difference variables.

Table 1 also includes heritabilities taken from Carey, Goldsmith, Tellegen, and Gottesman (1978) based on twin data from five different studies. The heritiabilities were calculated by the formula $h_j^2 = 2(r_{mz} - r_{dz})$, where r_{mz} and r_{dz} are the average intraclass correlations for the monozygotic and dizygotic twins, respectively. One might argue that better heritability estimates would be obtained from Horn, Plomin, and Rosenman (1976) insofar as those researchers created pure CPI scales with the overlapping items removed. Consequently, they obtained more variable estimates, indicating that the 18 scales are differentially inherited. Even so, because the criterion–trait correlations are based on the actual CPI scales rather than the "pure" scales, the former estimates were deemed more appropriate. Moreover, much of the interscale shared variance is reduced by the procedure adopted to calculate the standardized regression coefficients in Equations 2 and 3.

Table 1
California Psychological Inventory Scale Heritabilities, Criterion–Trait Correlations, and Standardized Partial Regression Coefficients for Two Criteria

Scale	h_j^2	SvNS r_{cj}	SvNS β_{cj}	CvLCS r_{cj}	CvLCS β_{cj}
Dominance	.56			.256	
Sociability	.66	.238	.079	.287	.096
Self-acceptance	.56			.326	.146
Tolerance	.40			.359	.217
Achievement via conformance	.30	.279	.098		
Achievement via independence	.32	.335	.244	.243	
Intellectual efficiency	.32			.252	
Psychological mindedness	.44	.247		.243	
Flexibility	.40			.265	.146

Note. SvNS = scientists versus nonscientists and CvLCS = creative scientists versus less creative scientists.

As indicated earlier, to estimate the β_{cj}s for all j presumes knowledge not just of the criterion–trait correlations but also of the correlations among the phenotypic traits. The latter should be based on the same samples as the former, or at least on samples drawn from the same population. In the absence of correlations satisfying this standard, I will instead resort to the scale intercorrelations reported in Gough (1987). These are based on 1,000 males and 1,000 females. Because males predominate among the samples in Feist's (1998) meta-analysis, the male correlations alone provided the information. Nonetheless, because the male and female correlations are very similar, the main results are unchanged if the latter were used instead. It should be observed that these correlations are probably biased upwards. The samples used in many of the studies in Feist's (1998) review are likely more select than the samples used by Gough (1987). This selectivity is especially conspicuous for the CvLCS criterion. Yet this positive bias would most likely work against finding large estimated h_c^2s.

When all zero-order correlates were included, several suppression effects emerged owing to the appreciable overlap among the CPI scales. As a consequence, criterion-trait correlates were progressively removed. The deletion began with the correlates in which there was a sign change between r_{cj} and β_{cj}, deleting first those with the biggest quantitative discrepancies between the two values. Removal of criterion–trait correlates ceased when r_{cj} and β_{cj} had the same sign for every jth trait. For example, in the case of the SvNS criterion the specified touchstone was quickly met once the Psychological Mindedness scale was omitted. The other criterion, however, required the deletion of about half of the correlates. Table 1 provides the standardized partial regression coefficients that emerged for each of the two criteria. Without exception the standardized partial regression coefficient is the same sign as, but smaller than, the original criterion-item correlation (i.e., $r_{cj} < \beta_{cj}$). This tells us that suppression effects have been removed from the analysis so that any remaining shared variance among the predictors represents mere redundancy.

The information in Table 1 is sufficient to provide estimates of h_{c1}^2, h_{c3}^2, and h_{c2}^2. The outcome is presented in Table 2. From these results it is evident that the criterion heritabilities range widely across estimators and criteria. Equation 1 (h_{c1}^2), which alone uses all predictor traits for each criterion, yields the largest estimates, ranging from 12% for SvNS to 30% for CvLCS. The estimates from Equation 2 are much more modest, ranging from 3% to 5% for the same criteria. Equation 3 yields estimates much closer to those of Equation 2 but slightly higher, namely, between 5% for SvNS and 9% for CvLCS. Despite this variation across the estimators, they all agree that the genetic contribution to the CvLCS criterion is about double that of the SvNS criterion.

Furthermore, the estimated genetic influence varies greatly across the traits defining a particular criterion. Some may contribute less than 1% and others much more, depending on the estimation equation. Yet most contributions are relatively small—seldom more than a .10 increment, and most often less. This is also apparent in the mean contributions of the genotypic traits. Hence, the only reason why the total genetic contribution can noticeably surpass a small amount is that the total effect is summed across three or more traits. This is an important general principle: As k increases, the ultimate size of h_c^2 can be large even if the average sizes of h_j^2 and r_{cj} or β_{cj} are small. Talent is based on the cumulative sum of the products rather than the separate contributions.

Finally, in the case of Equation 3 one can calculate the proportion of the total explained variance in the criterion that might be attributed to the genetic component. Specifically, between 37% and 48% of the explained variance might be ascribed to genetic variation. Hence, it seems sensible to conclude that somewhere between one third and one half of the predicted variance in a criterion might possibly be ascribed to genetic influence. The remainder may represent some combination of environmental influences and measurement error.

The last point deserves elaboration. The results reported in Tables 1 and 2 were not corrected for attenuation due to measurement errors. Because Gough (1987) provided reliability coefficients for each of his CPI scales, it would seem possible to rectify this omission. Unfortunately, the corresponding reliabilities for the criterion variables are unavailable (Feist, 1998). That means that although the item intercorrelations can be appropriately corrected, the criterion–item correlations can only be half corrected, a difference that would inflate the former relative to the latter. Given that the CPI scales are already highly intercorrelated, this would render the shared variance among the phenotypic traits even larger, and thereby create even more severe suppression effects. Hence, the correction for attenuation was left unimplemented. It seems reasonable to admit that the values of h_{c1}^2, h_{c2}^2, and h_{c3}^2 are underestimates, particularly in the case of h_{c2}^2 and h_{c3}^2.

Table 2
California Psychological Inventory Criterion Heritability Estimation for Two Criteria

Estimator	SvNS	CvLCS
Equation 1		
k	4	8
Minimum product ($r_{cj}^2 h_j^2$)	.0233	.0188
Maximum product ($r_{cj}^2 h_j^2$)	.0374	.0596
M ($1/k\ \Sigma\ r_{cj}^2 h_j^2$)	.0308	.0369
Sum ($\Sigma\ r_{cj}^2 h_j^2$) = h_{c1}^2	.1233	.2955
Equation 2		
k	3	4
Minimum product ($\beta_{cj}^2 h_j^2$)	.0029	.0061
Maximum product ($\beta_{cj}^2 h_j^2$)	.0191	.0187
M ($1/k\ \Sigma\ \beta_{cj}^2 h_j^2$)	.0087	.0113
Sum ($\Sigma\ \beta_{cj}^2 {}_{hj}^2$) = h_{c2}^2	.0260	.0454
Equation 3		
k	3	4
Minimum product ($r_{cj}\beta_{cj}h_j^2$)	.0081	.0155
Maximum product ($r_{cj}\beta_{cj}h_j^2$)	.0262	.0311
M ($1/k\ \Sigma\ r_{cj}\beta_{cj}h_j^2$)	.0156	.0229
Sum ($\Sigma\ r_{cj}\beta_{cj}h_j^2$) = h_{c3}^2	.0467	.0915
h_c^{32}/R_c^2	.3659	.4770

Note. SvNS = scientists versus nonscientists and CvLCS = creative scientists versus less creative scientists.

EPQ estimates.

I turn now to Feist's (1998) meta-analysis using the Eysenck Personality Questionnaire. The EPQ has only three factors, one of which, Neuroticism, does not discriminate any of the criteria. In comparison, the Psychoticism and Extraversion scales are both germane to the SvNS criterion. Scientists relative to nonscientists score higher on both of these scales. As in the CPI example, the analysis begins by converting Feist's d estimates to criterion–trait correlations. These appear in Table 3.

The next step is to obtain the heritabilities for the Psychoticism and Extraversion traits. These came from an analysis of monozygotic and dizygotic twins (N = 9,672) plus their siblings (N = 3,241) that derived reliability-corrected, broad-sense heritability estimates (Keller, Coventry, Heath, & Martin, 2005). Although the Extraversion estimates were identical for males and females in the sample, Psychoticism exhibited a small gender difference, and accordingly the male heritabilities were used for the same rationale mentioned in the CPI illustration. These coefficients are also presented in Table 3.

The calculation of β_{cj} is complicated by the existence of a small correlation between the Psychoticism and Extraversion factors. In Keller et al. (2005) this correlation was .13. When this value is combined with the two r_{cj} coefficients we get the two standardized partial regression coefficients also shown in Table 3. There were no suppression effects, and both regression coefficients have the same sign as their corresponding correlation coefficients but with some reduction in size due to the redundant variance. Given this information, it is now possible to calculate the three estimates: h_{c1}^2 = .036, h_{c2}^2 = .028, and h_{c3}^2 = .032. Hence, the genetic contribution to the SvNS criterion ranges between 3% and 4% using these two traits. In contrast, the squared multiple correlation (R_c^2) is .067, so in the case of h_{c3}^2 we can infer that about 47% of the variance explained by the EPQ might be credited to genetic influences.

Without knowing the exact correlations between the relevant EPQ and CPI scales, it is impossible to determine the precise degree to which these results add an increment to the previous estimates. Even so, it is probable that the h_c^2 estimates from the EPQ are partly independent of those derived from the CPI, and thereby raise the overall magnitude of heritability for the SvNS criterion.

Table 3
Eysenck Personality Questionnaire Heritabilities, Criterion–Trait Correlations and Standardized Partial Regression Coefficients for SvNS Criterion

Scale	h_j^2	r_{cj}	β_{cj}
Psychoticism	.43	.220	.202
Extraversion	.57	.163	.137

Note. SvNS = scientists versus nonscientists.

Intellectual Traits

The foregoing analysis provides a statistical estimate of scientific talent insofar as it is defined by personality traits with nontrivial heritabilities. To be sure, the analysis leaves much to be desired from the standpoint of the ideal data specifications. Especially problematic were the three criteria variables. Although these are supposed to be narrowly defined, in fact they were quite broadly conceived. For instance, the SvNS criterion was defined as "any sample from junior high school on through adulthood that showed special talent in science, majored in science, or that worked professionally in academic or commercial science" (Feist, 1998, p. 294). Even worse, "science" was obliged to include the physical, biological, and social sciences as well as mathematics, engineering, and invention. To the extent that the personality profiles are closely tailored to domain-specific training or performance criteria, this definitional inclusiveness implies that the h_c^2 estimates are too low. This criticism is not intended to fault Feist's (1998) meta-analytic review. To obtain sound effect size estimates he had no other option but to collate many diverse findings. Nevertheless, in this analysis of intellectual traits it is feasible to substitute somewhat more specific criteria for these more global contrasts. While introducing these criteria I will also narrow the number of traits examined. In fact, I wish to concentrate just on the impact of general intelligence, a trait that is most likely to be the common component in all talent profiles in the sciences (see, e.g., Gibson & Light, 1967; Roe, 1953).

I begin with the meta-analysis of Kuncel et al. (2004). The investigators examined the relation between various training and performance criteria and scores on the Miller Analogies Test (MAT; Miller, 1960). The authors argued that the MAT provides a good indicator of general intelligence (i.e., Spearman's g; Spearman, 1927). For example, on the basis of 15 studies of 1,753 participants they estimated a true-score correlation of .75. In addition, Kuncel et al. calculated the correlations between MAT and several academic criteria. These estimates are presented in Table 4 along with their squared values (i.e., r_{cM} and r_{cM}^2). The latter indicate the proportion of variance in each criterion that can be attributed to variation in MAT scores. These vary around 4% to 34%.

Multiplying these latter values by the heritability of general intelligence would then yield the proportion that might possibly be attributable to genetic endowment. Unfortunately, heritability estimates for general intelligence can vary greatly, a variability that reflects not just the diversity of measures but also the variety of estimation methods and the demographic characteristics of the samples (Bouchard & McGue, 1981; Plomin, 1990). However, because the criterion–MAT correlations concern adults in their mid-20s, a reasonable if perhaps slightly conservative estimate would be that the true heritability lies somewhere between .70 and .80 (cf. McGue, Bouchard, Iacono, & Lykken, 1993). So let us set $h_L^2 = .70$ and $h_U^2 = .80$. These then yield two estimates of the genetic contribution, namely, $h_{cL}^2 = r_{cM}^2 h_L^2$ and $h_{cU}^2 = r_{cM}^2 h_U^2$. Because this analysis concentrates on a single trait, it is not necessary to distinguish the three types of quantitative criteria. They all become equivalent when $k = 1$.

The estimates of h_{cL}^2 range from about 3% to 24%, whereas the estimates of h_{cU}^2 range from about 3% to about 27%. Although the smallest effect is for research productivity, this criterion has a very low base rate, was highly skewed, and was not corrected for measurement error (cf. Feist, 1993; Rodgers & Maranto, 1989). Moreover, the magnitude of the effect is still large enough to infer that even this criterion may have some genetic component. The only genuine peculiarity in Table 4 is the positive effect for time to finish degree. This relation is the inverse of what would be expected from the talent definition given earlier in this article. Scientific talent should take less time rather than more. Kuncel et al. (2004) admitted that this result was unexpected and could merely provide an ad hoc explanation, namely, "that more able students are likely to spend time in graduate school doing nondegree work (e.g., research) that may keep them from finishing as fast as other students" (p. 157). Because the students in their meta-analyses represent a great diversity of academic disciplines and subdisciplines, it is conceivable that a more complex process is going on here, including one that inserts some methodological artifact. This particular puzzle must be left for future research.

In any case, because general intelligence is largely uncorrelated with the personality traits used in the CPI and EPQ analyses (see, e.g., Brebner & Stough, 1995), we would expect that the inclusion of this intellectual trait would add a substantial increment to an overall h_c^2. Furthermore, the genetic estimated contribution of intellectual traits would no doubt increase if we were to incorporate more specialized intellectual traits that also have substantively important heritabilities (cf. the "specific factors" of Spearman, 1927). These traits include spatial reasoning, verbal reasoning, cognitive speed, and even spatial and verbal working memory (see, e.g., Bouchard et al., 1990). For example, spatial ability has been identified as a crucial component of math–science talent that exhibits predictive utility beyond that provided by both mathematical and verbal ability (Webb, Lubinski, & Benbow, 2007). Yet measures of spatial intelligence display heritabilities almost as high as general intelligence (Bratko, 1996; McClearn, Johansson, Berg, & Pedersen, 1997). Moreover, these more specialized intellectual abilities may be especially useful in differentiating distinct types of scientific talents. For instance, in Roe's (1953) classic study of 64 eminent scientists it

Table 4
Criterion–MAT Correlations and Lower- and Upper-Bound Criterion Heritability Estimates

Criterion (c)	r_{cM}	r_{cM}^2	h_{cL}^2	h_{cU}^2
First-year graduate grade point average	.41[a]	.168	.118	.134
Graduate grade point average	.39[a]	.152	.106	.122
Faculty ratings	.37[a]	.137	.096	.110
Comprehensive examination scores	.58	.336	.235	.269
Degree attainment	.21[b]	.044	.031	.035
Time to finish degree	.35[b]	.123	.086	.098
Research productivity	.19[b]	.036	.025	.029

Note. The column of criterion–MAT correlations (r_{cM}) are taken from the column of ρs given in Table 2 in Kuncel, Hezlett, and Ones (2004). The criterion of "Number of courses/credits completed" was omitted because its magnitude was too small to yield a nontrivial criterion heritability. The lower-bound estimate assumes that $h_L^2 = .70$ and the upper-bound estimate that $h_U^2 = .80$

[a] Criterion corrected for attenuation due to measurement error.

[b] Corrected for range restriction in the intellectual trait (MAT scores).

was found that theoretical physicists, experimental physicists, biologists, psychologists, and anthropologists display distinctive profiles with respect to verbal, mathematical, and spatial intelligence.

Discussion

I cautioned earlier that the preceding meta-analytic illustrations must be remote from what is required for an ideal assessment of the impact of talent. Rather than estimate the needed statistics from data on a single sample or from a sample drawn from a single population, I have been limited to piecing together the required information from a diversity of empirical studies. So the h_c^2 values calculated for intellectual and personality traits can be considered mere ballpark estimates. Because the first estimator seems to yield values too high,[8] it is best to use the second and third estimators to establish the most likely ranges for the contributions of the personality traits. Under that assumption, the estimates range between 3% and 9% for the California Psychological Inventory and between 3% and 4% for the Eysenck Personality Questionnaire. Presumably, a portion of the EPQ variance can be added to the CPI variance, and to that sum can be added the variance attributable to general intelligence as gauged indirectly by the Miller Analogies Test (see Table 4). It is not possible to say exactly when the final sum would be, but a conservative guess might be that between 10% and 20% of the variance in these criteria could be potentially attributed to genetic effects (cf. Simonton, 2007).

For the sake of this discussion, then, suppose that $.10 \leq h_c^2 \leq .20$ holds for the training and performance criteria examined here. Does this outcome imply that scientific talent is an important substantive phenomenon? To answer this question requires that we obtain some kind of baseline for comparison. One such baseline can be created by considering h_c^2 as the multiple correlation between the criterion c and a weighted sum of the indirect effects of the k genotypic traits mediated by the direct effects of the corresponding phenotypic traits. Accordingly, the estimate can be converted into Cohen's d with the use of the formula $d_c = 2h_c(1 - h_c^2)^{-1/2}$ (cf. Hunter & Schmidt, 1990). This transformation yields $0.67 \leq d_c \leq 1.0$, a range that can be qualitatively expressed as medium to large (Cohen, 1988). This range is about as good as can be expected of most effects in the behavioral sciences (Meyer et al., 2001; Rosenthal, 1990). To offer specific comparisons, the lower-end estimate is about the same magnitude as the relation between psychotherapy and subsequent well-being, whereas the upper-end estimate is about the same size as the correlation between height and weight among U.S. adults (Meyer et al., 2001). As a result, scientific talent would have to be viewed as a potent effect. This conclusion is reinforced from the following three considerations.

First, the criteria fall far short of what is necessary to capture the full impact of scientific talent. In the case of the personality traits, we only examined three rather global criteria, namely, scientists versus nonscientists and creative scientists versus less-creative scientists. These rudimentary contrasts ignore the conspicuous differences in how talent is realized in the physical, biological, and social sciences (Simonton, 2004, 2006). With respect to the single intellectual trait, we solely considered first-year graduate grade-point average (GPA), graduate GPA, faculty ratings, comprehensive examination scores, degree attainment, time to finish degree, and research productivity. Besides the fact that these criteria were defined with respect to academic disciplines in general, they still do not exhaust the available criteria. Most strikingly, both citations and awards or honors were ignored (cf. Feist, 1993; Simonton, 1992). What is decidedly missing is the analysis of much more narrow criteria, such as first-year GPA in chemistry graduate programs or citations received for publications in the earth sciences. If it is true that the profiles of predictive traits are tightly tailored to specific criteria, then the h_c^2 estimates should increase accordingly.

Second, we have by no means exhausted all of the conceivable phenotypic predictors. As already mentioned, the meta-analysis was con-

[8] If h_{c1}^2 is calculated from the same variables as h_{c2}^2 and h_{c3}^2, the estimates become more reasonable (e.g., .097 and .194 for the CPI scales applied to SvNS and CvLCS criteria, respectively). But if the investigator already knows what predictor traits must be excluded, the use of the first estimator could not be justified at all.

fined to a single indicator of general intelligence, when it is clear that more specific intellectual traits likely affect either training or performance. Yet it is equally manifest that numerous personality traits are also absent from the meta-analytic and behavior genetic integration. For instance, it should be apparent that the literature needs more investigations that apply the Big Five Factors (and their facets) directly to the prediction of scientific training and performance—a desideratum underlined by the availability of appropriate heritability estimates (e.g., Loehlin, McCrae, Costa, & John, 1998). Perhaps even more variance may be contributed by the vocational interests that play a major role in career development (e.g., Lubinski & Benbow, 1994) and that also feature substantial heritabilities (Bouchard et al., 1990). For example, Waller, Lykken, and Tellegen (1995) estimated a heritability of .59 for a scientist occupational interest factor. Thus, it is not unreasonable to conjecture that h_c^2 for certain criteria might eventually be doubled, yielding a range from 10% to 40%.

Third and last, estimates of genetic endowment will have a negative bias if scientific talent actually operates according to emergenic inheritance. Emergenesis occurs when a multiple-trait characteristic is a multiplicative rather than additive function of its component traits (Lykken, 1982). Expressed differently, the appearance of a given attribute requires the simultaneous inheritance of all contributing traits. Although emergenesis is a relatively new idea in behavior genetics, there is already some evidence that some complex characteristics are subject to such inheritance (Lykken, McGue, Tellegen, & Bouchard, 1992; Waller et al., 1993). If emergenesis applies to scientific talent as well, then the estimators defined in Equations 1, 2, and 3 are biased downward. The bias arises from the fact that all three estimators posit that talent is an additive function of intellectual and personality traits (Simonton, 1999). It is important to recognize that emergenesis is not to be confused with epistatis. The former involves the interaction across genetically inherited traits, whereas the latter involves the interaction between genes within polygenic traits (Falconer, 1987). Consequently, emergenic inheritance is not assessed by broad-sense heritabilities because the latter concern a single polygenic trait rather than configurations of numerous polygenic traits defining an individual-difference profile. Nevertheless, emergenesis has one property in common with epistasis: Inheritance will be less familial, again in contradiction to the basic premise underlying Galton's (1869) conception of talent. Hence, emergenesis, like epistasis, can help explain how scientific talents can emerge in families that appear otherwise to lack signs of scientific giftedness.

In light of the foregoing three points, it should be understandable why we are a long way from obtaining precise measures of scientific talent. Those assessments will require (a) more finely differentiated criteria of training and performance, (b) larger inventories of intellectual and personality traits, and (c) greater attention to the exact functional relation between the criteria and the predictor traits. So this is not an issue to be settled within a short time span. Fortunately, because the psychology of science is undergoing something of a revival in the 21st century (Feist, 2006b; Feist & Gorman, 1998), it is hoped that this specific substantive problem will attract more differential psychologists and behavior geneticists. If so, then in due course a more integrated demonstration can replace this more piecemeal argument.

Eventually it may be possible to construct complex structural equation models of scientific training and performance in which genotypic traits serve as exogenous variables alongside environmental influences (cf. Feist, 1993). Besides integrating genotypic and phenotypic traits (plus any applicable gene–environment interactions), such models could specify which individual-difference variables affect performance criteria directly and which are mediated by their impact on training variables (cf. Helmreich, Spence, Beane, Lucker, & Matthews, 1980; Rodgers & Maranto, 1989; Simonton, 1992). Besides capturing the full complexity of the phenomenon, comprehensive models of this type would provide a research paradigm for understanding the impact of talent in achievement domains beyond the sciences. For example, because artistic creativity displays even stronger links with personality than does scientific creativity (Feist, 1998), criterion heritabilities will be even higher than found in domains of scientific achievement.[9] In time, the nature–nurture issue that Galton (1874) first raised with respect to scientific talent may be successfully resolved for all forms of exceptional achievement.

[9] For example, when the same estimation methods are applied to the CPI effect sizes that Feist (1998) reports for artists versus nonartists one obtains the following figures: $h_{c1}^2 = .58$, $h_{c2}^2 = .184$, and $h_{c3}^2 = .212$. These are all larger than the CvNS and CvLCS results.

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Received April 1, 2007
Accepted June 21, 2007 ■