Intelligence and Social Inequality: Why the Biological Link?

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1. Introduction

Were he to survey life in Western democracies today, the proverbial Man from Mars might conclude that the notions of *intelligence* and *inequality* are both profane. Many of my undergraduate students interpret the United States Declaration of Independence's premise that "all men are created equal" to mean, not that all individuals are born with the same freedoms and unalienable political rights, but rather with equal natural endowments. For them, to suggest otherwise is not only undemocratic but a threat to the American polity.

Democracies seem particularly vexed by biologically-based variation in general intelligence. Human groups have always had to accommodate the natural diversity of their members. Modern nations, however, are far larger and more anonymous than societies past, and hence their members' relations and social niches are more bureaucratized and regularized by cultural arrangements such as schools, workplaces and layers of government. Nations expend increasing effort to measure, monitor and manage these relations, as well as the unevenness in life outcomes they produce. They struggle with two contentious questions. One is empirical: why is inequality so enduring? The second is political: how should a society react to it? This chapter addresses a more deeply contentious question: Why is socioeconomic inequality so entwined with a population's cognitive diversity?

Table 1, for fathers and sons, illustrates the typical pattern documented in hundreds if not thousands of studies. Son's IQ correlates modestly with father's education and occupational status (.3, .3) and more strongly with son's own level of education, occupation, and earnings (.6, .5, .3), although most strongly with education and least with income. The particulars vary across studies, populations, time, ages, sex, and measures of family background, IQ, and status outcomes, but the pattern is always the same. Individuals who rise higher on one social ladder tend to rise higher on the others, and intelligence level predicts rise on them all (the shaded entries in Table 1). Of particular concern to sociology, my native discipline, is that socioeconomic inequality is intergenerational. Specifically, children's differences in IQ and adult status outcomes are always correlated with those of their parents—only modestly so, yet substantially. This chapter focuses on how intelligence level might contribute to this parent-offspring similarity in adult socioeconomic attainments.

Insert Table 1 About Here

1.1. Population-Level Perspective on Human Inequality and Cognitive Diversity

Philosophical debates about the natural relation between man and society help frame our analysis. For instance, in his 1746 *Discourse on the Origin and Foundations of Inequality among Men,* Jean-Jacques Rousseau (1755/1964) argued that civil institutions magnify any natural differences among individuals. Thomas Henry Huxley (2009) argued the opposite in his 1871 and 1890 essays, "Administrative nihilism" and "On the natural inequality of men," namely, that civil institutions work to level the human inequalities that exist in nature. Both men accepted that humans are born unequal, but they disagreed about whether social institutions exaggerate or ameliorate the social differences that natural ones create. Thus, while they both imply that social differences are unjust and hence should be minimized if not eradicated, the two philosophers would seem to differ on whether civil institutions themselves are immoral or moral responses to natural human differences—Rousseau believing that civil institutions create unjust social differences and Huxley believing they decrease them.

Their debate helps to frame our modern one in two ways. It points to social institutions as organized reactions to natural differences within populations, whether those reactions are to exaggerate or moderate the differences. Next, by embodying the implicit assumption that inequality itself is unjust, this philosophical debate illustrates why empirical research on what creates and sustains it is so fraught with political tension. In fact, the all-too-common antipathy to evidence for the reality, importance, and durability of intelligence differences may reflect just such a reaction to natural differences and their social consequences.

Like variation in human height, cognitive diversity is a fact of nature. Every population exhibits a wide spread in general intelligence and it takes a predictable form (something close to a bell curve, where most people cluster around the group average). As best we can tell, variation in phenotypic intelligence is fairly stable over time for the same population of genotypes. It likely oscillates within narrow limits unless environmental effects on intelligence change dramatically. Average levels of ability may rise (or fall) over time, as suggested by the secular increase in IQ scores during the Twentieth Century, but this will not necessarily change cohort variation in intelligence.

Although psychological measures do not yet allow the ratio-level measurement required to know this, we can turn to secular increases in height, which have been comparable in magnitude in standard deviation (SD) units to the secular increases in IQ. The height of 18.5-year-old Dutch male military draftees (a compulsory draft) increased one SD between 1950 and 1978, but their variability in height remained the same (SD=6.5 cm; van Wierungen, 1986, calculated from Table 11, p. 319). Dispersion in phenotypes might contract or expand in succeeding generations if the mix of genotypes changed, but changes would be glacial unless the group experienced a sudden shift in genotypes owing to rapid non-random loss or gain in members through war, disease, famine, migration, and the like.

1.2. Chapter Topics and Conceptual Guide

This chapter focuses on a specific puzzle in the study of social inequality—why do differences in general intelligence, *g*, relate so pervasively, consistently, and substantially to different forms of socioeconomic status? Tackling it requires drawing evidence from the various disciplines that study individual differences in *g*, from their genetic sources, through their manifestations in the brain, to their practical consequences in social life. The following sections ask whether the evidence from these different disciplines forms systematic patterns (e.g., by age, type of task or inequality), whether they replicate across different forms of evidence (psychometric, physiological, etc.), and whether they appear at both the phenotypic and genetic levels (for any of the above). Single studies are never dispositive, but patterns may be—but even then, only when the full network of evidence has been considered.

Figure 1 provides a conceptual map by organizing questions and evidence according to the typical life course model, essentially a causal flow chart, used in status attainment modeling research. It adds two features to those models, however. It decomposes “Background Influences” (the leftmost column) into their genetic and environmental components, whereas status attainment research generally proceeds as if there were little or no genetic variance in family backgrounds or status attainment. Figure 1 also adds another phenomenon neglected in such models, which is differences in how well individuals actually perform jobs and other life tasks that might influence their status attainment (lower right of the figure).

Insert Figure 1 About Here

Sections 2 and 3 examine the meaning and measurement of the two sides of the equation in question: social inequality and intelligence differences. Section 2 describes the social inequalities to be explained, which are depicted in the upper right of the figure. Section 3 turns to the key predictor of interest, cognitive diversity, which is represented in the shaded box under “Personal Attributes.” To evaluate the meaning or *construct validity* of intelligence, Section 3 looks both backward and forward in Figure 1: back to the genetic and nongenetic roots of cognitive diversity (“Background Influences”) and forward to its manifestation in daily human performances outside mental test settings, particularly in school and work (“Task Performances,” to the lower right). Section 4 then introduces evidence on the phenotypic and genotypic links between the two realms, intelligence differences and social inequality, in order to test competing hypotheses about how cognitive diversity might generate social inequality as individuals compete to get ahead in life. The chapter concludes in Section 5 by revisiting the question of how societies attempt to accommodate cognitive diversity and why their efforts frequently have opposite their intended effects. The answer may be summarized as the *democratic dilemma.*

2. Meaning and measurement of social inequality

Inequality is studied at both the individual- and population-level of analysis, referred to respectively as the study of *status attainment* ("who gets ahead") and the *stratification* of populations into broad social classes.

2.1. Status Attainment of Individuals: Level of Education, Occupation, and Income

Research on individual differences in social inequality typically seeks to explain the spread of individuals across three social ladders: level of education, occupation, and income. These three achievements are sequentially contingent, as suggested by the life course model in Figure 1. Advancing further in school increases one's chances of getting a good job, which in turn increases the odds of earning a good income. Other things influence outcomes at each stage, but the range of possible outcomes is limited by achievements at earlier stages.

Education level (usually shortened to "education") is typically measured by self-reported years of schooling completed, ranges thereof (e.g., <8, 9-11, 12, 13-15, 16+), or highest degree earned (e.g., none, high school diploma, bachelors degree or more). Its meaning and causal significance usually remains vague and unspecified, or is supplied post-hoc. Depending on the study, it may be interpreted as length of exposure to instruction, amount of information learned, level of cognitive skills inculcated, amount of human capital amassed, number of institutional hoops jumped, degree of acculturation or indoctrination, and so on. The shape of the distribution for years of schooling attained has changed radically over the Twentieth Century, from skewed right to skewed left. Only 10% of American 14-17 year-olds were attending secondary school in 1910, but over 90% by 1970; 2% and 36% of 18-24 year-olds were attending college in 1900 and 1970, and by 2008 half were in college (National Center for Education Statistics, 1993, Figure 7 & Table 24; 2010, Table A-1-1). These are culturally seismic changes.

Occupational level ("occupation") is usually measured in units of prestige level (e.g., 0-96 on the Duncan scale; Duncan, Featherman, & Duncan, 1972) or a small set of ordered categories (e.g., Britain's socio-economic classification ranging from I for professional to V for unskilled work). The distribution of workers by occupation has likewise shifted greatly over the last century as economies evolved from primarily agricultural to mostly service-based. Almost 40% of the American civilian workforce worked in agriculture in 1900, under 5% in 1970, and less than 1.5% in 2008. In contrast, between 1970 and 2008 alone the percentage employed in the service sector (professional & business services [not financial], education, health and social assistance, leisure and household) rose from 26% to 46% (U.S. Bureau of the Census, 1990, Table 650; 2009, Table 607). Like many other sociologists, I see occupations as the key to understanding social inequality, so this chapter pays particular attention to that dimension of social inequality. Sociologists have tended to view occupations primarily as scaffolds on which societies hang social rewards, respect, and influence, but not as interesting entities in themselves. Section 3 will open up the black box of occupation to reveal a treasure trove of evidence. It shows that differences in task demands across these boxes matter a lot and also influence the social ornaments attached to them.

Measuring income level ("income" or "earnings") is a more complicated matter, and economic inequality is the province of economists. There are many potentially relevant measures, but few are conceptually equivalent or typically available to the researcher. They include wages (for hourly workers), yearly salary (for many others), or self-employment income;

income only from primary job vs. all sources, including investments; and income of head of household vs. for all members. For some purposes, wealth of different sorts is counted (e.g., personal property or investments). Income data are highly skewed—a few individuals have huge incomes but the majority quite modest ones—so researchers often log transform income data before analysis. They have been particularly interested in population-level changes in the distribution of income (Neckerman & Torche, 2007): has income inequality increased in recent decades, and why?

2.2. Stratification of the Population into Broad Social Classes

Sociologists do not statistically extract a general factor of social class, nor would that seem theoretically warranted. But the clustering of favorable vs. unfavorable outcomes does create and maintain *social classes*. We often speak of the upper, middle, and lower classes. Classes represent distinctions in more than material well being, but also in social norms and mores, family structures, aspirations and expectations for children, political behavior, and all other things cultural. There is a rich legacy of theoretical work in sociology on social class formation. Conflict theories in that field have emphasized how social groups compete for power and privilege and neo-Marxist ones on their relations to the means of production.

Sociologists have long studied the *permeability* of social strata by calculating rates of intergenerational *social mobility* across them. For instance, fathers and their adult sons are cross-tabulated by broad occupational category or self-designated social class, and then degree of father-son similarity calculated. Greater similarity (more father-son pairs in the diagonal) is interpreted as lack of social mobility, or more powerful *intergeneration transmission* of class. This inference rests on the assumption that parent-offspring similarity in adult status is not to be expected in a meritocratic society; that it reflects an unfair transmission of social advantages or disadvantages from one generation to the next. A recent chapter in the *Annual Review of Sociology* (Neckerman & Torche, 2007, p. 339) states it explicitly.

> The most common measure of inequality of opportunity is the intergenerational association of income, earnings, class, or other resources. A weak parent-child association indicates that individual well-being is not highly determined by parental resources and it thus reflects high equality of opportunity in a society.

Although status attainment research tries to unpack parent-child correlations to determine what "mediates" parent and child similarities, it too tends to treat nontrivial parent-child correlations in socioeconomic status as evidence for unjust transmission of family resources. The same belief pervades social policy and debate today when it presumes that children from all backgrounds would rise or fall in equal proportion but for a biased thumb on the scale. That, however, is a testable assumption addressed later in this chapter.

3. Meaning and measurement of intelligence

In order to understand *g*'s role in social inequality, we must first understand its properties in everyday behavior, that is, as a behavioral phenotype. (Unless I specify otherwise, any mention of abilities or intelligence is to phenotypes.) In terms of Figure 1, we are now looking at the shaded box under "Personal Attributes." Some scholars use the term intelligence to refer to everything included there; others to *g* alone, as do I. This reflects just taste in labeling, and it makes no difference as long as it is clear how the label is being used. Our concern here is to understand the phenomena that mental tests capture and what they mean, operationally, in daily affairs.

3.1. Phenotypic Structure of Human Cognitive Differences

Perhaps the most important discovery about individual differences in psychological traits, when psychometrically assessed, is that they are highly *structured*. By structure or *architecture* I mean predictable form and relatedness of diverse individual differences within a population, in this case, cognitive abilities (Carroll, 1993; Johnson et al., 2007). Besides being close to normally distributed, all cognitive abilities correlate with all others, and often substantially so, although some kinds (e.g., verbal, spatial) more tightly among themselves than with others (Reeve & Bonaccio, this volume). Clear order has emerged from the seeming welter of different human abilities, which is captured in their *hierarchical* organization, exemplified in Carroll's (1993) Three-Stratum Model (see Reeve & Bonaccio, this volume). Four features of this hierarchical integration of the evidence are especially important for understanding why human cognitive diversity is so deeply and thoroughly entwined in social inequality and why *g* in particular will hold the answer.

The first is that there is, in fact, only a single general latent factor (labeled *g*) at the top the hierarchical model, Stratum III in Carroll's model. Empirically, there is not a multiplicity of highly general abilities or "intelligences" comparable to *g*. Differentiation occurs only at lower levels of the hierarchy. In short, *g* seems to be the prime mover among abilities.

The second crucial feature is that *g* forms the thick core of all the narrower cognitive abilities in the strata below. There is often confusion about this point because the phenomenon of *g* (the *construct*) is often mistakenly equated with the *scores* on tests used to gauge it. IQ scores are calculated by summing an individual's scores on the various subtests in an IQ battery, such as the Stanford Binet. This summation procedure continues today, but not because intelligence is thought to be the sum of many independent specific abilities. Rather, IQ scores calculated in this manner happen to measure *g* well because, when subtest scores are summed, their common variance (what they all measure in common) accumulates while their more specific, non-*g* variances of each tend to cancel out. So, *g* is not an amalgam of the separate specific abilities located lower in the hierarchical model. Instead, the lower are increasingly complex, multifaceted psychometric amalgams of the higher. This means that ability tests usually measure mostly *g* regardless of their name or original intent. To illustrate, when a first factor is extracted from the 15 subtests of the WAIS-IV battery, seven provide good measures of *g* (*g* loadings of .71-.78), another seven provide fair measures (*g* loadings of .58-.70), and the fifteenth a poor measure (.44 for Cancellation; Sattler & Ryan, 2009, Table 2-12, p. 49).

The third feature is that cognitive abilities are best distinguished by their *generality* or breadth of application. The *g* factor is most general because it enhances performance in the widest range of cognitive tasks, although not necessarily equally in all. In contrast, abilities at successively lower, more content-specific levels in the hierarchical model enhance performance in successively fewer, narrower ranges of task content. Whereas *g* has domain-general application, narrower abilities (stripped of their *g* component) have only domain-specific application (e.g., Visual Perception and Auditory Perception at the Stratum II level, and Spatial Scanning and Temporal Tracking at the Stratum I level; Carroll, 1993, Figure 15.1).

Fourth, the structure of cognitive abilities seems largely independent of the structure of so-called non-cognitive traits (see chapters by Fergusson, Chamorro-Premuzic, Pickering, & Weiss; and von Stumm, Chamorro-Premuzic, & Ackerman, this volume). For instance, other than Openness to Experience, which reflects an interest in novel learning opportunities, there are few correlations of note between *g* and any of the Big Five (or Three, or Eight) dimensions of personality. Personnel psychologists summarize these cognitive and non-cognitive realms as the “can do” and “will do” elements of human performance. Both are important in human affairs, but for different reasons and in different patterns. Both may be required to explain social inequality, but their influence would tend to be independent. This chapter focuses on the relation between cognitive diversity and social inequality, so the independence of the two realms of individual differences removes the need for us to examine the non-cognitive realm in the current context.

3.2. Universality of Psychometric Structure Across Human and Nonhuman Populations

The hierarchical organization of cognitive abilities would be of scant interest were it specific to time, place, or demographic group, or—as sometimes suggested—simply manufactured by psychometric techniques, patterns of social privilege, or educational practices in Western schools.

Research to date indicates that intelligence test batteries actually do yield basically the same psychometric structure for different races and both sexes (Gottfredson, 2005). As for *g* in particular, the *g* factors derived from different samples converge on the same true *g*. This convergence occurs not only across different broad batteries of tests but also different ages, sexes, races, cultures, and countries (Jensen, 1998; Johnson, te Nijenhuis, & Bouchard, 2008). A general factor is also found in other species, including mice, when they are administered batteries of diverse problem solving tasks. Chabris (2007) refers to this as the Law of General Intelligence. For instance, he describes how a general factor emerged among both 2-3 year-old rhesus monkeys (accounting for 35% of test variance) and 5-6 year-old human children (accounting for 42% of the variance) when the two groups were administered the same five problem-solving tests. A general mental ability factor appears to be a pan-species phenomenon—not in level, of course, but in having a domain-general core around which most within-species cognitive variation revolves.

These regularities refute any claim that recurring variation in general intelligence within human populations is just an epiphenomenon of their cultural activities which might disappear if cultures organized themselves differently. A strictly socially induced cognitive inequality would not create phenotypic structures that are so consistent across time, place, and human groups, let alone species. This is not say that culture has no effect on intelligence (or height), but only that genetic diversity limits the range of effects culture might have on intelligence (or height) and how it achieves them.

3.3. Biological Correlates of Cognitive Ability in Human Populations

If cognitive diversity truly is a biological fact, then phenotypes should be moderately heritable and correlated with physiological variation in the brain.

Genetic architecture. The heritability of *g* (the ratio of genetic to phenotypic variation in *g*) increases linearly from .4 at age 9 to almost .7 at age 17 (Haworth et al., in press), reaches .80 by mid-adulthood, and remains there into old-old age (Plomin, Pedersen. Lichtenstein, & McClearn, 1994). Some behavior geneticists speculate that the increase in heritability over the life cycle results from individuals finding and creating personal niches that reinforce and magnify their genetic propensities, that is, from *gene-environment (g-e) correlation* (Bouchard, Lykken, Tellegen, & McGue, 1996; Scarr, 1996; Spinath & Johnson, this volume).

The .7-.8 heritability of *g* rivals that for weight (.7) and height (.9) in developed countries (Plomin, DeFries, McClearn, & McGuffin, 2008; see Towne, Demerath, & Czerwinski, 2002, for the heritability of other biometric measures). Variation in height and weight cannot be dismissed as just by-products of human imagination or social privilege, and neither can differences in *g*. Moreover, the phenotypic covariance among different major cognitive abilities (verbal, spatial, perceptual speed, memory, etc.) consists almost entirely of *genetic* variance in *g*, from adolescence into old-old age (Petrill et al., 1998; Spinath & Johnson, this volume). Each broad cognitive ability has other, independent sources of genetic or environmental influence, but those contributions are specific to that ability and, except for memory, small relative to genetic *g*.

Turning to strictly environmental influences on *g*, the only ones persisting into adulthood are ones that affect each sibling uniquely (*nonshared* environmental influences), not ones that affect siblings equally (*shared* environmental influences). That is, to the extent that differences in family advantage (e.g., higher parental education or income) have lasting influence on offspring intelligence, they do not affect all offspring equally or in the same way (Spinath & Johnson, this volume). In statistical terms, differences in rearing environments have no main effect on adult intelligence. The lack of lasting shared environmental effects on intelligence certainly does not mean that "parents don't matter." As behavior geneticists are quick to point out, it means only that rearing environments within the typical range in today's Western nations are "effectively equal" for supporting normal cognitive development (Scarr, 1996).

But might the systematic relatedness of abilities at the phenotypic level be socially induced? A growing body of research on the genetic correlations among cognitive abilities answers otherwise. The genetic architecture of cognitive abilities does, in fact, seem to mirror their phenotypic architecture: "It is a plausible working hypothesis that the taxonomic hierarchy of cognitive abilities is mirrored by (derived from?) an isomorphic structure of genetic influences" (Brody, 2007, p. 439). Johnson et al. (2006) illustrate such isomorphism using their Verbal-Perceptual-Image Rotation hierarchical model, an alternative to Carroll's. "Genetic correlations closely mirrored the phenotypic correlations" at all levels of the hierarchy, except for memory, revealing "high consistency…between the genetic and phenotypic structure" (pp. 542, 559). This suggests that any attempt to equalize intelligence phenotypes will eventually confront genetic resistance. Unless environmental advantages are arranged to correlate negatively with genetic ones, genetic variability will guarantee considerable phenotypic variability.

Brain architecture. Most research on the physiological manifestations of intelligence has focused on how psychometric *g* manifests itself in the physical realities of the brain. Investigators have recently begun examining whether the secondary dimensions of cognitive variation do too (Johnson et al., 2007). The most striking finding is that *g* has structural and functional correlates across the entire brain: volume of white matter, grey matter, and total brain; white matter lesions, organization, and integrity; rate of cerebral glucose metabolism and nerve conduction velocity; various characteristics of resting EEG and average evoked potentials; and much more (Colom & Thompson, this volume; Deary, Penke, & Johnson, 2010). General intelligence represents a distributed network, not isolated modules in the brain, and research is now apace to trace task performance in real-time as it recruits different parts of the brain (Jung & Haier, 2007). Studies have used a mish-mash of tests, some more *g*-loaded than others or capturing more non-*g* variance, which makes the ubiquity of correlates all the more impressive.

As Jensen (1998) has suggested, the *g* factor is so thoroughly enmeshed in brain physiology that it may actually represent a property of the brain as a whole, for instance, its overall efficiency (capacity, speed, integration) or integrity (resilience, developmental stability), rather than an ability as we usually think of them. The pattern of phenotypic covariation between *g* and brain attributes seems to be reflected in genetic covariation as well. Many specific aspects of brain structure and function are 70% to 90% heritable, and genetic influences on intelligence that are shared across brain regions are stronger than those specific to any one region (Deary, Penke, & Johnson, 2010). Revealing additional consilience across bodies of research, Deary, Johnson, and Houlihan (2009) note that age-related patterns of heritability in brain structure suggest a partial explanation for the age-related rise in the heritability of *g*.

Once again, nongenetic factors will influence brain phenotypes, in part by influencing how genotypes are expressed under different conditions, and some parts of the brain show more environmental variance than others (Deary et al. 2010), but nongenetic influences must work within the general confines laid down by the genetic substrate for brain physiology and typical human environments. There may be nongenetic means by which to decrease the environmental variance in phenotypic *g*, but they would likely have meaningful influence only if they altered brain physiology (e.g., drugs).

Evolutionary robustness. Evolution has left our species, like other surviving species, with a genome that allows its members to physically weather or rebound from ever-present biological adversities, including starvation, injury, parasites, and infectious disease. The biological resistance of humans' mental prowess to lasting perturbation extends to typical features of modern social environments too, as confirmed by decades of socioeducational interventions intended to decrease inequalities (variance) in intelligence and academic achievement (Brody, 2007). All have failed to leave much mark on individual differences in *g*. It is also confirmed by adoption studies, perhaps the strongest social intervention of all, because adopted children become more similar to their biological relatives and less like their adoptive ones by the time they reach adolescence.

External, contextual influences do contribute to phenotypic variation, which increases spread in the population and somewhat alters the rank order of individuals within it. But these within-cohort influences on rank order tend to be modest and temporary in research to date. Examples include preschool interventions, malnutrition, and intestinal parasites (Sternberg & Grigorenko, 2001). When these influences are withdrawn, the good effects of the former "fade out" and the bad effects of the latter are usually reversed by "catch-up" growth (see also Tanner, 1986, on catch-up and catch-down growth in height after deprivation and interventions).

3.4 Meaning (Construct Validity) of *g* as a Behavioral Phenotype

No longer is there dispute that psychometric *g* predicts diverse life outcomes. It does, and pervasively so (Gottfredson, 1997; Herrnstein & Murray, 1994). The following findings help to narrow possible explanations for why it does.

Three competing conceptions of g and its real-world utility. Hypotheses have come in three main versions, the spirit of which may be seen, respectively, in Fischer et al.(1996), Sternberg & Wagner (1993), and Jensen (1980).

- *g-pretense conception: No latent trait, just the pretense of one.* IQ tests do not measure cognitive ability, but something else, such as test-taking skill, past educational achievement, quality of instruction, or social class background. Society rewards these other things while seemingly only to reward cognitive ability, because we mistakenly believe, or are falsely led to believe, that IQ tests measure something special.
- *g-academic conception: Narrow academic trait of limited practical value.* IQ tests measure only a narrow range of abilities, mostly academic aptitude ("book learning"), but not practical or creative intelligence. Academic abilities reap major rewards because modern industrialized societies have chosen to privilege them, despite their limited real-world utility.
- *g-general conception: Broad latent trait of pervasive practical value.* IQ tests measure a latent trait, *g*, which enhances performance in important life realms. Higher standing on the latent trait reaps more rewards because society values such performances and the social goods they generate for the group.

The first two conceptions have not stood up well against data amassed in recent decades. The biological evidence just reviewed rules out the first conception. Whatever *g* is, it exists as a biologically-grounded axis of human differentiation. And although phenotypic *g* is influenced by many genes and its physiological embodiment is suffused through the brain, it manifests itself as unitary in psychometric measurements and everyday human performance. This favors the third hypothesis over the second, but not conclusively so, in explaining *g*'s role in status attainment.

Attributes of tasks that put a premium on g. We can get more purchase on *g* as a construct by identifying the attributes of life tasks and settings that call it forth most effectively (i.e., are most *g* loaded) and therefore most clearly reveal individual differences in *g*. Analyses of tasks in three different realms of human performance—mental tests, school work, and jobs—all point to the same ingredient. It can be summarized as the complexity of information processing required for effective performance.

Looking first at mental tests, Jensen (1980, p. 231) describes how the most discriminating (most *g* loaded) tests and test items are not distinguished by test format or surface content (words, pictures, etc.) but something subtler and less concrete, namely, the complexity of the information processing and mental manipulation they require for good performance. "[T]ask complexity and the amount of conscious mental manipulation required seem to be the most basic determinants of the *g* loading of a task. If we distill this summary generalization still further, the amount of conscious mental manipulation set off by the input would seem to be the crucial element." In order of increasing complexity would be tasks requiring associative memory, reproduction, production, and eduction. Reasoning tests exemplify the latter, regardless of whether the information to be manipulated is verbal, mathematical, spatial, or pictorial. The following hypothetical number series items illustrate how task complexity can be increased with the same simple surface content: 2, 4, 6, __ vs. 2, 4, 8, __ vs. 2, 4, 6, 4, 6, __. The three require inferring increasingly complex rules to fill in the blank.

Jensen (1980, pp. 327-329) shows how school tasks, too, are more *g* loaded when they require or allow more complex mental manipulation. For instance, success in learning is more highly correlated with *g* level when it is intentional, meaningful, insightful, age- (maturation-) related, permits or requires transfer from past learning, the material to be learned is hierarchical (as in science and math, which require mastery of building blocks), the material is moderately complex, learners are given the same fixed amount of time to learn, and they are at early stages of learning (material not already highly practiced).

Both the *g*-academic and *g*-general conceptions of *g* can claim to accommodate these findings, so we need to examine tasks performed outside of tests and schools. Job analysts in industrial-organizational psychology provide much data from employment settings. Jobs, not workers, are the units of analysis in their studies. Job incumbents and their supervisors rate the job in question according to a wide variety of characteristics. The same rating system is applied to a population of jobs, and factor analyses are performed on the ratings. The resulting factors reveal the underlying structure in the multitude of differences in task constellations and attendant aptitude and interest requirements. These factor analyses are thus parallel in aim and form to those performed by psychometricians on mental test scores for large groups of test-takers.

Job rating systems differ greatly, but all yield results that point to the centrality of task complexity and the amount of intentional mental manipulation that jobs require of workers. Table 2 samples such results. When the focus is on behavioral requirements (top panel), the dominant factor is “Judgment and Reasoning” (learning, reasoning, quick understanding, making judgments, spotting and solving problems). When job duties and responsibilities are factor analyzed as well (lower panel), the dominant first factor is the “Overall Complexity” of information processing and decision making (compiling, combining, analyzing information; writing, advising, negotiating, persuading). These separately derived first factors are just mirror images of each other, the first describing the behavioral manifestations of *g* and the second the stimuli that “set it off.” When working conditions and needs for workers to function independently are considered, the most complex jobs are also the ones requiring more self-direction, taking responsibility, independent judgment, and continual need to update job knowledge, especially under distracting, frustrating, conflict-laden, time-sensitive, and changing conditions. All these increase the complexity of work, cognitive load on the worker, and the need for more independent and more extensive mental manipulation of information.

Insert Table 2 About Here

Together, these findings echo descriptions of general intelligence itself (reasoning, judgment, problem solving, facility in learning), tests of fluid *g* (novel tasks, inferences required, spotting problems, integrating new information), and tests of crystallized *g* (writing, display of independently accrued general knowledge). The job analysis data are especially compelling because their relevance to *g* was neither of interest to nor initially recognized by job analysts (Arvey, 1986). These results for jobs' demands on workers converge with those for mental tests and school work, and the convergence is empirical, not by definition or design. It supports the *g*-general conception of intelligence by showing that mental tests, school work, and jobs are all distinguished primarily by the degree to which they require individuals to manipulate moderately complex information, regardless of content domain or how academic they seem.

g-narrow vs. g-general predictions for external validity in non-academic work. The proof of the pudding is in the eating, however. Does the *g*-general conception fare any better than the *g*-academic conception in actually accounting for patterns in job performance? The two conceptions make opposing predictions about when and where *g* will correlate most strongly with job performance.

Table 3 lists 10 pairs of competing predictions. Those for the *g*-academic conception are gleaned or inferred from well-known psychological and sociological writings that assert a more privilege-based view of why *g* predicts so many life outcomes. Those listed for the *g*-general conception follow directly from what might be called *g* theory, which I induce from the nomological network of empirical generalizations having *g* at its core. The 10 pairs of predictions can be tested by turning to meta-analyses in a different literature, personnel selection psychology.

Insert Table 3 About Here

The *g*-general conception of intelligence predicts a very particular, non-obvious pattern of correlations between *g* level and quality of job performance based on what is known about the nature of *g* and tasks that place a premium on it. As reviewed above, *g* is a general proficiency in learning and reasoning, and tasks are more *g* loaded when they require independent performance of moderately complex tasks (Chamorro-Premuzic & Furnham, 2010). The predictions from the *g*-academic conception follow from viewing *g* as a narrow ability of limited practical value.

The two conceptions therefore differ in how pervasively they expect *g* to correlate with on-the-job performance and how important other abilities will be relative to *g* in predicting it. The *g*-academic conception predicts that *g* will correlate with performance in only a small percentage of jobs, because only a minority are academic-like. The *g*-general conception, however, predicts a positive correlation in all jobs because all jobs require some learning and reasoning (Prediction 1). The rationale is spelled out in Hunter's (1986) model of job performance. First, *g* is an excellent predictor of job-specific knowledge for the same reason it predicts learning in any other subject area, and job knowledge is the best predictor of who performs well once on the job. Second, jobs both allow and require workers to keep updating their knowledge, appropriately apply what they know, and continually spot and solve new problems—all of which call for *g*.

The infrequent predictive value of *g* in the *g*-narrow view opens the door for other abilities to matter, especially in their own content areas. For instance, it would predict that tests of mathematical reasoning predict performance better in math-dependent jobs than in highly verbal work, and vice versa for tests of verbal ability, and that both will predict performance substantially better than *g* alone in their own content realms (Prediction 2). In contrast, the *g*-general conception predicts only low or no incremental validity for specific abilities, after controlling for *g*, because *g* forms the core of all abilities and is domain general. Because tests of broad abilities such as verbal and spatial tend to have only a fraction as much non-*g* variance as *g* variance, they are not likely to have much if any incremental validity in any content area.

Predictions 3-10 are more interesting because they deal with specific aspects of jobs and working conditions that are expected to increase or decrease (i.e., *moderate*) the correlations between *g* and performance outcomes. Neither conception expects that the same difference in *g* (say, a 15-point IQ advantage) will confer the same competitive advantage in all circumstances where *g* matters. Table 3 lists three types of moderators: attributes of the jobs to be performed (Predictions 3-5), the criteria by which overall job performance is evaluated (Predictions 6-8), and variability among the workers in a job (Predictions 9-10). These may be conceptualized as three types of levers that the two conceptions predict will ratchet *g*'s value up or down, the two differing only in which direction they expect the correlations to move.

The *g*-narrow conception mirrors prior expectations in personnel selection psychology, which once held to *specific aptitude theory* (Schmidt & Hunter, 2004), as well as still-extant presumptions in sociology. It expects that *g*'s predictive validity to rise under two conditions: first, the job is more academic, and second, there are more opportunities for some sort of (usually unspecified) social privilege to affect performance outcomes. So, correlations should rise when jobs are more academic-like, say, for clerical rather than crafts work (Prediction 4), regardless of the complexity of work (Prediction 3). Next, supervisors will have more opportunity to bias their performance ratings in favor of higher-IQ workers, thus increasing the IQ-performance correlation, when they use more subjective means of rating performance (Prediction 6) and when they focus more exclusively on evaluating worker compliance and conformity (Prediction 8) rather than technical acumen (Prediction 7). Finally, proponents of social privilege theory predict that the competitive advantage of higher *g* will fall when workers have more equal job-specific training and experience (Predictions 9-10) because they believe differences in job knowledge result primarily from differences in opportunities to learn, not differences in learning proficiency or problem solving.

The *g*-general conception predicts the opposite. *g*'s correlations with job performance outcomes should increase monotonically with the complexity of work performed regardless of its academic-ness (Predictions 3-4) and when workers perform more independently (i.e., without help or hindrance; Prediction 5). They should also rise when performance is assessed more objectively (Prediction 6) and emphasizes "can do" technical performance rather than "will do" citizenship criteria such as self-discipline and professional bearing (Predictions 7-8).

Finally, the *g*-general conception predicts that *g*'s correlations with job performance should remain robust, not disappear, when workers have equal job-specific training and experience (Predictions 9-10) and, of course, when there is no artificial ceiling on job performance. g will continue to matter for reasons outlined earlier. Namely, it predicts the acquisition of job knowledge both during and after formal training and it facilitates more effective exploitation of that knowledge to carry out job duties. Exposure to learning can be equalized, but knowledge gained per unit exposure cannot. Anticipated effects of equalizing workers' training and experience (exposure to learning opportunities) on the *g*-performance correlation will depend on whether workers' differences in exposure had been correlated with their *g* levels. If not correlated (the typical situation; Schmidt, Hunter, Outerbridge, & Goff, 1988), then predictive validities will not change; if exposure had been negatively correlated with *g*, then validities will rise somewhat; if positively correlated, they will fall somewhat. This is what we would predict for any *g*-loaded test.

Note that all the work characteristics that the *g*-general conception expects to boost IQ-performance correlations are essential to creating a good test of *g*, so these eight predictions can be reduced to a single more general one: the more closely that tasks and performance conditions mimic those of standardized tests of *g*, the better *g* should predict on-the-job performance. This is not to say that jobs should mimic IQ tests, but only that performance is better predicted when they do.

Evidence supports g-general predictions. Meta-analytic studies (listed in Table 3) confirm all 10 predictions derived from *g* theory. They contradict the competing *g*-academic conception, which has to invoke social privilege and bias to explain why *g* seems to provide more social rewards than its supposedly limited functional utility would warrant. Moreover, the *g*-general predictions have also been confirmed for performance in education and training as well (e.g., Jencks et al., 1979, chap. 4; 1986; Thorndike, 1986).

g theory suggests that life itself can be conceptualized as a test (Gordon, 1997), so it should forecast patterned sets of *g*-performance correlations in other life areas as well, such as health self-care (Gottfredson, 2004; see also Calvin, Batty, & Deary, this volume). Life's tests are hardly standardized, nor do they hew to other essential psychometric requirements for test reliability and validity, but that is partly the point. If we knew how much or little they replicate the conditions for valid testing of *g*, we could predict when and where *g* is likely to produce the most noticeable differences in performance and evoke differential rewards (Gordon, 1997).

Statistical artifacts. Meta-analysis in personnel selection warns us to anticipate statistical artifacts that would otherwise obscure the predicted pattern of *g*'s correlation with life outcomes: restriction in range, measurement error, and sampling error. Moreover, their effects are not random, because levels of all three often differ systematically over time, groups, or variables. This produces systematic biases in correlations we might wish to generalize to broader populations. To illustrate, it is hazardous to conclude that *g* matters less and less at higher levels of education just because *g*'s observed correlations with academic performance progressively shrink at the higher levels (from .6-.7 in elementary school to .3-.4 in graduate school). The reason they do, of course, is that the spread in student *g* levels has become successively narrowed at higher levels of schooling, precisely because *g* mattered: it was a basis of selection or self-selection into the higher levels. It would likewise be hazardous to automatically assume that higher correlations signal stronger effects when some variables were measured much less reliably than others.

The least recognized but most important of the three artifacts for the study of status inequality is restriction in range. Not only is restriction on *g* range common in status attainment research samples (e.g., some exclude high school dropouts), but it is theoretically relevant for understanding status attainment itself. Restriction in range is the intended effect of institutionalized gate-keeping procedures, such as academic promotion, admissions and credentialing, as well as of selection, placement, and promotion in military and civilian workplaces. It is the job of these institutions to filter, sort, channel, and segregate—to create restriction in range to meet operational needs. It is also the aim of individuals seeking to get ahead (enter more exclusive social environments) or to find a comfortable and rewarding niche in life where people like themselves can flourish, gain specialized expertise, and avoid conspicuous failure or displays of incompetence (Gordon, 1997). In short, systematic restriction in range is an inferential hazard when it remains unrecognized, but it can also provide valuable clues when viewed as evidence of social sorting machines at work.

4. Individual-Level Status Attainment Processes

Both the sociological study of social inequality and the psychological study of intelligence have amassed extensive nomological networks of evidence on what might be called their respective disciplines' master variables, social class and intelligence. Our question concerns how the two networks intersect and which direction the causal influences flow between them. In terms of Figure 1, we are now looking at the links (arrows) between "Background Influences," *g*, and "Socioeconomic Outcomes."

4.1. Status Attainment Modeling of Phenotypic Correlations

Research on status attainment (e.g., Duncan et al., 1972) is conducted on correlation matrices such as shown in Table 1. Researchers make (though rarely test) assumptions about the causal ordering of variables, depict them in a path diagram, and then use statistical modeling to estimate parameters ("effect sizes") along each pathway (arrows), say, from education to occupation. Pathways may be direct or indirect. In Figure 1, education would have an indirect path to income through occupation but possibly also a direct path, not mediated (accounted for) by occupation. Non-significant paths are deleted from the final model.

Debate over *g*'s place in this nexus of correlations has taken the form of pitting IQ against family background in predicting adult status, especially since publication of the *Bell Curve* (Herrnstein & Murray, 1994). The contest consists of seeing how large the direct "effects" of each are after partialing out their downstream indirect "effects" through other variables (e.g., education) and also controlling for the other (IQ or family background). The winner is the one with the largest partial correlations left standing. The contest sometimes includes attempts to drive the direct effects of *g* into statistical insignificance by controlling for a wide variety of family attributes (Fischer et al., 1996). Even when such attempts succeed (they rarely do), the results are causally ambiguous when conducted on genetically uninformative data, as the studies virtually always are. They usually commit the "partialing fallacy" besides (Gordon, 1968), which further muddies the interpretive waters. For instance, behavior geneticists would point out that family attributes and child's IQ are genetically correlated because each is genetically correlated with a common cause, parents' *g* (Spinath & Johnson, this volume). Controlling for family background thus removes valid genetic variance in child's IQ. However, this remains unacknowledged in most social science research, which usually attributes parent-child similarity in IQ to socialization (Scarr, 1996), even though a classic demonstration of this fundamental point appeared in the leading research journal in sociology over three decades ago (Scarr & Weinberg, 1978).

A recent meta-analysis (Strenze, 2007) confirms that son's IQ is a better predictor of son's educational, occupational, and income level than is father's status when son's IQ was measured before age 19 and outcomes after age 30. Corrected correlations for the three attainments were .42, .35, and .19 vs. .56, .45, and .23 with, respectively, father's occupation and son's IQ. Yet, as just noted, this means little without knowing why son's IQ correlates with his adult outcomes. It might reflect the functional value of higher *g*, but it could also reflect a "clubby snobbery" or irrational preference (Jencks et al., 1979, p. 84) on the part of institutional gatekeepers. The former process might be thought to be just but the latter not.

There is therefore only limited mileage to be gained from further modeling of phenotypic data from observational studies, one sample at a time—especially when the exercise is more statistical than theoretical, as it tends to be (Gordon, 1968). Additional mileage might now be gained, however, by capitalizing on the nomological network for *g* to take a more theoretically-informed approach. That is the approach taken below. How well do theories based on the *g*-academic and *g*-general conceptions of intelligence explain the *covariation* between *g* and successive outcomes shown in Figure 1, while respecting the larger network of evidence on *g*?

4.2. Social Privilege Theory vs. Functional Tool Theory on *g*'s Role in Status Attainment

Both sociology and psychology have actually offered the same competing explanations of *g*'s role in social inequality, which I label the *social privilege ("privilege")* and *functional tool* *("functional")* theories. Neither has been an explicit theory, but I have fashioned them here to capture the key distinctions in causal assumptions and inferences I observe in both disciplines.

Social privilege theory views *g* as just one among other sorts of social inequality that are manufactured or magnified by differences in advantages that siblings share (e.g., parental income). In contrast, the functional tool theory holds that *g* is a genetically-conditioned phenotype which confers competitive advantages when performance, not mere privilege, governs social advancement; social privilege does not create differences in *g* but it may affect whether individuals have the opportunity and encouragement to exploit their talents. Both theories agree that there are phenotypic differences in cognitive ability, as well as some genetic ones at birth. No theory that assumes otherwise would be viable, as some sociologists now argue (Freese, 2008). They hold to different conceptions of intelligence, however: social privilege theorists to the narrower *g*-academic conception of intelligence and functional tool theorists to the *g*-general conception.

Thus the two theories generate competing predictions about how and why higher *g* is translated into higher socioeconomic status over the life course. The most general difference concerns what would happen if a society provided all its members equal rearing environments and equal opportunity to succeed on the basis of individual merit. Social privilege theory predicts that it would drive down the correlation between IQ and socioeconomic success, possibly even to zero, because there would be no intergenerational transmission of social privilege. Functional tool theory predicts that it would drive up current IQ-outcome correlations and guarantee moderate intergenerational similarity *and* dissimilarity in status outcomes.

Table 4 lists 18 more specific pairs of predictions that can be tested with extant evidence from behavior genetic research, longitudinal studies, and changes in public policy (natural "interventions"). I rely most heavily on the behavior genetic strategy of examining the genetic and nongenetic components of covariance between two measures, whether they be of traits, behaviors, environments, or life outcomes. I do so because the phenotypic correlations between (covariation of) IQ and socioeconomic success are precisely the phenomena to be explained (see Freese, 2008, on the value of this approach). Given its novelty in this context, the next section describes what it means to focus on the components of covariance between two variables.

Insert Table 4 About here

4.3. Using Components of Covariance to Test Competing Hypotheses

Each box in Figure 1 represents a pot of phenotypic variance and the correlations between them constitute their covariation. Using Figure 3 as a conceptual aid, panel (a) depicts the variation in a particular variable, A. Of more interest, however, are its components (sources) of variation as depicted in panel (b). Some proportion of the phenotypic variance may be genetic (the trait's heritability) and the rest will be nongenetic (plus measurement error). In turn, there may be two types of nongenetic variance: influences felt by all siblings in a family (shared environmental effects) and ones experienced by individual family members (nonshared effects).

Insert Figure 3 About Here

Phenotypic correlations between different traits and outcomes are depicted in panel (c) of Figure 3 by the intersection of variables A and B. This is the variance they share in common. Most important for our purposes are the genetic and nongenetic components that make up that covariance as depicted by the intersection of A and B in panel (d). (See Jensen, 1971, for a psychometrically-oriented discussion of how to interpret genetic covariance.)

Cautions in interpreting genetic covariance. It is crucial at this point to note that the components of covariance of two variables, panel (d), need not be found in the same proportions as the components of variance in either one alone, (b). This is illustrated in panel (e), where the heritability of B is considerably smaller than the B's *bivariate* heritability with A. Bivariate heritability is the proportion of phenotypic *co*variance that is genetic. To take another example, if the covariance between A and B were mostly “shared family” rather than “genetic,” then their bivariate heritability would be zero despite both A and B being moderately heritable.

A second caution is that, just as phenotypic correlations are not self-explanatory, neither are genetic ones. Even if we were sure that some genetically-conditioned trait, A, is somehow influencing social outcome B (panel (d)), we still might not know why. Take, for instance, the .5 correlation between *g* and occupational status (Table 1). Brighter individuals may end up in better jobs because their greater intelligence allows them to perform better in school and work, but also because employers have an irrational or arbitrary preference for smart workers. The former would be an example of active gene-environment correlation (individuals seek out more intellectually-compatible work environments) and the latter a case of evocative (or “reactive”) gene-environment correlation (gatekeepers select individuals into different environments based on perceptions of their intelligence). The genetic correlation between family environment and child IQ, discussed earlier, is an example of a passive g-e correlation. In other contexts it might be called a spurious correlation, because child IQ and child’s rearing environment correlate simply because both are independent results of the same parental genotype.

Emergence of gene-environment (g-e) correlation between an adult’s g and attainments. The foregoing example of passive g-e correlation can be used to illustrate how active and evocative g-e correlations can emerge and increase the genetic covariation between *g* and social outcomes. The passive g-e correlation between child’s IQ and rearing environment comes about without any particular kind of activity on the part of the individuals involved. This might be the case, for example, if brighter parents read more to their pre-reading children than do less bright parents, without regard to whether the children ask to be read to or express any preferences about what to have read to them. Once children can read for themselves, purely passive gene-environment correlation is virtually impossible because children begin to generate active g-e correlation when they choose different amounts and kinds of material to read. Relatives and teachers are likely to reinforce further a bookish child's self-investment in reading by giving them books rather than other gifts, an example of evocation g-e correlation. The distinctions among the three types of g-e correlation become increasingly blurred with development, but active and evocative g-e correlations both serve to amplify the pre-existing genetic correlation based on passive g-e correlation alone. If g-e correlations influence the development of intelligence itself, say, by recruiting environments that further develop and maintain differences in *g*, then the heritability of IQ will increase as development proceeds (because the active and evocative g-e correlations will add variance to both the numerator and denominator in calculating the heritability of *g*).

When g-e correlation between *g* and status attainment magnifies differences in status outcomes, not *g*, then their bivariate heritability should increase, as would the heritability of status outcomes but not *g*. Some social scientists interpret this as environmental advantages being piled upon pre-existing genetic ones (Adkins & Vaisey, 2009, athough they mistakenly refer to it as g-e interaction). So, in their view, some portion of the overall (*broad*) heritability of intelligence may actually reflect the influence of advantageous social contexts masquerading as genetic variance. Jensen (1969, pp. 38-39) anticipated this concern. He suggested that *narrow* heritability of intelligence (its additive genetic component) might therefore be used as a minimum estimate of genetic effects, but he also argued that its broad heritability has greater ecological validity for understanding the social consequences of genetic variation in intelligence because it represents how genotypes actually operate in the real world. They are not passive, but generate their own advantages and disadvantages. He notes elsewhere (Jensen, 1981, pp. 121-123) that a society might be able to abolish passive g-e correlations by reassigning children to different rearing environments and perhaps discourage the emergence of g-e correlations of the evocative type, but it could never eliminate active g-e correlation. “No matter how hard we may try to create the same environmental opportunities for all children, we could never, even under the most rigidly totalitarian system of control, be able to eliminate the environmental differences that persons fashion for themselves in accord with their own particular genotypes.”

4.3. Opposing Assumptions of the Two Theories

The social privilege and functional tool theories of intelligence and social inequality predict different components of variance in all variables moving from left to right in Figure 1 and, in addition, different effects of social interventions on those variables’ variance and covariance when social policies attempt to reduce *g*’s impact on status attainment. Those predictions, discussed shortly, rest on the following causal assumptions.

Social privilege theory postulates that: (a) differences in shared family resources (top box in left-most column of Figure 1) create differences in all personal traits and circumstances (second column), including *g*; (b) these two sets of privileges—pre-existing family and newly-generated personal ones—provide the social credentials necessary for surmounting the many class barriers to advancement that gatekeepers erect for directing only the higher classes to higher rungs on the social ladder (outcomes in upper right); (c) differences in task performance (lower right) matter primarily to the extent that gatekeepers use them to reinforce or legitimate social privilege, not because good performance has any inherent value; and (d) *g* therefore matters to the extent that it transmits socioeconomic advantages from one generation to the next.

These and similar assertions pervade many sociological treatises. For instance, Adkins and Vaisey’s (2009) attempted reconciliation of the sociological and genetic perspectives on status attainment portrays genes and family resources as independent influences on ability and level of social inequality as affecting how easily ability is “translated” into status (Figure 1).

Bowles and Gintis's (1972/1973) classic article, "IQ in the U.S. class structure," is of particular interest because it was written to rebut Jensen's (1969) conclusions about the importance of IQ in education and hence economic success as well (but see also their recent conclusion that "the genetic inheritance of IQ explains little of the intergenerational transmission process [of income]," Bowles & Gintis, 2002, p.13).

- "IQ is in fact *not* a crucial determinant of job adequacy" (italics in original, p. 12).
- "[We do] not deny that for some individuals or for some jobs, cognitive skills are economically important. Rather, we assert for the vast majority of workers and jobs, selection, assessed job adequacy, and promotion are based on attributes other than I.Q" (p. 7).
- "I.Q. is not an important cause of economic success….[Instead] the emphasis on intelligence as the basis for economic success serves to legitimize an authoritarian, hierarchical, stratified, and unequal economic system of production, and to reconcile the individual to his or her objective position within this system" (p. 2).

Functional theory emphasizes a different flow of influence across Figure 1: (a) shared environmental influences have no lasting impact on *g*, so child's *g* transmits only the genetic advantages of parents into adulthood; (b) differences in *g* generate differences in performance on tasks having practical utility (lower right of Figure 1); (c) their functional utility encourages gatekeepers to sort and advance individuals somewhat on the basis of *g*-correlated traits and credentials; which (d) discourages their sole reliance on mere whim or social prejudice. In short, privilege theory minimizes the importance of genes and task performance, but functional theory emphasizes them. Where privilege theory would draw thick arrows across the top of Figure 1, functional theory would draw thin ones and then add thick ones across the bottom of the figure.

4.4. Competing Predictions from the Two Theories

Table 4 lists 18 pairs of predictions derived from the two theories' contrary assumptions. There are three types. Predictions 1-3 concern the components of variance in *g*—genetic, shared environmental, and nonshared environmental—to be expected at different ages:. Predictions 4-12 concern the components of covariance between an individual's *g* and own educational, occupational, and income attainments. Predictions 13-18 turn to a different matter: how social interventions intended to reduce differences in social advantage or nullify their influence in later generations will change degree of social inequality or its dependence on intelligence.

Predictions 1-3: Genetic and nongenetic variation in g at different ages. Both theories predict that age will moderate the heritability of *g,* but in opposite directions. Privilege theorists believe that although there may a modest genetic component to intelligence differences in childhood, the impact of family privilege on *g* cumulates and compounds with age while genetic influences recede (Prediction 1). If modeling adults, they might erase any arrow from genes to *g* (Prediction 3). As noted earlier, behavior genetic research (Haworth et al., in press) has consistently provided evidence that the opposite is true, which is why functional theory states that shared environmental variance in *g* will disappear by adulthood.

A few cautions are in order. Shared family influences (perhaps of schools, neighborhoods, and the like) account for as much variation in childhood intelligence as do genetic differences, although it remains unclear which particular aspects of rearing environments are responsible. It is clear, however, that even seemingly big differences in family advantage may have no effective influence on offspring intelligence, and that the impact they do have across all siblings in a family turns out to be temporary. This does not rule out the possibility that even temporary influences on intelligence might have lasting impact on *other* sorts of outcomes, such as selection into good private elementary schools. Nor does it rule out the possibility that one sibling will exploit the resources that were available to all in a family, such as good school instruction. When such exploitation is genetically-driven, this generates g-e correlation and any resulting increase in *g* relative to age-mates will show up as non-additive genetic variance. When environmental influences on IQ are random with regard to both family origin and intelligence genotype, they will show up as nonshared environmental variance.

Social privilege theorists might claim that g-e correlations inflate the seeming importance of genes relative to environments by allotting their joint action to genes. This may be true in a purely statistical sense, but it does not enhance the plausibility of social privilege theory because narrow heritability remains substantial. As well, it is not clear how one can conceptualize the e in g-e correlations as a form of social “privilege” and, by implication, an unwarranted or socially manufactured advantage that might be leveled by social policy, because it is self-generated and uncorrelated with family background. Eradicating self-generated advantages would require restraining individuals from acting or reacting differently toward other individuals on the basis of their individual genotypes, which are unknowable in any case.

Predictions 4-12: Genetic and nongenetic covariation between g and level of education, occupation and income. Both theories acknowledge the moderate to high correlations of *g* with the three outcomes, but differ on whether to expect age-related shifts in this covariation (Predictions 4-6). Privilege theorists appear not to expect any, but functional theorists would, though most confidently for occupation and income. Their reasoning is that workers normally advance up job and pay ladders during their careers, which allows *g*-based performance differences to influence promotion (or demotion) over the decades.

Next, social privilege theorists would expect little or no of the covariance of *g* with education, occupation and income to be genetic. This assumption is reflected in the common practice in status attainment modeling of ignoring genetic covariance on the apparent presumption it is trivial. In contrast, functional theorists would expect most of *g*'s covariance with status to be genetic (Predictions 7-9). Further, privilege theorists would expect the environmental variance to be mostly of the shared variety because it would originate in the cumulating effects of family privilege, which that they expect to jointly influence *g* and adult status and increase over time. The functional tool theory would predict no shared environmental covariance between *g* and attainments because *g* itself has no shared environmental component; any environmental covariance between the two would be of the nonshared type. Note that although nonshared environmental influences cannot contribute to correlations between family members (say, in *g*), they can contribute to the covariance of different traits for the same individual (say, their own *g* and level of education).

Finally, to the extent that each of the theories expects some genetic covariation between *g* and socioeconomic status (for privilege theory, very little; for functional theory, a lot), they appear to differ in the type of g-e covariance they expect it to reflect: mostly evocative vs. mostly active (Predictions 10-12). As noted before, social privilege theorists emphasize the social credentialing functions that intelligence and educational achievements serve. These reflect evocative (other-generated) g-e covariance if, as noted before, higher intelligence allows individuals to get ahead by evoking favorable treatment from college admissions officers, employers, and other gatekeepers, not necessarily because higher intelligence matters per se, but because gatekeepers have a "clubby" taste for it. In this case, getting ahead on the basis of genetic *g* would be similar to getting ahead on the basis of irrelevant physical traits (e.g., height, skin color or sex): it matters only because of what others read into the phenotype (stereotypes or expectations), rather than true effects of the trait in question.

This is in keeping with the sociological perspective, which generally views individuals as passive objects of social influence. Those who rise less far were blocked from doing so on the basis of their *ascribed* (rather than *achieved*) characteristics. Adkins and Vaisey (2009) describe this as *social closure*—"the process by which social collectivities seek to maximize rewards by restricting access to resources and opportunities to a limited circle of eligibles. This entails the singling out of certain social or physical attributes as the justificatory basis of exclusion" (Adkins & Vaisey, 2009, p. 112, quoting Parkin, 1974).

In contrast, functional tool theorists would argue that differences in *g* have instrumental value for the individual and society too, so *g*'s large genetic component thereby does too. Moreover, they see individuals as active agents who shape their own environments in response to their internal, individualized, genetic propensities. That is, they are not passive creatures of either their genes or environments. Higher *g* enhances performance (lower right of Figure 1), which in turn influences what individuals seek and attempt in life (e.g., see applicants in Figure 2), but also how successfully they negotiate or exploit the social sorting process (represented in the arrows between *g*, performance, and status outcomes). Thus, any g-e correlation between *g* and social outcomes probably represents mostly active (self-generated) gene-environment correlation.

The evidence for testing Predictions 4-6 is sparse, but it favors functional tool theory because it shows age-related increases in the correlation between *g* and status outcomes. Jencks et al.'s (1979, p. 121) analyses of multiple large datasets indicated that "the effects of test performance on earnings increase with age." The recent meta-analysis by Strenze (2007) also found that age moderated the correlations of attainment with IQ: they rose in the late 20s for occupation and in the early 30s for income. In testing the "gravitational hypothesis" for occupational advancement, industrial-organizational psychologists have found that, over time, brighter workers tend to move up job ladders but less bright workers move downward (Wilk & Sackett, 1996).

Another large longitudinal study (Judge, Klinger, & Simon, 2010, p. 92) documented how over 28 years "the more intelligent achieve higher levels of extrinsic career success [income and occupational status] not only by realizing early career advantages but also by having steeper trajectories of success that unfold over time." One reason they have steeper trajectories was that they got more education, more training, and gravitated toward more complex jobs. This finding implies not only a growing gene-environment correlation, but also one of the self-generated sort, whereby individuals increasingly shape and differentiate their life niches over time (Bouchard et al., 1996; Scarr, 1996). Judge et al. (2010, p. 92) suggest that it is this sort of *g*-related growth in skills that fuels the steeper ascension for higher-*g* workers: "We argue that these trajectories provide environments in which high-GMA [general mental ability] individuals' skills are often reinforced and amplified, setting the stage for later academic and employee success."

A small but growing body of multivariate behavior genetic research (e.g., Lichtenstein & Pedersen, 1997; Rowe, Vesterdal, & Rodgers., 1998) decomposes the covariance between individuals' *g* levels and their socioeconomic outcomes, so it provides evidence relevant to Predictions 7-9. It, too, remains sparse but it also leans toward functional tool theory. Some of it (Rowe et al., 1998) has explicitly engaged the sociological debate over *g*'s role in social inequality. To begin, level of education, occupation, and income appear to be moderately heritable samples studied so far, respectively, about 60-70%, 50%, and 40-50%. The heritability of both *g* and educational level increases with age and their phenotypic correlation is driven mostly by their genetic correlation, even in childhood when each is still substantially influenced by shared family effects (Petrill & Wilkerson, 2000). Half to two-thirds of the heritability of education, occupation, and income level overlaps the heritability of IQ, meaning that both *g* and adult status are both substantially influenced by the same genes. Rowe et al. (1998) calculated that two-thirds of both the .63 IQ-education correlation and the .34 IQ-income correlation in their sample was genetic variance and one-third shared environment, which accords somewhat better with functional tool theory. (The authors also provide an excellent discussion of caveats in interpreting such evidence.)

Although evidence may exist for testing Predictions 10-12, I am not aware of it. They concern the relative amount of active vs. evocative g-e correlation that the two theories expect in the genetic covariance between *g* and status outcomes. In light of the difficulty of distinguishing the two forms of g-e correlation in behavior genetic studies, data would have to be collected on specific mechanisms—worker and gatekeeper behaviors—that are thought to generate active or evocative g-e correlations.

It is important to note at this point that family background does, in fact, affect the degree to which individuals exploit higher *g* for purposes of social advancement. This is illustrated by the fact that bright youngsters from lower class backgrounds both aspire to and attain fewer years of education—they “invest” less of their *g* in it—than do equally bright peers from higher social class family backgrounds (Gottfredson, 1981).They therefore earn a lower return on it. Although *g* affects life chances more strongly than often acknowledged, this clearly does not mean that social advantages lack importance independently of *g*. But that is not been the question here. The question is why *g* seems to play such a central role in status attainment.

Predictions 13-18: Impact of social interventions on variation and covariation in g and status attainment. Another way to evaluate the theories is to compare what they expect social interventions to accomplish against what actually happens after they are implemented. There are now decades of experience in the United States and elsewhere with interventions guided by the assumptions of social privilege theory, principally, that inequality of outcomes is caused primarily or solely by inequality of opportunity and social capital. Our two philosophers would describe these interventions as attempts to use civic institutions to reduce social inequality.

Table 4 lists six pairs of predictions involving education, where the interventions aim either to equalize educational opportunities or to break the link between education and either IQ or occupation. Much policy targets schooling because democracies view it as their "great equalizer." Accordingly, many educational interventions since the 1960s have sought to equalize students' quality and quantity of education with the expectation that this would reduce their differences in *g* and also weaken if not eliminate the intergenerational transmission of social inequality. It would allow individuals to "learn their way out of poverty." By weakening the influence of family advantage and disadvantage, equalization would reduce the correlation between IQ and attainment (Prediction 13), shrink the variance in IQ and educational outcomes (e.g., raise low IQs, narrow social class differences in college-going; Prediction 14), and drive the parent-child correlation in education toward zero (i.e., increase "social mobility"; Prediction 15). Such policies may be desirable for various reasons, but the question here is whether they have the good effects that adherents of social privilege theory said they would.

Others policies, again rooted in social privilege theory, have aimed to shrink differences in socioeconomic outcomes by ensuring good developmental environments or services for all children and families (e.g., pre-school interventions such as Head Start, universal kindergarten, subsidized school lunches for the poor, more demanding curricula, national health care), on the assumption that this will shrink inequalities by bringing the disadvantaged bottom up closer to the privileged top (Prediction 16).

Next are the efforts, often driven by affirmative action policies in employment, to weaken the link between IQ and occupational level either by reducing the importance of IQ in obtaining essential educational credentials (Prediction 17) or by reducing the importance of academic credentials in getting good jobs (Prediction 18). Efforts to weaken the link between *g* and educational attainment have included mastery learning, abolition of ability grouping for instruction, open admissions to college, and dropping the SAT as a requirement for college admissions. The social privilege theorists' two-part rationale for these expectations is, first, that educational sorting and credentialing places too much emphasis on narrow *g*-based entry criteria such as the SAT and too little on non-cognitive strengths such as leadership and, second, that initial, privilege-based academic weaknesses can be overcome when opportunities to learn are equalized.

Policies to weaken the link between past academic accomplishments and future occupational attainments have included scaling back the educational degrees required for job entry (e.g., no longer requiring a college degree to enter police work or fire fighting; a proposal for system-wide "de-credentialling," Collins, 1979), not using tests of basic skills to hire for seemingly non-academic jobs (again, police and fire fighting work), grouping scores on *g*-loaded tests of job aptitude into a few broad levels (e.g., test score "banding"), and altering employment test content to lower its *g* loading (Gottfredson, 1996). The rationale for these proposals is that either that these academic credentials and skills are not relevant to performing the job (in legal terms, not "job related") or else that the vast majority of individuals could pick up required skills once on the job (Collins, 1979). Requiring them thus discriminatorily screens out disadvantaged individuals who could do the work.

Note that these policy efforts target different nodes in the life course model in Figure 1. Some aim to reduce the variance in some presumed or real predictor of educational attainment in the leftmost columns (e.g., family resources, IQ, school quality) or to reduce their influence on outcomes down the line, that is, by driving down their covariance. All are inspired by the notion that social inequality is the root cause of social inequality, differences in mental competence are overrated, and any reference to genetic differences is blaming the victim. By this view, emphasizing intellectual competence is discriminatory. It rigs the competition against individuals from non-privileged social settings while at the same time justifying the rigging as fair.

Functional tool theory predicts that these interventions will not only fail but also have self-defeating side-effects. On Predictions 13-15, functional theorists would argue that high intelligence would still be an advantage and low intelligence a disadvantage even if environments were equalized, mental tests banned, everyone labeled equally intelligent, and all given the same level of education and training, because the business of living would continue to be complex and higher *g* provides an competitive edge in dealing with complexity. Moreover, the edge provided by higher *g* increases as the complexity of tasks and jobs increases. Family privilege matters but cognitive diversity, especially within biological families, is constantly redistributing it. If nongenetic differences in social privilege are eradicated, socioeconomic inequalities may be reduced somewhat, but the correlation between *g* and outcomes would rise and become more heritable as a result.

Rates of intergenerational mobility would increase somewhat, but only to the limit imposed by genetic similarity, which is 50% between parent and child. A moderate parent-child correlation in socioeconomic fates would thus remain for genetic reasons, as would moderate *differences* in siblings' attainments. The genetic correlation between siblings is only .5 and their IQs differ by about 11 points, on average (Jensen, 1980).

This chapter has already reviewed some of the pertinent evidence for Predictions 13-15. Jensen (1969) wrote his famous *Harvard Educational Review* article precisely because compensatory education was not having its expected benefits, and Brody's (2007) more recent assessment confirms a broader range of frustrated policy attempts. The intervening decades saw decade-to-decade oscillation between policies for promoting educational equality (e.g., 1960s compensatory education programs) and ones for promoting educational excellence (e.g., as set forth in the 1983 call for educational reform, *A Nation at Risk*). Such oscillation is a fact of life in education because the pursuit of one goal (reducing variance in outcomes) leads to institutional behavior that works against achieving the other (raising mean levels of performance): easing standards for high school graduation vs. raising them; not grouping students for instruction vs. grouping them; investing education dollars in special education vs. advanced placement classes. Other failed large-scale interventions, rarely mentioned, include efforts by the new Communist regime in post-WWII Warsaw, Poland, to break the transmission of social class privilege. It assigned families to apartments and schools without regard to parental status, but this apparently had no discernible effect on the intergenerational transmission of *g* (Firkowska et al., 1978).

On Prediction 16, functional tool theorists would predict that interventions to improve environments across the board would increase, not narrow, *g*-based differences in knowledge, performance, and socioeconomic attainment. Their rationale, given earlier, is encapsulated by Jensen's three laws of individual differences in *g* (Sarich & Miele, 2004, p. 258): (1) individual differences (variance) in performance will increase as task complexity increases, (2) increases in mean levels of performance will be accompanied by increased variance in performance (the gap between top and bottom), and (3) individual differences in performance will increase as tasks are practiced over time (more education, training, experience), as long as there is no artificial ceiling on performance. From the social privilege perspective, these are perverse effects, but they are precisely what follow interventions aimed to reduce variance, raise means, or do both at the same time. Ceci and Papierno describe such effects in their 2005 article, "The rhetoric and reality of gap closing – When the 'Have-Nots' gain but the 'Haves' gain even more."

For recent evidence on efforts to "level up the playing field" in education, we might look at the cascade of events after enactment in the United States of the 2001 *No Child Left Behind*

Act, whose stated aim is to reduce the long-standing demographic gaps in academic achievement (The White House, 2001). It attempts to do so by mandating that public schools bring all students up to the same high level of proficiency by 2014 and punishing them if they do not. Events unfolded just as functional tool theory would predict: school administrators started acknowledging that not all students learn equally proficiently even in the best of schools; state governments started (and kept) lowering the bar for what they counted as "proficient" performance; and any progress in closing demographic gaps was achieved primarily by lowering standards and restricting the range of student achievement by ignoring the needs of brighter students while concentrating on raising the lowest performing groups.

As for attempts to weaken the link between *g* and occupational status (Predictions 17-18), functional tool theory predicts that lowering the *g* loading of educational credentials will result in employers hiring less competent workers to the extent that employers rely on such credentials. This will lead to higher rates of costly worker errors and subpar performance, which will generate skepticism about educational credentials and perhaps cause employers to turn to more *g*-loaded selection tools, including tests. If the *g*-loading of credentials is not restored first, this sequence of events would cause occupational attainment's correlation with education to fall and its correlation with *g* to rise—just the opposite of what was originally intended.

Burden of proof. We have now seen many sorts of evidence that converge in supporting the predictions of functional tool theory and contradicting social privilege theory. Where the evidence has been ample, the patterns have been clear, consistent, and consilient—across the behavior genetic data and brain studies; the task attributes of tests, academic work, and jobs that call forth *g*; and predictive validity studies in employee selection. The burden of proof now lies with social privilege theory to demonstrate that it remains a plausible explanation for why *g* predicts who gets ahead. It is not enough to pick apart isolated bits in the web of evidence. The theory must account for the evidence in its entirety and it must do so more effectively than functional tool theory currently does.

6. The Democratic Dilemma

Genetic differences in a population create dilemmas for democratic societies. Social inequality is inevitable when a society's members vary in a genetically-conditioned trait, such as g, that is highly useful and therefore confers a competitive advantage and garners social rewards. Equal opportunity to use one's natural talents will guarantee unequal results.

6.1. The Democratic Passion for Equality of Condition

Even to suggest the necessity of such tradeoffs risks offending democratic sensibilities, so strong is the commitment to social equality in democratic regimes. The sense of offense may be observed especially in educational circles, which have sometimes flown the banner of EQuality to express the belief that educational excellence (Quality) and equality of outcomes (Equality) are mutually reinforcing goals, never conflicting ones.

These sensibilities are hardly new, as we learn from that early student of democracy, the Man from France, Alexis de Tocqueville. Although penned almost two hundred years ago, his observations about inequality and natural differences in American life remain apt today. He observed that democratic societies have a love of freedom but an insatiable passion for equality of social condition that only grows as inequalities shrink. "When inequality of conditions is the common law of society, the most marked inequalities do not strike the eye; when everything is nearly on the same level, the slightest are marked enough to hurt it. Hence the desire of equality always becomes more insatiable in proportion as equality is more complete" (Tocqueville, 1840/1972, p. 138). He noted further (p. 138) that "even if they unhappily attained that absolute and complete equality of position, the inequality of minds would still remain, which, coming directly from the hand of God, will forever escape the laws of man." Here is his stronger message to us. “I think that democratic communities have a natural taste for freedom; left to themselves, they will seek it, cherish it, and view any privation of it with regret. But for equality their passion in ardent, insatiable, incessant, invincible; they call for equality in freedom; and if they cannot obtain that, they still call for equality in slavery. They will endure poverty, servitude, barbarism, but they will not endure aristocracy” (p. 97).

So, while Rousseau and Huxley seem to judge the moral standing of civil society by its degree of inequality, Tocqueville would caution against elevating equality of condition above all else, as we are wont to do. The moral choice is not that simple, as we have seen, and assuming otherwise can harm the collective welfare. One such cost was alluded to earlier. Scholars of inequality and crusaders against it both focus tightly on variance in outcomes—“inequality”—with scant attention to means. However, as Jensen’s laws of individual differences foretell and hard experience confirms (Ceci & Papierno, 2005), means levels of performance tend to drop when variance shrinks, that is, inequalities narrow. Conversely, when more information and resources are pumped into the system, means levels of performance and well-being rise but variance does too because some people more effectively exploit the new resources than do others (e.g., Gottfredson, 2004, on health knowledge, behavior, and outcomes). It is active g-e correlation at work.

6.2. Example of Alternative Responses to the Democratic Dilemma

Some commentators acknowledge the societal tradeoffs imposed by cognitive diversity and have pondered how a polity might best deal with them. Consider two books that tackle the conundrum from different ends of the political spectrum: *Excellence: Can We Be Equal and Excellent Too?* by John Gardner (1984) and *The End of Equality* by Mickey Kaus (1992). Both authors would refocus our efforts away from seeking equal outcomes only in the material, instrumental spheres of life, where *g* matters most, and direct more attention to the socioemotional realms where humans, as social beings, find deep meaning and satisfaction but *g* matters least.

For Gardner, the challenge is how to “provide opportunities and rewards for individuals of every degree of ability so that individuals at every level will realize their full potentialities, perform at their best, and harbor no resentment toward those at any other level [of ability]” (p. 113). The rewards include not just self-respect but the regard and gratitude earned in personal spheres of activity and influence for performing one’s job well, whatever its nature (as he says, both a plumber’s and philosopher’s work must hold water), as well as serving as a leader and upstanding member of one’s local communities. Kaus, on the other hand, looks to national governments to break down the sense of cultural separation and animosity between different economic classes. He would do this by ensuring equality in highly public spheres of national life. The federal government would provide everyone the same level of basic services (universal health and child care) and create shared spaces where individuals from all social backgrounds would work in common cause (mandatory national service). The first, equal services to individuals, would signal a nation’s equal regard for all its citizens and the second, common service by individuals, would break the barriers to mutual regard across economic lines.

One might protest that their solutions are no solutions at all because socioeconomic inequality remains. But that misses their point. Although democracies cannot eliminate inequality of condition, they can find better ways to modulate it. To point out that cognitive diversity contributes to their dilemma does not signal that intelligence is “all important” or that it should be. However, the more important socioeconomic inequality is to us, the more it behooves us to understand its roots in human biological diversity and *g* in particular.

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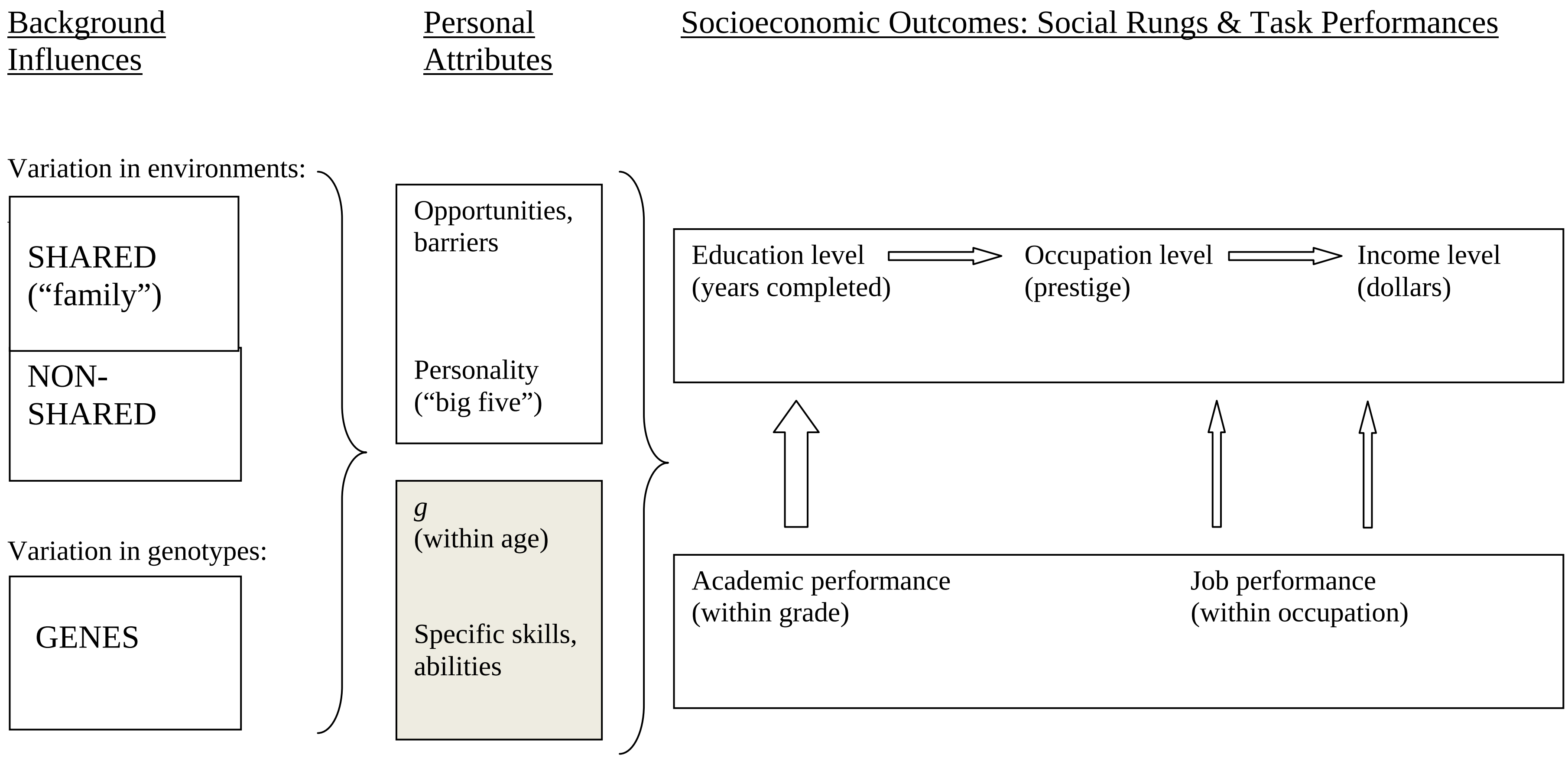
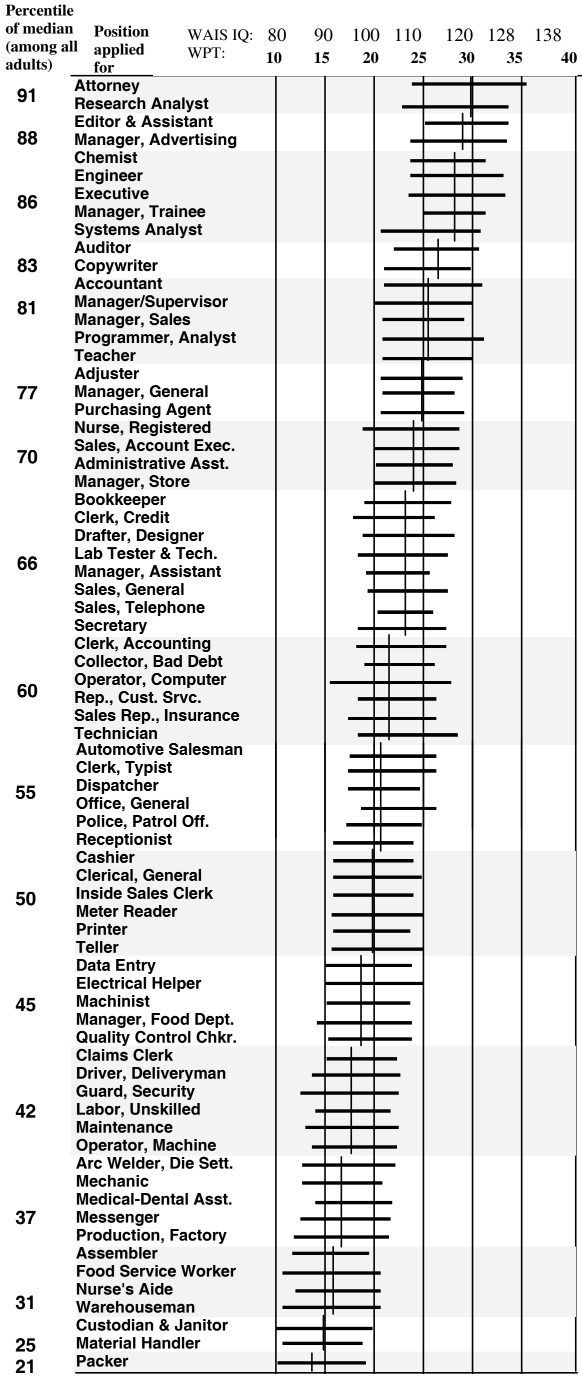
Figure captions

Figure 1. Life course model of causes and consequences of social inequality

Figure 2. Test scores by occupation applied for (1992). The bold horizontal line shows the range between the 25^{th} and 75^{th} percentiles. The bold crossmark shows the 50^{th} percentile (median) of applicants to that occupation. Reprinted from Gottfredson (1997, Figure 1). WPT = Wonderlic Personnel Test.

Figure 3. Venn diagrams illustrating components of genetic and environmental variation and covariation.


Background Influences
Personal Attributes
Socioeconomic Outcomes: Social Rungs & Task Performances
Variation in environments:
SHARED ("family")
NON-SHARED
Variation in genotypes:
GENES
Opportunities, barriers
Personality ("big five")
g (within age)
Specific skills, abilities
Education level (years completed)
Occupation level (prestige)
Income level (dollars)
Academic performance (within grade)
Job performance (within occupation)



Training Potential

WPT 28 and Over

Able to gather and synthesize information easily; can infer Information and conclusions from on-the-job situations (IQ 116 and above)

WPT 26 TO 30

Above average individuals; can be trained with typical college format; able to learn much on their own; e.g. independent study or reading assignments (IQ 113-120)

WPT 20 TO 26

Able to learn routines quickly; train with combination of written materials with actual on the job experience. (IQ 100-113)

WPT 16 to 22

Successful in elementary settings and would benefit from programmed or mastery learning approaches; important to allow enough time and "hands on" (on the job) experience previous to work. (IQ 93-104)

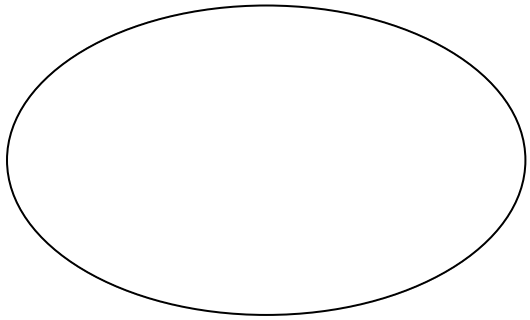
WPT 10 to 17

Need to be "explicitly taught" most of what they must learn; successful approach is to use apprenticeship program; may not benefit from "book learning" training. (IQ 80-95)

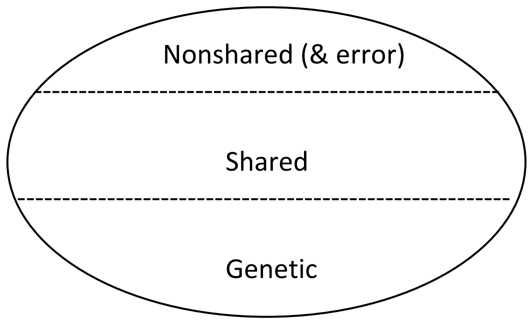
WPT 12 OR LESS

Unlikely to benefit from formalized training setting; successful using simple tools under consistent supervision. (IQ 83 and below)

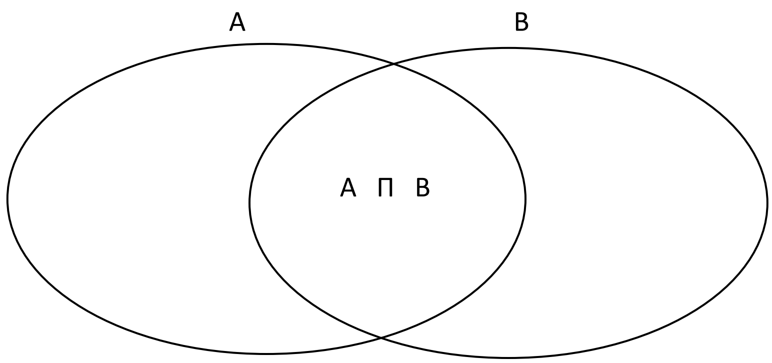
(a) Variation in A



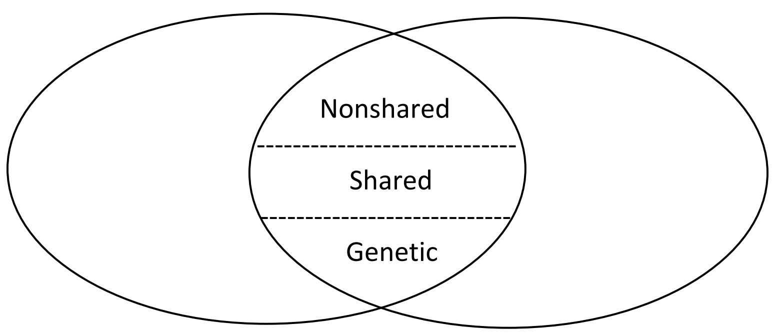
(b) Components of variation



(c) Covariation of A and B



(d) Components of covariation



(e) Example of how components of variance and covariance can differ

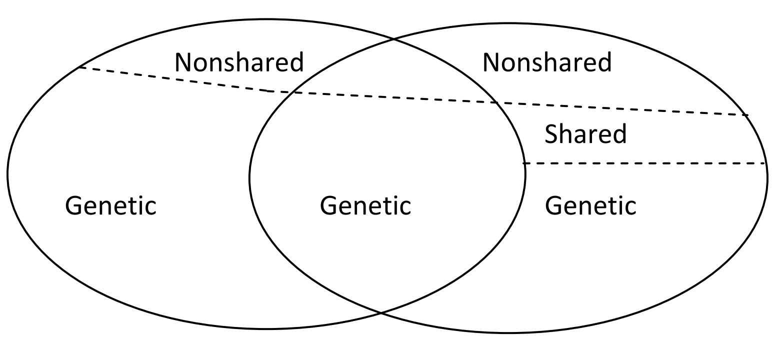


Table 1
Typical correlations between family background, IQ, and adult status[1]

	Father's occupation	Son's IQ	Son's Education	Son's Occupation	Son's Earnings
Father					
Education	.48	.27	.40	.28	.20
Occupation		.29	.38	.31	.22
Son					
IQ			.57	.46	.28
Education				.61	.38
Occupation					.43

[1] Entries are averages from 4 studies analyzed in Jencks et al. (1979, Tables A2.8, A2.9, A2.11, and A2.12).

Table 2

Correlations in two job analysis studies of selected job attributes with first factor

Job attributes	Correlation with factor
"Judgment and Reasoning" factor (140 Jobs in petrochemical industry)[a]	
Deal with unexpected situations	.75
Able to learn and recall job-related information	.71
Able to reason and make judgements	.69
Able to identify problem situations quickly	.69
React swiftly when unexpected problems occur	.67
Able to apply common sense to solve problems	.66
Able to learn new procedures quickly	.66
Alert and quick to understand things	.55
Job "Complexity" factor (PAQ and DOT data for 276 broad Census occupations)[b]	
Compiling information (importance)	.90
Self-direction (amount)	.88
Reasoning (level), DOT	.86
Advising (importance)	.86
Update job knowledge (importance)	.85
Complexity of dealings with data (level), DOT	.83
Analyzing information (importance)	.83
Planning/scheduling (amount)	.83
Negotiating (importance)	.79
Work under distractions (importance)	.78
Frustrating situations (importance)	.77
Criticality of position (degree)	.71
Repetitive activities (importance)	-.49
Supervision (level)	-.73

[a] Source: Arvey (1986, p. 418).

[b] Source: Gottfredson (1997, pp. 100-104). PAQ = Position Analysis Questionnaire, DOT = Dictionary of Occupational Titles.

Table 3
Differential predictions from competing conceptions of *g*'s practical utility:
External validity by type of work, workforce, and performance criteria

#	Correlations between *g* and performance	Competing conceptions of *g*'s utility		Reports on illustrative meta-analyses
		g academic	*g* general	
Average correlations				
1	Correlations > 0	low %	100%	Schmidt & Hunter, 1998
2	Incremental validity of specific abilities	frequent & moderate	infrequent & small	Thorndike, 1986
Moderators of correlations				
	Work tasks			
3	more complex	no independent effect	higher	Hunter, 1986
4	more academic	higher	no independent effect	see Figure 3
5	more independently performed	no effect?	higher	Hunter, 1986
	Performance criteria			
6	more objective	lower	higher	Hunter, 1986
7	more exclusively technical	no effect?	higher	McHenry et al., 1990
8	more exclusively citizenship	higher	lower	McHenry et al., 1990
	Workforce			
9	more equal training	lower	higher	Hunter & Schmidt, 1996
10	more equal experience	lower	higher	Schmidt, Hunter, Outerbridge, & Goff, 1988.

Table 4
Opposing Predictions on *g*'s Role in Social Inequality: Social Privilege vs. Functional Tool Explanations
(*g* = *g* level after adolescence)

#	Predictions[1]	Competing explanations	
		Social privilege	Functional tool
	A. Components of genetic and environmental variation in g		
1	Early childhood	mostly shared	equally shared and genetic
2	Adolescence	increasingly shared	decreasingly shared
3	Adulthood	increasingly shared	not at all shared
	B. Covariation between g and socioeconomic success		
	Phenotypic correlation		
4	education level	moderately high	moderately high
5	occupation level	moderately high	moderately high, rises with age
6	income level	moderate	moderate, rises with age
	% of covariance that genetic		
7	education level	low	high
8	occupation level	zero-low	high
9	income level	zero-low	high
	g-e component of genetic variance		
10	education level	mostly evocative	mostly active
11	occupation level	mostly evocative	mostly active
12	income level	mostly evocative	mostly active
	C. Impact of social interventions on sorting process		
	Interventions aimed at:		
13	Equalizing educational opportunity	*g*- education correlation falls	*g*- education correlation rises
14	Equalizing educational opportunity	variance in educational outcomes shrinks	variability falls, heritability rises
15	Equalizing educational opportunity	parent-child education correlation falls toward zero	parent-child correlation remains moderate, becomes 100% genetic
16	Improving developmental environments for all	variability in outcomes narrows	variability in outcomes widens
17	Weakening link of IQ to years of education	*g* -occupation correlation falls	education-occupation correlation falls
18	Weakening link of education to occupation	*g* -occupation correlation falls	*g* -occupation correlation rises

[1] All apply to broad populations, not to samples that may be restricted in range.