

Time Is on My Side: Time, General Mental Ability, Human Capital, and Extrinsic Career Success

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The present study linked general mental ability (GMA) to extrinsic career success using a multilevel framework that included time and 3 possible time-based mediators of the GMA–career success relationship. Results, based on a large national sample, revealed that over a 28-year period, GMA affected growth in 2 indicators of extrinsic career success (income and occupational prestige), such that the careers of high-GMA individuals ascended more steeply over time than those of low-GMA individuals. Part of the reason high-GMA individuals had steeper growth in extrinsic success over time was because they attained more education, completed more job training, and gravitated toward more complex jobs. GMA also moderated the degree to which within-individual variation in the mediating variables affected within-individual variation in extrinsic career success over time: Education, training, and job complexity were much more likely to translate into career success for more intelligent individuals.

Keywords: intelligence, general mental ability, career success, pay, human capital

General mental ability (GMA) can be considered one of the more useful constructs in psychological science (Gottfredson, 2002; Schmidt & Hunter, 2004). One durable finding is the substantial relationship between GMA and job performance (Schmidt & Hunter, 1998), which generalizes across both jobs (Schmidt, 2002) and cultures (Salgado & Anderson, 2002). GMA has also been shown to predict many other work-related criteria, including job satisfaction (Ganzach, 1998), leadership (Judge, Colbert, & Ilies, 2004), creativity (Kuncel, Hezlett, & Ones, 2004), and counterproductive behavior (Dilchert, Ones, Davis, & Rostow, 2007), as well as non-work-related criteria, including marital and familial stability, health, and longevity (Gottfredson, 1997; Gottfredson & Deary, 2004). In reviewing the vast array of criteria that GMA predicts, Gottfredson (1997) unequivocally concluded, “Intelligence is important in social life” (p. 79). Given these findings, it is somewhat surprising that relatively few studies have linked GMA to career success. Although there are some such studies—according to a recent meta-analysis by Ng, Eby, Sorensen, and Feldman (2005), eight studies have linked GMA to salary ($\bar{r}_c = .27$)—the literature could not be described as voluminous. Moreover, although some studies suggest that the GMA–career success link is due to education (Deary et al., 2005), other possible explanations remain to be discovered.

In the effort to better understand mechanisms underlying career success, one is well advised to consider the temporal nature of careers (Bailyn, 2004). Although GMA itself is quite

stable (Schmidt & Hunter, 1996), the mechanisms by which the intelligent acquire greater levels of career success may themselves be time variant. Developmental psychologists have long understood the notion of *critical periods*—time frames after which it becomes a good deal more difficult to acquire certain proficiencies (Bruer, 2001). Might such critical periods exist for one’s career? Indeed, recent evidence suggests that decisions arrived at during specific time periods can produce cumulative advantages that accelerate career success (Judge & Hurst, 2008). Such time-based conceptions of cumulative advantage are inspired by Merton’s (1968) Matthew effect. Drawing from an eponymous verse in the Bible (see Matthew 25:29, King James Version), Merton (1968) coined the term to describe the disproportionate accumulation of rewards and resources by scientists who were successful at the outset of their careers. This idea of cumulative advantage has since been extended to an array of phenomena beyond scientific careers and has garnered renewed interest from scholars wishing to explain achievement and success across the life span (Ceci & Papierno, 2005). In short, when it comes to one’s career, timing matters, and it might well matter to some (i.e., those with high GMA) more than others.

In this paper, we draw from contest mobility and sponsored mobility perspectives (Rosenbaum, 1979; Turner, 1960) and the intelligence literature (Gottfredson, 1997, 2002) to argue that the intelligent achieve higher levels of extrinsic career success not only by realizing early career advantages but also by having steeper trajectories of success that unfold over time. We argue that these trajectories provide environments in which high-GMA individuals’ skills are often reinforced and amplified, setting the stage for later academic and employment success.

Our objectives in examining these phenomena are threefold. First, we examine whether GMA is linked to the within-individual change in extrinsic career success over time. Second,

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we seek to identify the mechanisms through which the intelligent might establish successful careers. To do so, we consider the role of three potential mediators: educational attainment, training experience, and job complexity. Last, we examine whether the dynamic processes through which the timing and quantity of educational attainment, job training, and job complexity are achieved can lead to accelerated career trajectories resulting in extrinsic (e.g., salary and occupational prestige) cumulative advantages for the intelligent. In the next section of the paper, we develop these arguments further and posit specific hypotheses designed to test the relationships among GMA, time, the time-variant mediators, and extrinsic career success.

Theoretical Background and Hypotheses

Consistent with past research (Judge, Cable, Boudreau, & Bretz, 1995), we define extrinsic career success as the objective accomplishments—those accomplishments that are observable, assessable, and verifiable by an impartial third party (Gattiker & Larwood, 1988; Hughes, 1937)—individuals achieve as a consequence of their work experience. Such elements include pay, occupational mobility, and occupational status or prestige (Heslin, 2005).¹ To the above-mentioned portrayal of extrinsic career success, we add a temporal dimension. A temporal perspective is necessary because, although cross-sectional studies have provided valuable “snapshots” of the predictors of career success, careers unfold throughout the course of one’s life, with prior successes and failures shaping prospects for future successes and failures (Judge & Hurst, 2008). Our focus on temporal dynamics is also consistent with recent calls to incorporate the role of time into applied research designs. As noted by Kozlowski (2009), “Advancing theories that address the dynamics of how important phenomena emerge, evolve, and change over time is the next frontier” (p. 3).

On the basis of the foregoing review, we use income and occupational prestige (or status) as indicators of extrinsic career success. Pay is perhaps the most prevalent operationalization of extrinsic career success (Heslin, 2005; Judge et al., 1995; Ng et al., 2005). Additionally, occupational status—defined as the power, prestige, and authority provided by an occupation as viewed by society (Blaikie, 1977)—has been described as sociology’s “great empirical invariant” (Featherman, Jones, & Hauser, 1975, p. 331). Thus, it is also a relevant indicator of career success in contemporary society (Gelissen & de Graaf, 2006).

The hypothesized models guiding the investigation are provided in Figures 1a and 1b. Figure 1a portrays GMA as a between-individual (Level 2) predictor of between-individual variance (intercepts) and within-individual (Level 1) variance (slopes or growth rates) in extrinsic career success and human capital (e.g., education, training, job complexity). Here, we suggest that growth in human capital acquisition and extrinsic career success occurs more quickly for high-GMA individuals than for low-GMA individuals. (The figures also reflect intercept differences that we explain shortly.) Figure 1b similarly models GMA as a between-individual predictor of within-individual slopes but looks at rates of return (in terms of extrinsic career success) on human capital, rather than rates of growth. In particular, education, training, and job complexity

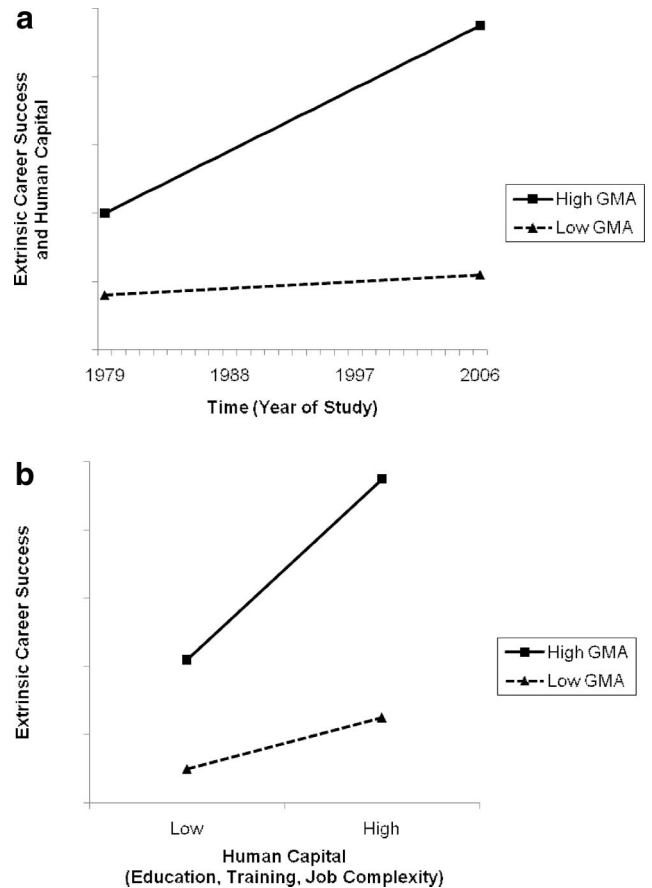


Figure 1. Multilevel model of general mental ability (GMA) as (a) a between-individual predictor of initial differences (intercepts) and within-individual rates of growth in human capital and extrinsic career success and (b) a between-individual predictor of extrinsic career success intercepts and within-individual variance in human capital–extrinsic career success slopes.

are shown to translate into extrinsic career success more positively for high-GMA than low-GMA individuals.

Before offering specific multilevel hypotheses, we also consider GMA as a predictor of between-individual differences in initial levels of human capital and extrinsic career success (intercepts). These differences are represented in both panels of Figure 1 as discrepancies in intercepts for high- and low-GMA individuals. Our multilevel hypotheses thus consider early career advantages and assume that, even in the likely event that high-GMA individuals begin their careers on more solid footing (Strenze, 2007), they augment these early advantages over time. Moreover, though this is not explicitly graphed, in conceptually integrating the abovementioned figures and in attempting to

¹ Though, clearly, intrinsic success is an integral part of any reasonable definition of career success, we do not focus on intrinsic career success here because the literature linking GMA to indicators of intrinsic career success, such as job satisfaction (Ganzach, 1998), life satisfaction (Gow et al., 2005), or career satisfaction (Lounsbury, Gibson, Steel, Sundstrom, & Loveland, 2004), has suggested inconsistent or weak relationships.

better explain the proposed growth in extrinsic career success, we examine the extent to which education, training, and job complexity mediate the effects of GMA on extrinsic career success over time. Finally, because the effects may not be constant over time, we investigate nonlinearity in the degree to which GMA moderates the effects of time on extrinsic success.

In all of our multilevel analyses, we control for the effect of time as a within-individual variable. Individuals' careers generally ascend as time elapses (Gattiker & Larwood, 1988). In terms of our study, this means that although extrinsic success may decline over time for some individuals, or may remain stagnant for others, most individuals' careers should advance with time. Because time and concepts intimately related to time (e.g., organizational and job tenure, seniority, age) may not be "causal factors in and of themselves" (Sturman, 2003, p. 626), we do not offer explicit hypotheses relating time to extrinsic career success. However, we do model the "main effects" of time on extrinsic career success. In the next section of the paper, we consider whether these temporal effects on extrinsic career success (i.e., extrinsic career success trajectories) vary by GMA.

Moderating Role of GMA on Extrinsic Career Success Trajectories

Despite an overall tendency for individuals to become better off over time, it is clear that not all careers start at the same place or reach the same end points. Do intelligent individuals have greater extrinsic career success (Ng et al., 2005) "simply" because they begin their careers on better footing? Or, do their careers ascend more steeply over time as well? Though we are aware of no direct evidence to answer these questions, sponsored and contest mobility concepts suggest an answer. Through sponsored mobility mechanisms and the manner in which awards are channeled (Turner, 1960), the intelligent are likely to be recognized and identified as candidates for increasingly better opportunities. Indeed, according to Ng et al. (2005), those "identified by the elites are allowed to start the race earlier, gain momentum more quickly, and are more likely to be declared as winners" (p. 370).

With respect to contest mobility systems (Turner, 1960), the intellectually gifted are better able to capitalize on the advantages of their assets and of the opportunities they are provided as a result of these assets (Lubinski, Benbow, & Webb, 2006). The literature on how GMA influences work adaptation is neither extensive nor consistent. LePine, Colquitt, and Erez (2000) found that high-GMA individuals better adapt to task changes, whereas Lang and Bliese (2009) found that GMA hindered "transition adaptation," or early adaptive task performance (i.e., in response to unexpected task changes, the performance of high-GMA individuals showed more within-individual decline than did the performance of low-GMA individuals), and did not improve "reacquisition adaptation," or later adaptive performance. At a micro (short-term task performance) level, these studies suggest that the relationship between GMA and performance is complex and likely moderated by cognitive, situational, and temporal elements. However, at the macro (long-term career success) level, the situation may well be different. Changes are less likely to be unilaterally imposed, and adjustments take place over months and years rather than minutes and hours. Indeed, long-term evidence

suggests that high-GMA individuals better respond to challenges, such as solving complex problems, coping with risk factors, and adapting to changes in work (Gottfredson, 2002). Thus, from a macro perspective, the careers of intelligent individuals should ascend more steeply because they differentially utilize, and benefit from, the early advantages conferred by sponsored and contest mobility systems.

Hypothesis 1 (H1): GMA moderates the relationship of time with income (H1a) and occupational prestige (H1b), such that income and occupational prestige have steeper trajectories for those with high GMA than for those with low GMA.

Moderating Role of GMA on Human Capital Trajectories

If the acquisition of human capital is a race run across the landscape of time, then H1 posits that the intelligent are clear winners. But why do they win? Echoing the Matthew effect, cumulative advantage frameworks in the sociology literature emphasize the role of timing in human capital acquisition (DiPrete & Eirich, 2006). Indeed, for both particularistic (sponsored mobility) and universalistic (contest mobility) reasons, three mediators—education, training, and job complexity—should explain why the trajectories of extrinsic career success are steeper for high-GMA individuals.

Intelligence is a desired attribute among employers, peers, and team members (Dunn, Mount, & Barrick, 1995; Gottfredson, 2002). Observer ratings of general intellectual ability correlate positively with measures of occupational prestige and status (Feist & Barron, 2003). Moreover, early (prekindergarten) teacher impressions of intelligence have lasting effects on student academic performance many years later, even once conditioned by independent-test-based measures of GMA (Alvidrez & Weinstein, 1999). These results might be explained by how those perceived to be intelligent are treated by others: Such individuals are given disproportionate attention by educators and are steered into prestigious educational institutions and occupations. Thus, one might argue that there are few things that more clearly drive social stratification than the perception of intelligence.

Though the particularistic aspects of intelligence may be important, that is not to suggest that the beneficial aspects of intelligence are solely or even mainly perceptual. From a universalistic perspective, everyone benefits from education, but because learning is cumulative, as new, ever more complex concepts build on previously learned ones, the link between GMA and learning should become stronger (e.g., the advantages of GMA are more important to learning differential calculus than simple arithmetic). Indeed, the greater one's intellectual gifts, the more distinctive one's intellectual accomplishments and academic progress become (Lubinski, Webb, Morelock, & Benbow, 2001). If the complexity of learning suggests disproportional cumulative educational benefits to high-GMA individuals, the same logic should apply to training. Indeed, Gottfredson (1997) notes that the degree to which individuals benefit from training depends on GMA, with high-GMA individuals benefiting most from training on complex skills and activities. Finally, it is well known that the validity of

GMA in predicting job performance increases as job complexity increases (Schmidt, 2002; Schmidt & Hunter, 2004) and that intelligent individuals gravitate toward complex jobs (Wilk, Desmarais, & Sackett, 1995). This, too, suggests that levels of complexity should increase more rapidly over time for high-GMA individuals.

Hypothesis 2 (H2): GMA moderates the relationship of time with educational attainment (H2a), training (H2b), and job complexity (H2c), such that educational attainment, training, and job complexity have steeper growth curves for those with high GMA than for those with low GMA.

GMA, Human Capital, and Extrinsic Career Success

Related to the issue of human capital acquisition is whether certain individuals are more adept than others at extracting benefit from their experiences. It is one thing to simply endure education, training, and complex work and another to capitalize on the advantages these opportunities afford. Although training, education, and experience with complex tasks can contribute to one's accumulation of knowledge over time—and thus to extrinsic success—novel situations are bound to arise in the workplace that reach beyond the application of job knowledge (Gottfredson, 2002). Thus, although the accumulation of human capital affects job knowledge acquisition over time and increased experience on the job (and in training and education) provides access to knowledge acquisition channels, “it is GMA that turns experience into increased job knowledge and hence higher performance” (Schmidt & Hunter, 2004, p. 167). Put simply, it is not only the amount one learns that matters but also the flexibility and ease with which what is learned can be applied and manipulated. With these capabilities, the intelligent possess an advantage—one likely to translate into higher pay and greater occupational prestige (Schmidt & Hunter, 2004).

Hypothesis 3 (H3): GMA moderates the relationships of educational attainment, training, and job complexity with extrinsic career success, such that educational attainment, training, and job complexity have a stronger positive relationship with income (H3a) and occupational prestige (H3b) for those with high GMA than for those with low GMA.

Human Capital as Mediators of Growth in Extrinsic Career Success Across Levels of GMA

We have already noted that although most individuals' careers ascend over time, time itself is unlikely to be a causal determinant of such ascendance. Rather, it is how time is invested that determines, at least in part, the trajectory of one's career. Human capital theory (Becker, 1964) posits that efforts to develop knowledge, skills, and abilities—through factors like education and training—increase individuals' value to firms and that this value is rewarded, presumably in the form of higher wages and upward mobility. Recent meta-analytic evidence supports this theory, demonstrating that, indeed, investments in factors such as education and training are related to promotions and higher salary (Ng et al., 2005). Thus, although additional factors, such as health (Judge & Hurst, 2008) and

social capital (Ng et al., 2005), influence extrinsic career success, it seems likely that human capital, in the form of education, training, and job complexity, partly mediates (explains) growth in career success, regardless of one's level of intelligence. Because the acquisition of human capital happens only over time (Heckman, 1976) and may result in cumulative advantage (where the benefits accrue over time; Merton, 1968), we believe that

Hypothesis 4 (H4): Human capital—in the form of education (H4a), training (H4b), and job complexity (H4c)—partially mediates growth in extrinsic career success (income, occupational prestige) over time.

Though human capital likely mediates growth in extrinsic success, individuals are neither equally likely to avail themselves of opportunities for education, training, and complex work nor equally likely to benefit from such opportunities. H2 and H3 suggest that prospects for profiting from and procuring human capital are more promising among the intelligent. Here, we argue that mediation of growth in extrinsic career success through human capital intensifies for high-GMA individuals. Why might mediation be stronger for the intelligent? High-GMA individuals maximally benefit from career-related cumulative advantage processes because they are more likely than low-GMA individuals to spend their time acquiring and leveraging human capital (Gottfredson, 1997). Because of the ease and flexibility with which they learn and apply knowledge to complex situations, high-GMA individuals tend to perform well both when acquiring human capital and when applying it to the job (Schmidt & Hunter, 2004). These successes likely set in motion a virtuous cycle, with high-GMA individuals becoming identified as fitting candidates for increasingly selective, complex, and rewarding opportunities that afford higher return on prior human capital investment. In sum, if, as we suggest, high-GMA individuals are more likely to acquire and leverage human capital than are low-GMA individuals, mediation of growth in extrinsic career success through education, training, and complex work should be greater for the intelligent.

Hypothesis 5 (H5): The degree to which human capital—in the form of education (H5a), training (H5b), and job complexity (H5c)—mediates growth in extrinsic career success over time is stronger for individuals with high GMA than for those with low GMA.

Role and Relevance of Core Self-Evaluations

In a previous investigation (Judge & Hurst, 2008), the effects of personality (core self-evaluations [CSE]) on career success over time were examined but effects of GMA were not considered. Because the present study utilized the same longitudinal data set as did Judge and Hurst (2008), it is relevant and important to ascertain the degree to which this study's focus on GMA was affected by the inclusion of CSE and, on the other side of the coin, the degree to which Judge and Hurst's (2008) results were affected by the inclusion of GMA. Thus, we examine the relative contribution of GMA and CSE to career success trajectories and the stability of the GMA effects once CSE is taken into account.

Method

Participants and Procedure

Participants were individuals enlisted in the National Longitudinal Survey of Youth (NLSY79), a nationally representative probability sample of 12,686 men and women. NLSY79 participants were enrolled by the National Opinion Research Center at the University of Chicago; currently, the NLSY79 is administered by the Center for Human Resources and Research at Ohio State University. Participants were interviewed annually from 1979 until 1994, when a biennial interview schedule was adopted.

Over the study's 28-year time period, sample attrition has occurred. Of the 12,686 individuals in the original NLSY79 cohort, 7,654 (60.3%) remained in 2006. Primary reasons for sample attrition can be grouped into five categories: (a) intentional attrition due to budgetary constraints (53.7% of all attrition); (b) participant refusal (27.7% of all attrition); (c) participant death (9.4% of all attrition); (d) inability to locate the participant (6.2% of all attrition); and (e) other reasons, such as participant incarceration or active military duty (3.0% of all attrition). The overall retention rate for eligible respondents (those respondents who were living at the time of the study and who had not been deliberately dropped from the sample due to budgetary constraints) was 85.4% as of 2006.

Level 1 (Within-Individual) Measures

Pay. Pay was measured by aggregating responses to open-ended interview questions regarding pretax money received in the form of wages, salary, commissions, and tips. In order to measure real wage growth, we used the Consumer Price Index (see <http://www.bls.gov/cpi/>) to convert pay from each year into present (2008) dollars. Accordingly, pay was treated as a Level 1 variable when participants' level of pay for each study period was used in the analysis.

Occupational prestige. Each time period, participants reported their current occupation, which was converted into a three-digit code based on the 1970 U.S. Census classification of occupations (U.S. Bureau of the Census, 1971). We then converted these codes into occupational prestige ratings using the Duncan Socioeconomic Index (SEI; Duncan, 1961; Hauser & Warren, 1997). Scores on the SEI range from 3 to 96, with low scores represented by maids (SEI = 7) and garbage collectors (SEI = 8), midrange scores represented by photographers (SEI = 50) and bank tellers (SEI = 52), and high scores represented by engineers (SEI = 87) and lawyers (SEI = 92). Although the index is based on occupational data collected over a half century ago, subsequent research supports the notion that there is little change in occupational prestige ratings over time (Hauser & Warren, 1997). Like pay, occupational prestige was treated as a Level 1 variable and was assessed at each study period.

Educational attainment, training, and job complexity. Each time period, participants reported their "highest grade or year of regular school" completed. For example, scores were coded 0 (*no formal schooling*), 12 (*graduated high school*), 16 (*completed four years of college*), and so on. Similarly, in each time period, participants were asked whether they had attended any training programs or on-the-job training designed to help them find a job,

improve job skills, or learn a new job. Scores were coded 1 if the participant had attended some form of training and 0 if the participant had not attended any form of training.

Consistent with Gerhart (1987) and Spector and Jex (1991), we used the *Dictionary of Occupational Titles (DOT)* (U.S. Department of Labor, 1991) classification scheme to operationalize job complexity. First, the three-digit census codes were converted to nine-digit DOT codes using crosswalks available from the U.S. Department of Labor's Bureau of Labor Statistics (Meyer & Osborne, 2005) and the Occupational Information Network (O*NET; U.S. Department of Labor, 2008). The fourth, fifth, and sixth digits of the DOT codes include information pertaining to a job's complexity dealing with data, people, and things, respectively. For each occupation, we summed the scores across these three categories, such that scores ranged from 0 to 21, with higher scores signaling more complex jobs. For instance, according to the DOT classification, dentists and physicians score highest (19) in job complexity; bakers and carpenters have midrange scores (10); and maids, janitors, and busboys (0) are rated as having some of the least complex jobs. Cain and Green (1983) reported more on the psychometric properties of DOT-based job complexity measures.

All three mediators—educational attainment, training, and job complexity—were considered at the same level of analysis as the extrinsic success variables (pay and occupational prestige). That is, for the multilevel analyses, these mediators were measured each year and treated as Level 1 variables with within-individual (periodic) variation.

Level 2 (Between-Individual) Measures

GMA. In 1980, 11,914 participants completed the Armed Forces Qualifying Test, which consists of four test sections: arithmetic reasoning, word knowledge, paragraph comprehension, and mathematics knowledge. Because participant age varied at the time of test administration, all scores were standardized by participant age. Then, following previous research (e.g., Wilk et al., 1995), GMA was operationalized as the first unrotated factor extracted from a principal-components analysis (Jensen, 1986). In this case, the first factor explained 80.12% of the variance in the measures, and the average factor loading was .90.

Control variables. We recorded participant age, gender (coded 1 [*male*] and 0 [*female*]), and race (coded 1 [*White*] and 0 [*other*]), in addition to the primary variables of interest. Consistent with Bradley and Corwyn's (2002) review, we formed a standardized composite socioeconomic status (SES) variable based on (a) parental occupational prestige, using the highest Duncan SEI score across parents; (b) parental education, using the education level of the most schooled parent; and (c) poverty status at the onset of the study, using the poverty income guidelines of the U.S. Department of Health and Human Services. All three variables (occupational prestige of most esteemed parent, level of education of most educated parent, and poverty status, reverse-scored) were standardized and aggregated to form the SES measure.

Analyses

Because within-individual change, or change over time, is a necessary condition for our hypothesis tests (i.e., if extrinsic career

success or the mediators do not change over time, there is no within-individual [Level 1] variation to predict or be predicted), it is important to assess whether there was substantial within-individual variation in our Level 1 variables. We used hierarchical linear modeling (HLM 6.0; Raudenbush, Bryk, Cheong, & Congdon, 2004) to estimate separate one-way, random-effects analysis of variance models. This allowed us to partition the variance of our repeated-measures variables into within- and between-level components (see Raudenbush & Bryk, 2002, pp. 67–71). The results indicated that for each of the Level 1 variables, a significant proportion of total variation was within-individual (income = 63.6%, occupational prestige = 55.5%, education = 20.3%, training = 90.1%, and job complexity = 68.2%). This substantiated our decision to use HLM to test each of our hypotheses rather than treat this within-individual variance as random error.

In accordance with Raudenbush & Bryk (2002), we treated time as a Level 1 independent variable when testing our hypotheses. Training, education, and job complexity were treated as Level 1 independent and dependent variables, depending on the hypothesis being tested. Finally, when appropriate, we included GMA and the control variables as Level 2 variables. For the controls, we accounted for the effects of age, gender, race, and socioeconomic status, as these factors have been shown to differentially impact extrinsic success (e.g., Ng et al., 2005).

Results

Table 1 presents descriptive statistics and intercorrelations between the study variables. For this table, the Level 1 variables were averaged across the 28-year time frame. Because there was considerable within-individual variation in each of these variables over time, caution must be taken in interpreting relationships involving aggregated Level 1 variables (i.e., they do not properly represent Level 1 or within-individual relationships).

Effects of GMA on Extrinsic Career Success Growth Trajectories

Hypothesis 1 predicted that GMA would moderate the relationship between time and extrinsic career success, such that income and occupational prestige would have steeper trajec-

ries over time for individuals with high GMA than for those with low GMA. In accordance with the recommendations of Bliese and Ployhart (2002), we implemented a five-step random coefficient modeling approach for assessing between-individual differences in our growth trajectories. The first step involves estimating random intercepts models and calculating intraclass correlation coefficients (ICCs) for each criterion. Previously, we determined that there was ample *within*-individual variance to justify a longitudinal analysis of change in career success. Here, we are interested in determining whether ample *between*-individual (ICC1) variance exists to warrant examination of GMA as a potential predictor of this variance (Raudenbush & Bryk, 2002). The results for this model indicate substantial between-individual variance in both income (ICC1 = .36) and occupational prestige (ICC1 = .45).

Next, Bliese and Ployhart (2002) recommended determining the nature of the growth trajectories by modeling time as a within-individual predictor of each criterion. Here, the goal is to establish whether a linear, quadratic, or other higher order function best captures each trajectory. Results indicated significant linear and quadratic, but not cubic, growth in both income and occupational prestige. For both models, the linear component of growth was positive and significant, income: $t(191, 507) = 54.20, p < .001$; occupational prestige: $t(136, 537) = 46.08, p < .001$, and the quadratic component was negative and significant, income: $t(191, 507) = -18.76, p < .001$; occupational prestige: $t(136, 537) = -25.87, p < .001$, indicating a general pattern of decelerated growth in extrinsic career success over time. That is, individual income and occupational prestige grew more rapidly early rather than later in participants' careers. Although nonlinear growth was not hypothesized, following the guidance of Bliese and Ployhart (2002), we modeled both linear and quadratic time functions in subsequent analyses.

Step 3 involves determining the variability in the intercept and growth parameters. Bliese and Ployhart (2002) recommended contrasting increasingly complex models in which fixed effects were successively freed to vary in order to determine whether significant sources of between-individual variance exist for the intercept and growth parameters. First, using log-likelihood ratio tests, we compared baseline models that treated the intercept and growth

Table 1
Means, Standard Deviations, and Intercorrelations Between Study Variables

Variable	<i>M</i>	<i>SD</i>	1	2	3	4	5	6	7	8	9	10
1. Age (L2)	46.90	2.31	—									
2. Gender (L2)	0.50	0.50	-.01	—								
3. Race (L2)	0.69	0.46	.05	-.01	—							
4. SES (L2)	-0.04	0.92	.10	.03	.27	—						
5. General mental ability (L2)	0.00	3.07	.23	.11	.44	.52	—					
6. Educational attainment (L1)	12.30	2.22	.15	-.06	.08	.44	.60	—				
7. Training (L1)	0.13	0.13	.02	.02	.03	.19	.28	.26	—			
8. Job complexity (L1)	7.05	2.63	.08	-.12	.13	.30	.42	.47	.25	—		
9. Income (L1)	20,999.80	18,289.37	.01	.28	.14	.28	.38	.37	.25	.35	—	
10. Occupational prestige (L1)	45.30	15.97	.09	-.24	.11	.35	.47	.61	.30	.67	.39	—

Note. $N = 11,272$ – $12,686$. L1 = Level 1 (within-individual) variables; L2 = Level 2 (between-individual) variables. The L1 variables reported here were created by averaging scores across the 28-year time frame and thus do not properly reflect L1 relationships. Correlations greater than .03 are significant at the $p < .01$ level (two-tailed). SES = socioeconomic status.

parameters as fixed across all individuals with more complex models that allowed for between-individual variation in the intercepts. For both extrinsic career success criteria, model fit was improved by allowing estimates of the intercept to vary between individuals: income, $\Delta\chi^2(1) = 77,818.69, p < .001$; occupational prestige, $\Delta\chi^2(1) = 61,197.71, p < .001$. That is, results suggest that initial career success varied significantly between individuals in our sample.

Next, models in which the linear (but not quadratic) time components were freed to vary were compared with models that allowed only between-individual variation in the intercepts. Again, the more complex models that allowed for between-individual variation in the linear growth parameters fit the data better than did models that constrained linear growth across individuals: income, $\Delta\chi^2(2) = 81,825.73, p < .001$; occupational prestige, $\Delta\chi^2(2) = 6,907.72, p < .001$. Finally, the quadratic growth parameters were freed to vary between individuals. As with previous comparisons, the more complex models provided better model fit: income, $\Delta\chi^2(3) = 18,352.11, p < .001$; occupational prestige, $\Delta\chi^2(3) = 6,352.49, p < .001$. The results of this step suggest there is significant between-individual variation in both initial extrinsic career success and changes in career success over time and thus substantiate tests of our hypotheses concerning GMA as a between-individual predictor of extrinsic career success trajectories.

Because failure to accurately model within-person error structures can lead to biased standard errors (Bliese & Ployhart, 2002; Raudenbush & Bryk, 2002), we assessed model fit for four competing error structures: (a) homogeneous (within-individual random effects are modeled as independent with homogenous variance); (b) first-order autoregressive (an autocorrelation term is modeled to allow for correlated errors across time); (c) heterogeneous (separate variance terms are estimated for each time point to allow for heteroscedasticity); and (d) unrestricted (a parameter for each unique variance and covariance term in the error structure is modeled). Table 2 presents the results of our model comparison tests. As is evident from the significance of the chi-square difference tests, models with unrestricted error structures provided better overall fit to the data than did any of the more parsimonious models; thus, they were retained in subsequent analyses.

To summarize the previous four steps, as suggested by Bliese and Ployhart (2002), before testing for the effects of between-individual GMA on within-individual extrinsic career success growth trajectories, we ensured that trajectories differed across individuals (Step 1), modeled growth in the trajectories over time (Step 2), confirmed that between-individual differences were present for both initial extrinsic career success (intercept parameters) and growth in career success over time (slope parameters; Step 3), and identified the appropriate technique for modeling the error structures of our longitudinal data (Step 4). In this, the final step, we specified models whereby the outcome variables—income and occupational prestige—were predicted by time (at Level 1), GMA (at Level 2), and the control variables (at Level 2). In addition, we modeled cross-level interactions whereby the slope of the relationship between time and the extrinsic career success criterion was predicted by GMA (see Table 3). To assess early career advantages, we did not center the Level 1 time variables and coded time such that

1979 = 0, 1980 = 1, and so on. Furthermore, we centered the Level 2 (between-individual) variables so that the coefficients for the intercepts of the Level 1 equations represent the expected value of the criterion in 1979 when all between-individual predictors were controlled at their mean values.

The results in Table 3 provide support for H1. GMA was positively related to the slope of time for both income (H1a) and occupational prestige (H1b).² Not only did high-GMA individuals have higher levels of extrinsic career success in 1979 (income, $B_{05} = 121.14, p < .001$; occupational prestige, $B_{05} = 0.59, p < .001$), but their success increased at a quicker rate (income, $B_{11} = 119.61, p < .001$; occupational prestige, $B_{11} = 0.12, p < .001$). Finally, although nonlinear effects were not hypothesized, interactions between the quadratic time trends and GMA were negative and significant (income, $B_{21} = -0.50, p < .001$; occupational prestige, $B_{21} = -.00, p < .001$), indicating that the diminishing returns of time on career success are greater (more negative, or diminishing to a greater degree) for low-GMA individuals than for high-GMA individuals.

Figure 2 depicts the sizes of these effects graphically. As shown in Figure 2a, in terms of income in 1979, all controls held equal; individuals scoring one standard deviation above the mean on GMA made, on average, \$1,574.82 more than individuals scoring one standard deviation below the mean on GMA. By 2006, this difference increased more than twentyfold to \$38,819.43. Likewise, in terms of occupational prestige, Figure 2b shows that a typical individual with a low GMA score could expect to achieve a modest 1-point increase in SEI over the course of the study (e.g., from an apprentice plumber [32] to a plumber [33]), whereas an individual with a high GMA score might expect a 43-point increase (from a vehicle dispatcher [40] to a civil engineer [83]).

Isolating the Between-Individual Effect of GMA on Extrinsic Career Success Growth

In the previous section, we showed that GMA moderates the relationship between time and extrinsic career success. We now attempt to isolate the moderating effects of GMA by showing that moderation occurs across each stage of the indirect pathways through which time influences extrinsic career success. First, we test whether GMA predicts within-individual growth in education, training, and job complexity over time (H2). Then we test whether GMA predicts within-individual relationships between changes in these three mediators and changes in extrinsic career success (H3).

Before assessing H2 concerning GMA as a predictor of human capital growth trajectories, we again followed Bliese and Ploy-

² We assessed the normality of our variables and found that, of them, only pay showed significant deviations from normality (it was positively skewed). However, maximum likelihood estimates are robust to violations of normality when sample sizes are large (Maas & Hox, 2004). Moreover, because our analyses themselves are nonlinear and the distribution of the quadratic of a logged variable is not clear, we decided, for ease of interpretation, not to transform the variable. That being said, we ran supplemental analyses (available from Timothy A. Judge) that showed the pattern of results were unchanged in the case where the natural log of pay was analyzed.

Table 2
Comparison of Different Level 1 Error Structures

Error structure	Income			Occupational prestige		
	Deviance	<i>df</i>	χ^2 , Model-Unrestricted (<i>df</i>)	Deviance	<i>df</i>	χ^2 , Model-Unrestricted (<i>df</i>)
1. Homogeneous	511,383.31	10	213,225.51 (246)**	866,441.99	10	12,220.84 (246)**
2. First-order autoregressive	431,292.86	11	133,135.06 (245)**	860,358.86	11	6,137.71 (245)**
3. Heterogeneous	441,039.03	31	142,881.23 (225)**	863,465.28	31	9,244.13 (225)**
4. Unrestricted	298,157.80	256		854,221.15	256	

Note. Deviance = $-2(\log\text{-likelihood ratio})$ for the model with the given error structure. *df* = degrees of freedom.
** $p < .01$ (two-tailed).

hart's (2002) stepwise recommendations for building the appropriate Level 1 growth models. As evidenced by the intraclass correlation coefficients, all three human capital outcomes contained between-individual variability, though more with education than with training (education, ICC1 = .80; training, ICC1 = .10; job complexity, ICC1 = .32). In addition, as was the case with the extrinsic career success outcomes, for all three human capital trajectories, there was significant positive linear growth and significant negative quadratic growth. In terms of the variability of the Level 1 parameters, chi-square difference tests indicated significant between-individual variation in intercept and growth parameters for all three human capital trajectories. Finally, an examination of error structures revealed that the unrestricted approach to modeling Level 1 error resulted in superior model fit for all three human capital trajectories. Thus, on the basis of the previous steps, we assessed H2 by estimating models with unrestricted Level 1 error structures whereby education, training, and job complexity were predicted by time (at Level 1), GMA (at Level 2), and the control variables (at Level 2). In addition, we modeled cross-level interactions whereby the slope of the relationship between time and the human capital criterion was predicted by GMA (see Table 4).

Supporting H2, Table 4 shows that GMA predicts between-individual differences in human capital at the onset of the study (B_{05}) as well as growth in human capital acquisition trajectories (B_{11}). More intelligent individuals begin with human capital advantages that only grow over time. Results reveal, moreover,

that the GMA advantage accelerates over time in that the diminishing returns of time on human capital is greater (more negative) for low-GMA compared to high-GMA individuals (B_{21}). Figure 3 portrays the strengths of these moderating effects by graphing the average within-individual growth in human capital of individuals one standard deviation above and below the mean on GMA.

As is evident in Figure 3a, as individuals' careers progressed, high-GMA individuals had, on average, continued to seek post-secondary education to a greater degree than did low-GMA individuals. Figure 3b shows that, in terms of training, the discrepancy between average training rates of high- and low-GMA individuals grew from a 2% difference in 1979 to a 38% difference in 2006. Finally, as shown in Figure 3c, the predicted levels of job complexity for low-GMA individuals increased by one point over the 28-year time frame, whereas the average job complexity of high-GMA individuals increased by over four points. On the surface, this may not appear to be that strong of an effect, but small differences in the *DOT* job complexity scale often translate into considerable differences in actual complexity. For example, a two-point difference can mean the difference between a registered nurse (job complexity index = 17) and a brain surgeon (job complexity index = 19) or a typist (job complexity index = 6) and a playwright (job complexity index = 8).

Next, we tested whether GMA influences the extent to which changes in education, training, and job complexity translate into

Table 3
General Mental Ability (GMA) as a Predictor of Growth in Extrinsic Career Success

Parameter	Income			Occupational prestige		
	<i>B</i>	<i>SE</i>	<i>t</i>	<i>B</i>	<i>SE</i>	<i>t</i>
Intercept, B_{00}	4,403.25	103.05	42.73**	35.70	0.16	219.13**
SES, B_{01}	888.08	115.42	7.69**	2.33	0.16	14.45**
Age, B_{02}	1,471.67	38.64	38.08**	0.53	0.05	10.69**
Sex (male = 1, female = 0), B_{03}	4,190.39	159.32	26.30**	-9.29	0.22	-41.73**
Race (White = 1, other = 0), B_{04}	1,826.78	191.80	9.52**	-3.69	0.27	-13.63**
GMA, B_{05}	121.14	17.87	6.78**	0.59	0.03	20.48**
Time (linear), B_{10}	2,136.95	28.56	74.83**	1.62	0.03	50.74**
Time (linear) \times GMA, B_{11}	119.61	4.26	28.11**	0.12	0.00	23.09**
Time (quadratic), B_{20}	-26.35	1.23	-21.46**	-0.04	0.00	-28.98**
Time (quadratic) \times GMA, B_{21}	-0.50	0.19	-2.70**	-0.00	0.00	-18.76**

Note. *B* = unstandardized regression coefficient; *SE* = standard error; SES = socioeconomic status; Time = 0 for the year 1979.
** $p < .01$ (two-tailed).

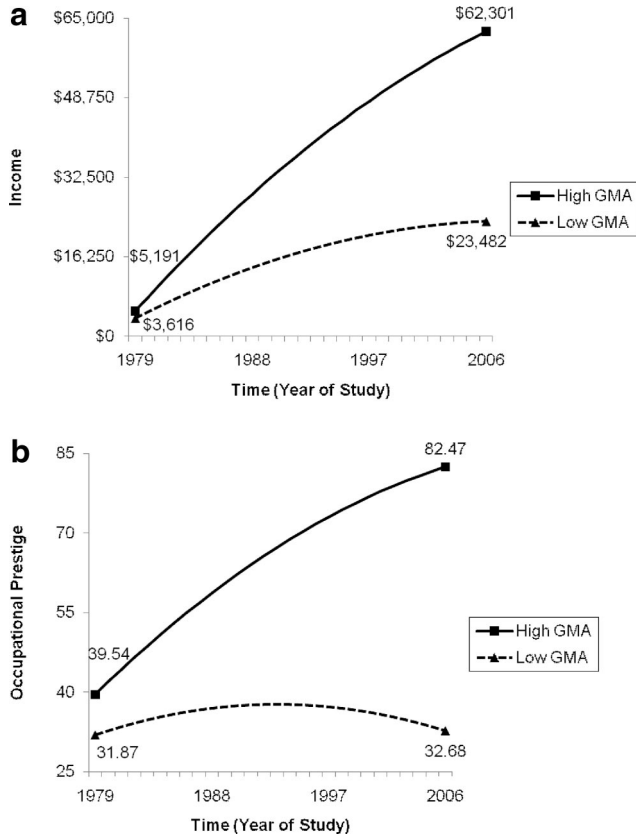


Figure 2. Within-individual changes in (a) income and (b) occupational prestige over time as a function of between-individual differences in general mental ability (GMA).

changes in income (H3a) and occupational prestige (H3b). In Tables 5, 6, and 7, we see that as GMA increases, the relationships between changes in income and changes in education ($B_{11} = 344.64, p < .001$), training ($B_{11} = 422.22, p < .001$), and job complexity ($B_{11} = 89.14, p < .001$) all become stronger and more positive. (Because nonlinearity was not supported with these models, no quadratic term is included.) These results

are shown graphically in Figures 4 and 5. Figure 4a shows that the relationship between educational attainment and income was stronger for high-GMA individuals, Figure 4b shows that the relationship between training and income was similarly more positive (though somewhat less strongly so) for high-GMA individuals, and Figure 4c shows that the job complexity–income relationship was more positive for high-GMA than low-GMA individuals.

Tables 5–7 also display the results concerning occupational prestige. As for income, the positive relationships between changes in education ($B_{11} = 0.17, p < .001$), training ($B_{11} = 0.16, p < .001$), and job complexity ($B_{11} = 0.07, p < .001$) and changes in occupational prestige all strengthen as GMA increases. Furthermore, as the graphical representations in Figures 5a (educational attainment and occupational prestige), 5b (training and occupational prestige), and 5c (job complexity and occupational prestige) illustrate, the relationships between human capital and extrinsic career success were anywhere between one and a half to eight times stronger for high-GMA than for low-GMA individuals.

Human Capital as Mediators of Growth in Extrinsic Career Success Across Levels of GMA

In H4, we hypothesized that the human capital variables would mediate the relationships between time and extrinsic career success, and we further hypothesized that this mediation would be stronger for high-GMA individuals (H5). Therefore, we tested whether growth in extrinsic career success could be explained by the acquisition of human capital and whether the within-individual effects of human capital on growth in career success varied across individuals of differing intelligence.

Although moderated multilevel mediation techniques are still in the infancy stages of development, Bauer, Preacher, and Gil (2006) have explicated a procedure for estimating and assessing mediation (“unconditional” indirect effects) and moderated mediation (“conditional” indirect effects) in multilevel applications (see Preacher, Rucker, & Hayes, 2007, for a review of moderated mediation). Derivation of the statistical technique for analyzing conditional indirect effects is beyond the scope of the study (and was provided by Bauer et al., 2006). However, Bauer et al. (2006) provided a SAS macro (available at www.quantpsy.org) for exam-

Table 4
General Mental Ability (GMA) as a Predictor of Growth in Mediators: Education, Training, and Job Complexity

Parameter	Education			Training			Job complexity		
	B	SE	t	B	SE	t	B	SE	t
Intercept, B_{00}	10.520	0.011	984.72**	0.058	0.002	34.70**	5.529	0.033	166.59**
SES, B_{01}	0.192	0.015	12.56**	0.009	0.001	6.05**	0.269	0.029	9.34**
Age, B_{02}	0.517	0.005	109.91**	0.001	0.000	1.76	0.080	0.009	8.98**
Sex (male = 1, female = 0), B_{03}	-0.396	0.021	-18.62**	-0.005	0.002	-2.34*	-0.918	0.040	-23.09**
Race (White = 1, other = 0), B_{04}	-0.622	0.025	-24.41**	-0.023	0.002	-10.02**	-0.331	0.048	-6.88**
GMA, B_{05}	0.120	0.002	56.42**	0.002	0.000	6.64**	0.102	0.006	17.93**
Time (linear), B_{10}	0.114	0.002	64.60**	0.013	0.000	33.24**	0.234	0.006	39.84**
Time (linear) \times GMA, B_{11}	0.005	0.000	17.19**	0.001	0.000	14.16**	0.010	0.001	11.25**
Time (quadratic), B_{20}	-0.003	0.000	-55.27**	-0.000	0.000	-24.90**	-0.005	0.000	-25.04**
Time (quadratic) \times GMA, B_{21}	-0.000	0.000	-14.85**	-0.000	0.000	-10.48**	-0.000	0.000	-7.46**

Note. B = unstandardized regression coefficient; SE = standard error; SES = socioeconomic status; Time = 1 for the year 1979. * $p < .05$ (two-tailed). ** $p < .01$ (two-tailed).

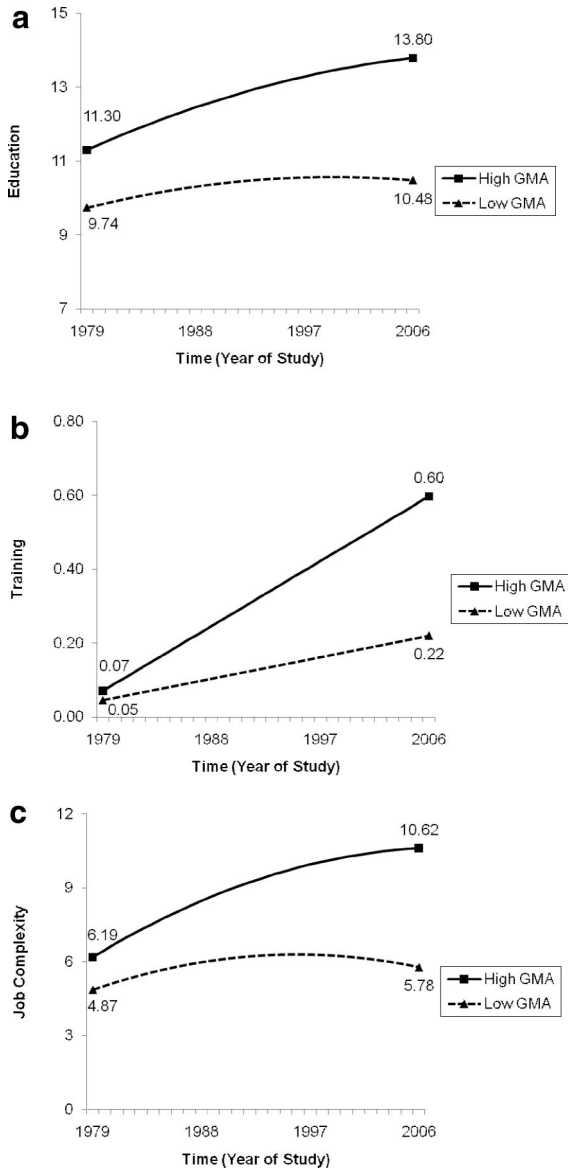


Figure 3. Within-individual changes in (a) educational attainment, (b) training, and (c) job complexity over time as a function of between-individual differences in general mental ability (GMA).

ining the strength and significance of the indirect effects of mediators at different values of a particular moderator.

Table 8 presents the results of our multilevel mediation analyses using the SAS macro provided by Bauer et al. (2006). The unconditional indirect effects provide information pertaining to the degree to which human capital acquisition explains growth in extrinsic career success over time. For both income and occupational prestige, the indirect effects of education and job complexity, but not training, were significant.³ Thus, H4 was partially supported; education and job complexity mediate growth in extrinsic career success.

According to H5, the degree to which human capital acquisition mediates growth in extrinsic career success is dependent on GMA,

such that as GMA increases, the strength of mediation also increases. Bauer et al. (2006) provided a technique and macro for examining the strength and significance of Level 1 mediation at different values of a Level 2 moderator. Table 8 presents the results of our conditional indirect effect analyses, which assessed mediation under high (one standard deviation above the mean) and low (one standard deviation below the mean) conditions. As shown, in support of H5, the indirect effects of the mediators on the relationship between time and extrinsic career success were larger across high- than low-GMA individuals. Thus, as GMA increases, the extent to which human capital acquisition accounts for growth in extrinsic career success increases. However, for training, mediation was not significant even under conditions where GMA was high.

Joint Effects of GMA and CSE

As noted at the end of the introductory section, because recent research using the NLSY79 has shown personality to be an important predictor of extrinsic career success (Judge & Hurst, 2008), it is of interest to consider the relative effects of GMA and personality on extrinsic career success over time. In doing so, we simultaneously entered standardized scores on measures of GMA and core-self evaluations—one's general self-concept—as Level 2 predictors of growth in extrinsic career success. When we used our measure of GMA and Judge and Hurst's (2008) 12-item CSE measure to predict growth in extrinsic success over time,⁴ both variables significantly predicted growth in each outcome variable. The GMA coefficients were $B_{11} = 621.38$, $p < .01$, for income and $B_{11} = 0.18$, $p < .01$, for occupational prestige. The CSE coefficients were $B_{12} = 245.70$, $p < .01$, for income and $B_{12} = 0.03$, $p < .05$, for occupational prestige. When these results are compared to the Judge and Hurst (2008) findings, it is clear that controlling for GMA substantially reduces the effect of CSE on growth in extrinsic success over time, whereas the reverse is less true. However, the effects remain significant and suggest that both GMA and CSE make independent contributions to growth in extrinsic career success over time, though the effects are generally larger for GMA.

³ On an earlier draft of this paper, a reviewer suggested that all GMA interactions should be entered simultaneously into one regression. Although this approach has merit, we view the various interactions as instantiations of the various GMA effects rather than simultaneous events. That is, we do not see the process of cumulative advantage as occurring simultaneously, or conditionally, across the variables. Rather, the attainment of education, on-the-job training, and job complexity likely generally follows a sequence that is not simultaneous (i.e., an individual acquires education, then on-the-job training, and this culminates in job complexity over time). Despite our rationale, we acknowledge that our decision may be arguable, and we should note the following. When all interactions were entered simultaneously, the unique effect sizes for each interaction were smaller (on average, 39.18%) than when the interactions were entered individually. However, in no case did the significance of the GMA interaction change.

⁴ Because the items needed to constitute the 12-item CSE measure used by Judge and Hurst (2008), and reanalyzed here, were not all collected in a single year, items in their 12-item measure were obtained from different time periods (2 from 1979, 5 from 1980, 2 from 1987, and three from 1992).

Table 5
Relationship of General Mental Ability (GMA), Education, and Their Interaction in Predicting Extrinsic Career Success

Parameter	Income			Occupational prestige		
	<i>B</i>	<i>SE</i>	<i>t</i>	<i>B</i>	<i>SE</i>	<i>t</i>
Intercept, B_{00}	21,732.86	151.09	143.84**	45.86	0.12	377.46**
SES, B_{01}	2,344.80	179.29	13.08**	2.89	0.18	16.17**
Age, B_{02}	-296.95	60.09	-4.94**	-0.08	0.05	-1.45
Sex (male = 1, female = 0), B_{03}	6,273.56	255.94	24.51**	-9.66	0.24	-41.00**
Race (White = 1, other = 0), B_{04}	-604.75	295.43	-2.05*	-4.77	0.29	-16.68**
GMA, B_{05}	959.14	30.10	31.86**	1.21	0.02	51.04**
Education, B_{10}	6,782.82	100.32	67.61**	4.37	0.08	54.36**
Education \times GMA, B_{11}	344.64	16.11	21.39**	0.17	0.01	13.08**

Note. *B* = unstandardized regression coefficient; *SE* = standard error; SES = socioeconomic status; Time = 0 for the year 1979.
 * $p < .05$ (two-tailed). ** $p < .01$ (two-tailed).

Discussion

A vast literature has developed both supporting the importance of GMA in employment settings and explicating why it figures so prominently in individual and organizational success (Viswesvaran & Ones, 2002), but, as Gottfredson (1997) noted in her comprehensive review, there remain many unanswered questions as to how and why high-GMA individuals realize many advantages in their work and in their lives. We have argued that one area in need of attention is understanding the effects of GMA on within-individual career success trajectories. One of the limitations in past research—even past longitudinal research—is confounding intercepts and slopes. Whereas there clearly are between-individual differences in career success that can be traced to individual differences, such as GMA, such designs ignore half of the picture—namely, that whereas people differ in their career success, careers unfold over time, and that unfolding varies by person.

Although one might conclude that this limitation is a methodological nuance of little theoretical import, it is more than that. Career success is a complicated phenomenon, not only in its composition or indicators but in its progression. It is inherently longitudinal, with different beginnings and endings—and thus different trajectories. Those trajectories themselves will vary across individuals. Some individuals have early success and never quite capitalize on these precocious beginnings. Other individuals have an unremarkable start to their careers but have a steep

trajectory. Our results inform the career success literature by their temporal focus and, more important, by showing that GMA plays an important role in establishing the shape and form of extrinsic career success. High-GMA individuals realize advantage both in their intercepts (where they begin their careers) and in their slopes (their careers advance more rapidly over time).

Turning an early advantage into even greater reward—as high-GMA individuals apparently do—is in the spirit of Merton's (1968) Matthew effect. In keeping with Merton's original formulation, there are particularistic reasons why this might occur. Intelligent individuals may be given more challenging assignments or may better fit leadership prototypes. Though our results do nothing to rule out these explanations, they do point to the importance of more universalistic reasons. As noted by Stanovich (1986) and confirmed in numerous subsequent studies (see Ceci & Papierno, 2005, for a review), many aspects of learning follow a Matthew effect in that early learning advantages (and disadvantages) become magnified over time. The results of our study similarly point to the importance of learning—as reflected in education, training, and job complexity—as an explanation for the “fan spread” (Ceci & Papierno, 2005, p. 153) of career success based on GMA. In particular, if learning new material inherently builds on previously learned material, the application of knowledge and skills to one's job and career may well also have a hastening effect. Indeed, an ascendant career likely requires the development

Table 6
Relationship of General Mental Ability (GMA), Training, and Their Interaction in Predicting Extrinsic Career Success

Parameter	Income			Occupational prestige		
	<i>B</i>	<i>SE</i>	<i>t</i>	<i>B</i>	<i>SE</i>	<i>t</i>
Intercept, B_{00}	21,681.20	149.74	144.79**	45.90	0.12	377.70**
SES, B_{01}	2,758.18	209.15	13.19**	2.93	0.18	16.25**
Age, B_{02}	-406.59	66.37	-6.13**	-0.17	0.05	-3.16**
Sex (male = 1, female = 0), B_{03}	9,063.52	292.11	31.03**	-9.69	0.24	-40.65**
Race (White = 1, other = 0), B_{04}	-1,003.20	317.62	-3.16**	-4.54	0.29	-15.76**
GMA, B_{05}	920.58	30.01	30.68**	1.21	0.02	50.89**
Training, B_{10}	3,470.22	191.02	18.17**	3.06	0.17	17.78**
Training \times GMA, B_{11}	422.22	38.49	10.97**	0.16	0.03	5.55**

Note. *B* = unstandardized regression coefficient; *SE* = standard error; SES = socioeconomic status; Time = 0 for the year 1979.
 ** $p < .01$ (two-tailed).

Table 7
Relationship of General Mental Ability (GMA), Job Complexity, and Their Interaction in Predicting Extrinsic Career Success

Parameter	Income			Occupational prestige		
	<i>B</i>	<i>SE</i>	<i>t</i>	<i>B</i>	<i>SE</i>	<i>t</i>
Intercept, B_{00}	25,826.70	154.23	167.46**	45.77	0.12	375.90**
SES, B_{01}	2,329.42	208.09	11.19**	2.57	0.17	14.82**
Age, B_{02}	197.65	64.39	3.07**	0.01	0.05	0.23
Sex (male = 1, female = 0), B_{03}	9,425.88	280.44	33.61**	-8.51	0.23	-36.78**
Race (White = 1, other = 0), B_{04}	-2,247.56	328.93	-6.83**	-4.73	0.28	-16.96**
GMA, B_{05}	1,095.99	32.37	33.86**	1.21	0.02	51.91**
Job complexity, B_{10}	946.89	25.74	36.78**	2.47	0.02	123.21**
Job complexity \times GMA, B_{11}	89.14	4.69	19.02**	0.07	0.00	24.74**

Note. *B* = unstandardized regression coefficient; *SE* = standard error; SES = socioeconomic status; Time = 0 for the year 1979.

** $p < .01$ (two-tailed).

and application of an increasingly complex set of skills, such that, over time, the role of automated or noncognitive skills (Schmidt & Hunter, 2004) becomes lower as attainment increases.

In inspecting the tables, one might be tempted to conclude that the between-individual GMA results swamp the GMA within-individual results. Such a conclusion, however, might be misleading or erroneous. Unless there is restriction of range to consider, between-individual differences and within-individual changes act relatively independently of one another: One can observe within-individual effects when the intercepts are quite different. Indeed, an inspection of the figures reveals the scope of possibility. For income, differential growth by GMA occurs even though the intercepts (individual differences in income at the onset of the study) do not strongly differ for the high- and low-GMA groups. For occupational prestige, conversely, there are both strong intercept differences by GMA and significant within-individual effects by GMA (occupational prestige increases more steeply for high-GMA than for low-GMA individuals). Thus, the results show that GMA is important both to between-individual differences in career success and to changes in career success over time and as a function of the human capital mediators.

Statistical and Practical Significance

Though discussed briefly in the Results section, the practical significance of the effects found in our study deserves further mention. Because outcomes of hypothesis testing are strongly influenced by sample size, large samples, like the one used in this study, can cause results to be statistically significant when they are of little practical value (Krueger, 2001). Inspection of the study tables and figures reveals, however, that our statistically significant findings are not driven solely by high statistical power (though the use of a large sample does suggest that results are robust; Hollenbeck, DeRue, & Mannor, 2006; Hunter & Schmidt, 2004). The effect sizes are nontrivial and translate into important differences for high- and low-GMA individuals. For instance, in 1979, compared with low-GMA individuals, high-GMA individuals earned 43% more income, obtained 16% more education, were 58% more likely to have received formal training, and secured jobs that were 27% more complex and 24% more prestigious. These percentages grew to 165%, 32%, 171%, 84%, and 152%, respectively, by 2006. Additionally, in

translating the effects of human capital on extrinsic career success, even low levels of education, training, and job complexity resulted in considerably higher percentages of income (34%, 65%, and 55%, respectively) and occupational prestige (34%, 40%, and 40%, respectively) among high-GMA individuals than low-GMA individuals. These differences in return on human capital were exacerbated for higher levels of education, training, and job complexity (discrepancies were 88%, 87%, and 94%, respectively, for income and 46%, 42%, and 43%, respectively, for occupational prestige).

In framing the discussion of these percentages using a more tangible metric, it is perhaps easiest to consider the links between GMA and income. Individuals with high GMA were able to increase their salary by \$57,110 over 28 years, whereas individuals with low GMA enjoyed an increase of only \$19,867 over the same time period. Over the course of a 28-year career, the average high-GMA individual outgained the average low-GMA individual by over \$580,000. When formal schooling is considered, highly educated, high-GMA individuals earn \$23,455 more per year on average than do similarly educated, low-GMA individuals. Taken together, the above-mentioned interpretations confirm that findings are indeed significant from both practical and statistical perspectives.

Limitations and Future Research

The most obvious limitation of this study is that we examined only a few of the many possible mediating mechanisms underlying the GMA relationships. Although education, training, and job complexity appear to explain, to a significant degree, both between-individual and multilevel effects for the GMA-extrinsic career success relationship, they certainly do not exhaust the list of mediators that should be studied. In fact, a supplementary analysis of the proportion of growth in extrinsic career success mediated by the set of three human capital variables across levels of GMA reveals that 63% of growth in occupational prestige and 83% of growth in income is not accounted for by our three human capital variables. This is the first study to link GMA to time-based conceptions of career success; future research should build on these results by linking other universalistic variables (e.g., task performance, job knowledge) and particularistic variables (e.g., differential receipt of challenging assignments, perceptual mea-

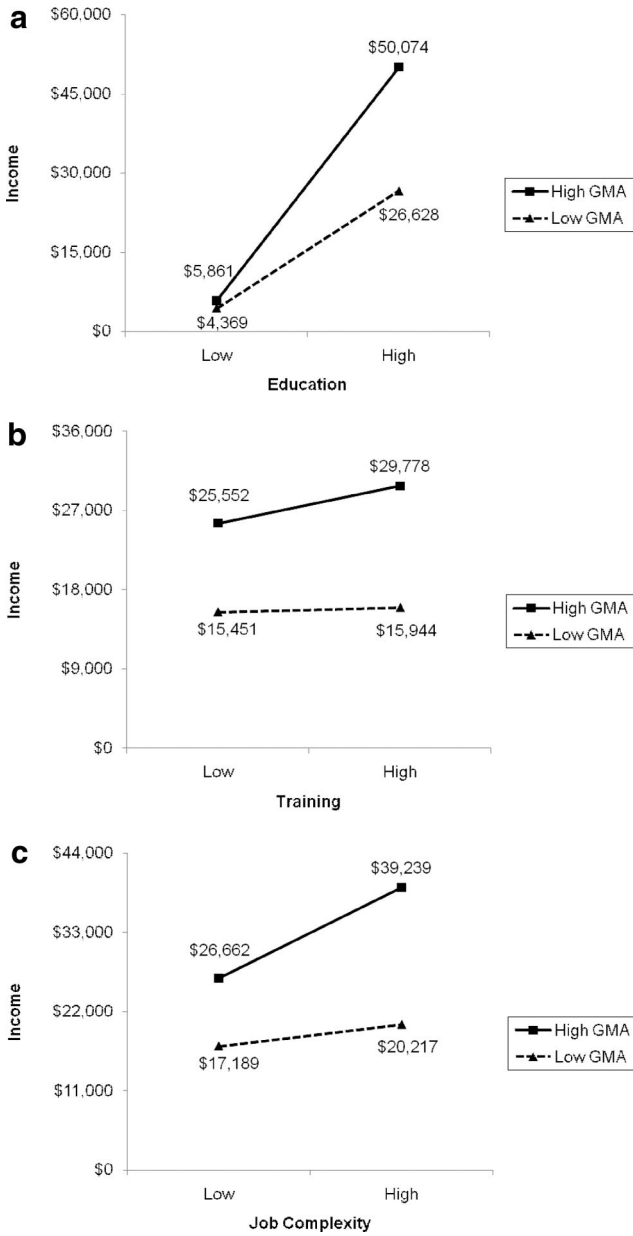


Figure 4. The within-individual (a) educational attainment–income relationship, (b) training–income relationship, and (c) job complexity–income relationship as a function of between-individual differences in general mental ability (GMA).

asures of intelligence, leadership perceptions) to the relationships between time and extrinsic career success.

Furthermore, the results for one human capital variable—training—were mixed. High-GMA individuals received more formal training early in their careers, and these early training discrepancies increased over time. In addition, high-GMA individuals were more successful at reaping income and status benefits from training. However, training was not a statistically significant mediator of growth in extrinsic career success. Part of this may be due to limitations in the operationalization of the training construct.

Due to the nature of the data, there was no way to distinguish between optional training programs designed to increase employee job skills and responsibilities and, for instance, more formalized training programs designed to socialize employees into a new organization.

Another limitation of the study is in the criteria. Though income and occupational prestige are reasonable indicators of extrinsic

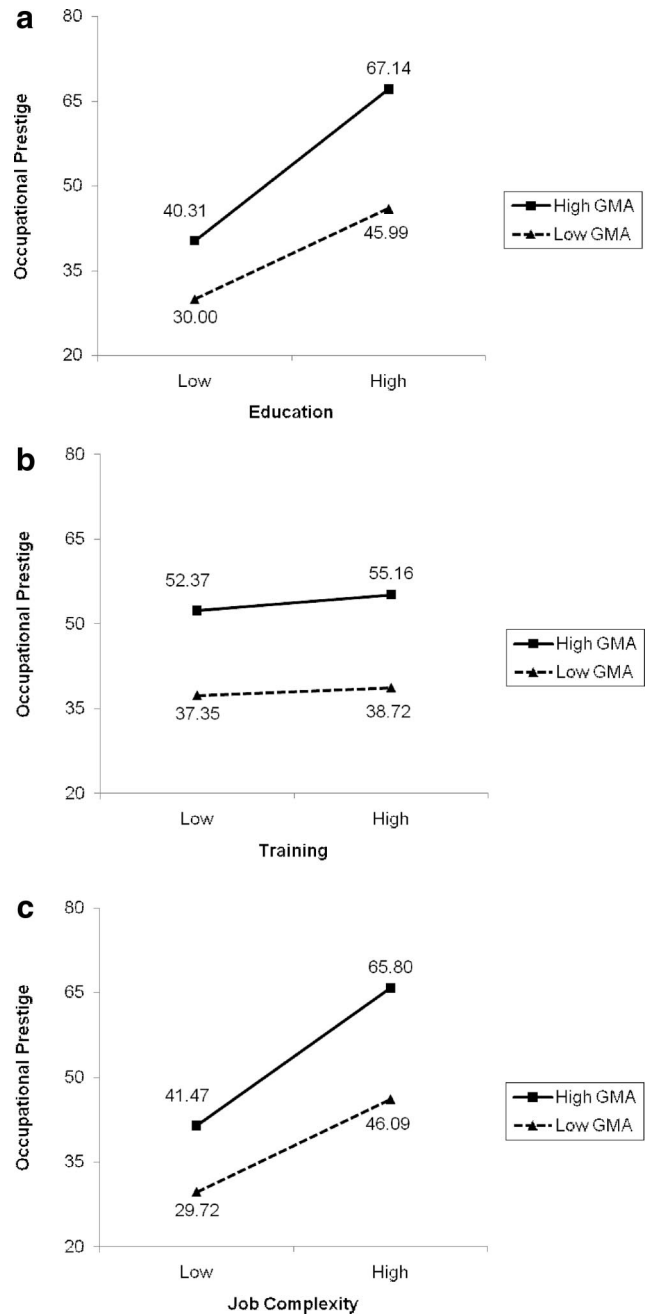


Figure 5. The within-individual (a) educational attainment–occupational prestige relationship, (b) training–occupational prestige relationship, and (c) job complexity–occupational prestige relationship as a function of between-individual differences in general mental ability (GMA).

Table 8
 Mediation Results for Education, Training, and Job Complexity Across Levels of General Mental Ability (GMA)

Criterion	Income			Occupational prestige		
	Indirect effect	SE	z	Indirect effect	SE	z
Education						
Unconditional	12.11	1.55	7.82**	0.05	0.00	19.06**
Conditional (high GMA)	27.86	2.87	9.72**	0.08	0.00	17.76**
Conditional (low GMA)	1.50	1.55	0.97	0.02	0.00	8.23**
Training						
Unconditional	0.55	2.62	0.20	0.00	0.00	1.21
Conditional (high GMA)	3.62	5.91	0.61	0.01	0.01	1.21
Conditional (low GMA)	-0.77	2.71	-0.29	0.00	0.00	0.42
Job complexity						
Unconditional	10.98	0.39	28.43**	0.32	0.00	71.77**
Conditional (high GMA)	22.15	0.87	25.35**	0.21	0.01	28.53**
Conditional (low GMA)	3.34	0.30	11.26**	0.13	0.01	24.50**

Note. ** $p < .01$ (two-tailed).

career success (Judge et al., 1995), there are other indicators—such as promotion opportunities, job level, and life satisfaction—that were not included in this study due to the limits of relying on an archival database.⁵ Moreover, there are other life criteria to which this multilevel model can and should be applied. A recent research stream has focused on the GMA–health relationship, finding that intelligent people live longer because they are more physically fit, are less likely to be obese, smoke and drink less, and have better nutrition (see Gottfredson & Deary, 2004). Though this research clearly indicates that intelligent individuals enjoy better health and has suggested some mechanisms by which this is the case, we are not aware of any multilevel investigations that might disentangle the intercept and slope confounds that we noted earlier.

Finally, it is interesting to note that, for low-GMA individuals, job complexity and occupational prestige tend to peak early and then markedly decline (though the linear trend remains positive throughout the time frame). Alternatively, for high-GMA individuals, job complexity and occupational prestige continue to grow throughout the study period, albeit at a decelerating pace in later years. One explanation for this pattern is that the range of opportunities afforded to high-GMA individuals (Gottfredson, 1997) slows possible career plateau and decline. A second, perhaps complementary, explanation is based on the premise that reactions to career plateau differ. Feldman and Weitz (1988) argue that, although career plateau originating from certain causes (e.g., need for job security) can elicit positive reactions, responses to plateau resulting from lack of employee skill or ability are especially negative (e.g., poor performance and negative job attitudes). Ineffective coping with career plateau likely leads to negative distal outcomes, such as burnout and involuntary turnover, that can channel individuals into less complex and prestigious jobs. High-GMA individuals, however, may be less prone to the negative consequences of career plateau, provided that their mechanisms for coping with it are more constructive than those of low-GMA individuals. Given the growing prevalence of career plateau as organizational hierarchies flatten (Chao, 1990), future research should consider the role of intelligence and other individual differences in coping with its occurrence.

Implications

One rather disconcerting aspect of our results is the degree to which GMA may contribute to growing economic inequality. Income dispersion has increased dramatically in the U.S. economy and, to a lesser degree, in other national economies (Gordon & Dew-Becker, 2007). As work continues to become increasingly complex (Gottfredson, 1997) and as technological changes continue to require new skill acquisition and adaptability, which in turn fuel productivity growth (Autor, Katz, & Kearney, 2008), the degree to which GMA spurs economic success may well continue to accelerate. If society is increasingly “winner take all” (Frank & Cook, 1995), then, even more than today, the future may belong to those with high GMA. What are the implications for employers and for individuals?

For employers, our results suggest that as trends toward the increasing complexity of work continue (Gottfredson, 1997), the economic benefit of employers hiring based on GMA should accelerate. Task complexity has a strong bearing on the economic value of a job to an organization (Hunter, Schmidt, & Judiesch, 1990), and, as noted earlier, validities of GMA in predicting performance increase rather markedly with increasing job complexity (Gottfredson, 2002). As time marches on, if the trends found in this and other studies continue, the economic value of high GMA should continue to increase. Moreover, given the increasing complexity of work and the GMA “fan spread” found in this study, past estimates of the economic value of hiring based on GMA test scores may well underestimate the future economic value realized by utilizing such tests.

If our results suggest support for the economic benefit of using GMA in selection decisions, the implications for individuals, and for institutions designed to help individuals, are less clear. If the

⁵ The NLSY79 archived promotion and career satisfaction data at irregular intervals over the course of the longitudinal time frame. We did perform supplementary analyses on both promotions and career satisfaction, for the years in which such a measure could be composed. The results suggested support for the hypotheses, albeit at a somewhat weaker level.

career benefits disproportionately accrue over time to those with high GMA, then those on the other side of the bell curve are disproportionately punished. Paradoxically, interventions ostensibly designed to help the disadvantaged often do just the opposite. For example, initiatives to reduce kindergarten to 12th-grade class size appear to disproportionately benefit high-achievement students (Konstantopoulos, 2008). Our results suggest a similar pattern. Ostensibly, training is targeted toward skill deficits. Our results, however, suggest that high-GMA individuals benefit disproportionately from training (and general education). As Ceci and Papierno (2005) argued, these apparent antinomies do not mean abandonment of interventions but, rather, a design of interventions with the possible paradoxes in mind.

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