HOW BROADLY DOES EDUCATION CONTRIBUTE TO JOB PERFORMANCE?

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This study looks at the effects of education level on job performance in 2 ways. First, it provides a meta-analysis on the relationships between education level and 9 dimensions of job behaviors representing task, citizenship, and counterproductive performance. Results here show that, in addition to positively influencing core task performance, education level is also positively related to creativity and citizenship behaviors and negatively related to on-the-job substance use and absenteeism. Second, we investigate the moderating effects of sample and research design characteristics on the relationships between education and job performance. Significant results were found for gender, race, job level, and job complexity. The article concludes with implications for future research and the management of an increasingly educated workforce.

According to U. S. National Center for Education Statistics, the proportion of Americans attaining more education continues to increase. For example, the percentage of individuals completing high school increased from 69% in 1980 to 86% in 2006; the percentage of individuals (aged 25 and older) who have completed college increased from 17% in 1980 to 28% in 2006. In both the labor economics and organizational sciences literatures, there is substantial evidence that individuals’ educational attainments are associated with positive career outcomes, including salary level, number of promotions, development opportunities, and job mobility (Cappelli, 2000; Howard, 1986; Lazear, 1981; Ng, Eby, Sorensen, & Feldman, 2005).

Because most organizations use education as an indicator of a person’s skill levels or productivity (Benson, Finegold, & Mohrman, 2004), they frequently employ it as a prerequisite in hiring decisions. However, over the past 2 decades, there has been very little research directly examining the relationship between educational level and job performance. This is particularly surprising given that it was during this time period...
when educational opportunities increased substantially (Trusty & Niles, 2004), when many organizations raised their educational qualifications for jobs (Kroch & Sjoblom, 1994), and when the conceptualization of job performance expanded considerably to include more extrarole behaviors (Welbourne, Johnson, & Erez, 1998). In this study, we provide a quantitative analysis of the relationship between education level and a wide range of inrole and extrarole performance dimensions.

For organizations, this study has relevance for at least three reasons. First, if highly educated workers contribute only marginally more to organizational effectiveness than less educated workers do, then the higher costs of staffing with highly educated workers are unlikely to be recouped. For example, many organizations subsidize current employees to acquire bachelor’s or advanced degrees (Benson et al., 2004) but do not rigorously assess the short-term returns (e.g., improved performance) or long-term returns (e.g., heightened occupational commitment) on those investments.

Second, past research in this area has focused primarily on the effects of educational level on core task performance (Karatepe, Uludag, Menevis, Hadzimehmedagic, & Baddar, 2006; Kaufman, 1978; Maglen, 1990). However, as noted above, there are numerous other job-related behaviors that legitimately fall under the umbrella of job performance, too (Borman & Motowidlo, 1997; Hunt, 1996; Rotundo & Sackett, 2002). Thus, it is important to examine the impact of educational level on multiple dimensions of performance.

Third, the extent to which education affects productivity can affect corporate support for governmental subsidies for education. Individuals’ educational attainments are not only part of a company’s human capital but also a part of a community’s core assets (Lepak & Snell, 1999). In many localities, generous subsidies for education are largely based on the assumption that governmental investments in human capital will strengthen the economy as a whole by enhancing employees’ productivity (Lanzi, 2007; Trusty & Niles, 2004). When education does not build human capital proportionate to expenditures, though, organizations may oppose tax increases for education, move to localities with better educational systems, or develop their own internal education programs to supplant publicly financed ones (Vinod & Kaushik, 2007).

In the next section of the article, we first discuss the constructs of “education level” and “job performance.” Then, we discuss the theoretical reasons for expecting specific relationships between education level and various job performance dimensions and for expecting moderator effects in those relationships. In the following section, we present the results of a meta-analysis examining these relationships. Finally, in the concluding section, we discuss the implications of our findings for future research and the management of an increasingly educated workforce.
Definitions of Key Constructs

Education Level

Education level refers to the academic credentials or degrees an individual has obtained. Although education level is a continuous variable, it is frequently measured categorically in research studies. Here, we use the term “educated employees” to refer to those individuals who hold at least bachelor’s degrees because these degrees are necessary for entry into many higher-paying occupations (Howard, 1986; Trusty & Niles, 2004).

For practical reasons, we are not investigating differences among school majors. Because few organizational studies have considered differences in majors, we are constrained in that regard in the current meta-analysis. In any event, individuals with specialized skills (such as accounting) will gravitate to specific kinds of firms (such as major accounting firms). As a result, it is difficult to assess differences between accountants and nonaccountants in the same firm in any meaningful way. For much the same reasons, we are not examining the effects of obtaining vocational education here. There is little previous research, for example, on the impact of vocational education on citizenship behaviors. Moreover, it is difficult to compare college graduates to those who received vocational training because they do not have similar access to, or similar rates of participation in, each other’s labor markets.

Job Performance

The conceptualization of job performance has been expanded in recent years to include core task behaviors, citizenship behaviors, and counterproductive behaviors. Core task performance refers to the basic required duties of a particular job. Citizenship performance refers to those extra behaviors engaged in by employees, over and above their core task requirements, which actively promote and strengthen the organization’s effectiveness (e.g., helping coworkers; Hunt, 1996; Organ, 1988). Counterproductive performance refers to voluntary behaviors that harm the well-being of the organization (e.g., theft; Bennett & Robinson, 2000).

Rotundo and Sackett (2002) compared the relative importance of these three groups of performance behaviors in managerial ratings of subordinates’ overall job performance. They found that each of these three categories of performance behaviors contributed to overall performance rating, with core task performance given the highest weight, followed by counterproductive performance and citizenship performance. Consistent with these findings, then, this study also focuses on three categories of performance behaviors, too.
Human Capital Theory

Human capital theory suggests that the abilities and knowledge acquired by individuals are likely to be rewarded with higher earnings in the labor market (Becker, 1964). Education and work experience are the two forms of human capital individuals are most likely to acquire during their careers (Myers, Griffeth, Daugherty, & Lusch, 2004; Singer & Bruhns, 1991; Strober, 1990). It should be noted, though, that in numerous cases educational level and amount of work experience are likely to be negatively correlated. Those who spend more years in school will have less time available in which to accumulate work experience, whereas those who enter the labor market early typically accumulate less formal education.

There has been mounting research evidence indicating the career benefits of human capital investments. For instance, in one of the earliest studies of the effect of education on salary, Mincer (1974) found that an additional year of schooling yielded a net increase of 11.5% in annual earnings. A meta-analysis conducted by Quiñones, Ford, and Teachout (1995) showed that work experience was positively related to job performance at .27. Further, the positive effects of human capital investments (e.g., in schooling) in early career on subsequent earnings are large (Sweetland, 1996). Thus, human capital theory is particularly useful for explaining income dispersion across social and occupational groups, for identifying the rate of return on educational expenditures, and for explaining national differences in economic growth (Becker, 1964; Denison, 1962; Sweetland, 1996).

Previous research suggests that human capital can affect earning potential in two ways. First, human capital is a short-hand signal to organizations of individuals’ abilities and accumulated knowledge and, therefore, grants individuals with more human capital greater access to higher paying professional jobs (Sicherman & Galor, 1990; Strober, 1990). Second, human capital is often a short-hand signal to organizations about personal attributes frequently desired by organizations, such as diligence and self-motivation (Ceci, 1991; Swenson-Lepper, 2005). Organizations are often willing to pay higher wages to individuals possessing these attributes, too.

Ability and Knowledge

Ability has generally been discussed in terms of an individual’s power, strength, or capacity to perform a task (Hunter, 1986; Ree, Earles, & Teachout, 1994). General mental ability has been the focus of much of
this research, and the results suggest that individuals with higher levels of education have both greater fluid and crystallized intelligence (Ceci, 1991; Neisser et al., 1996). Fluid intelligence refers to the capacity of working memory, abstract reasoning, attention, and processing complex information, whereas crystallized intelligence refers to general knowledge, extent of vocabulary, and verbal comprehension related to vocational and a-vocational topics and areas. Fluid intelligence tends to decay more quickly as individuals age (Kanfer & Ackerman, 2004).

By and large, intelligence and education level are positively and significantly correlated. Individuals who have high fluid intelligence are more likely to get into college and stay in school, whereas those with less fluid intelligence are more likely to be weeded out along the way (Kaufman, 1990; Trusty & Niles, 2004). At the same time, education stimulates the development of students’ minds and promotes the growth of crystallized intelligence. For example, researchers have found that those who attended college scored higher on IQ tests than did those who did not attend colleges (Howard, 1986; Kuncel, Hezlett, & Ones, 2004). Individuals with more education are also likely to have greater indepth, analytical knowledge (crystallized intelligence) as well (Ceci, 1991).

Knowledge typically refers to the understanding of information related to job duties (McCloy, Campbell, & Cudeck, 1994). Researchers usually differentiate between two forms of knowledge, namely, declarative and procedural knowledge (Campbell, 1990). Declarative knowledge refers to expertise regarding facts, rules, and principles, whereas procedural knowledge refers to the application of declarative knowledge in practice (Ree, Earles, & Teachout, 1994).

Education also promotes core task performance by providing individuals with more declarative and procedural knowledge with which they can complete their tasks successfully. For example, more education in accounting helps students acquire the expertise needed to become CPAs and advance in the accounting profession. The underlying premise is that, by equipping students with greater declarative and procedural knowledge, schools help students develop deeper competence in their chosen vocations and help them move up organizational and occupational career ladders more quickly.

Taking these findings together, then, we expect that education will be positively related to core task performance. In two major studies, Hunter and his colleagues (Hunter & Hunter, 1984; Schmidt & Hunter, 1998) found that cognitive ability was strongly related to job performance (.51) and was an important contributor to success on virtually every job. Further, Hunter (1986) suggests that cognitive ability facilitates the learning of job-relevant knowledge and thereby indirectly promotes stronger job performance as well.
Hypothesis 1: Education level is positively related to core task performance.

Work Values

Values are intrinsic, enduring perspectives on what is fundamentally right or wrong (Judge & Bretz, 1992; Ravlin & Meglino, 1987; 1989). In high school and college, rarely is the focus of education only on enhancing cognitive ability and job knowledge. Instead, through classroom instruction and extracurricular activities, students are trained to follow rules, respect discipline and tradition, maintain high moral standards, and exercise mature judgment after graduation (Bear, Manning, & Izard, 2003; Ford, Olmi, Edwards, & Tingstorm, 2001; Rest, 1986; Swenson-Lepper, 2005). Furthermore, education also promotes self-confidence, self-motivation, carefulness, and the desire and ability to set personal goals for the future (Di Vesta & Thompson, 1970; Howard, 1986; UNDP, 1995).

Thus, another reason why education is likely to increase individuals’ earning potential is that it imparts work values frequently necessary for job success. Although ability and knowledge are likely to contribute most directly to core task performance, work values such as responsibility, concern for others, social relationships, and honesty are likely to promote stronger citizenship performance. For instance, Johnson and Elder (2002) found in a longitudinal study that, compared with high school graduates, those who have college degrees tend to attach greater importance to altruistic rewards (e.g., helping others) and social rewards (e.g., developing good relationships with others). Rose (2005) and Lindsay and William (1984) found similar results in cross-sectional studies.

Furthermore, researchers have found that years of education were positively related to Conscientiousness, even when controlling for other sociodemographic variables (Dudley, Orvis, Lebiecki, & Cortina, 2006; Goldberg, Sweeney, Merenda, & Hughes, 1998). In addition, Brenner (1982) compared individuals with different levels of education—8 years or less, 9–11 years, 12 years, 1–3 years of college, 4 years of college, some graduate work, master degree, and PhD—in terms of their achievement motivation. This study suggests that, as level of education increased, achievement orientation increased as well.

Conversely, values acquired through education (such as responsibility and moral integrity) should be negatively related to counterproductive performance. For example, college-educated individuals tend to display a greater adherence to rules regarding attendance and protection of organizational property (Konovsky & Organ, 1996). Workers with more years of education are also less likely to impose danger on coworkers or customers by ignoring safety instructions (Oh & Shin, 2003; Taylor & Thompson,
Thus, many organizations use educational attainment as a selection criterion not only because education level reflects higher levels of values associated with good citizenship behaviors but also because education level reflects lower levels of values associated with counterproductive behaviors (Berry, Gruy, & Sackett, 2006).

**Hypothesis 2:** Education level is positively related to citizenship performance.

**Hypothesis 3:** Education level is negatively related to counterproductive performance.

**Moderating Effects of Work Experience**

In this study, we adopted job and organizational tenure as measures of work experience because they are the most frequently used time-based operationalizations of this construct (Quiñones et al., 1995). By virtue of participating longer in the labor market, individuals develop greater knowledge about how to perform their jobs more effectively and more quickly (Tesluk & Jacobs, 1998). Consequently, individuals with greater work experience are likely to be compensated more generously by their employers and be given even more developmental opportunities in the future (Ng et al., 2005).

We suggest that work experience may strengthen the relationship between educational level and job performance. Work experience is likely to provide tacit, practical knowledge less frequently provided by formal education. When coupled with the in-depth, analytical knowledge provided by formal education, work experience may enhance job performance even further. In addition, the knowledge and skills necessary for effective job performance are likely to be strengthened and sharpened over years of service and learning by trial and error (Schmidt, Hunter, & Outerbridge, 1986). Therefore, we predict that:

**Hypothesis 4:** The relationships between educational level and the dimensions of job performance are moderated by both job tenure (Hypothesis 4a) and organizational tenure (Hypothesis 4b). The relationships will be stronger for individuals with higher job and organizational tenure.

**Moderating Effects of Job Level and Job Complexity**

Managerial jobs differ from other employees’ jobs in that they are usually less structured and more ambiguous in nature (Staw & Barsade, 1993). In these “weak” situations, managers’ abilities, knowledge, and work values become even stronger determinants of job performance (Pavett &
Lau, 1983). Thus, although education facilitates performance in most jobs (Hunter, 1986; Kuncel et al., 2004), its effects are likely to be more pronounced in the case of managers. For example, it is particularly critical for managers to be persistent in their efforts and to seek out more responsibility (Rose, 2005). Greater cognitive ability may be especially important on abstract managerial tasks like developing market strategy, whereas greater emotional intelligence may be especially important in managerial tasks like leading change. Although counterproductive behavior, by definition, hurts organizational effectiveness, its effects are far more widespread when initiated by managers. Consequently, we predict that the relationship between educational level and job performance will be stronger for managerial jobs than for nonmanagerial jobs.

Hypothesis 5a: The relationships between educational level and the dimensions of job performance are moderated by job level. The relationships will be stronger for managerial jobs than for nonmanagerial jobs.

Based on similar reasoning, we expect that the relationships between education and job performance will be stronger for individuals in high-complexity jobs. Avolio and Waldman (1990) define job complexity as the level of general intelligence, verbal ability, and numerical ability required to perform a job. Jobs of high complexity (e.g., doctors, engineers, lawyers, scientists) not only demand greater intellectual capacity and job knowledge, but also require incumbents to have strong motivation and persistence in order to excel (Klehe & Anderson, 2007). In contrast, jobs of low complexity (e.g., file clerks) are unlikely to put the same demands on individuals’ abilities, knowledge, and effort levels. As a result, the positive outcomes of education (e.g., greater cognitive ability, greater job knowledge, and greater achievement motivation) are likely to accelerate performance on jobs with high complexity even further.

Hypothesis 5b: The relationships between educational level and the dimensions of job performance are moderated by job complexity. The relationships will be stronger for high complexity jobs than for low-complexity jobs.

Moderating Effects of Gender and Race

Scholars often argue that the workplace experiences of women and racial minorities differ markedly from those of white males and that these differences result in poorer workplace outcomes for them (Lyness & Thompson, 1997, 2000; Stroh, Brett, & Reilly, 1992). There is some evidence that women and minorities may have more difficulty entering
higher-paying occupations, suffer some unequal treatment after being hired, and may be less likely to get promoted or promoted quickly (Lyness & Thompson, 1997; Powell, Butterfield, & Parent, 2002; Ragins, 1997). As a result, the career payoffs of educational investments may be weaker for women and racial minorities than for other employees.

For example, women may receive less sponsorship from their mentors and consequently have less access to high-paying positions that allow them to demonstrate their abilities and knowledge acquired in school (Baron, Davis-Blake, & Bielby, 1986; Lancaster & Drasgow, 1994). Women’s more pronounced struggles with work–family balance (Hochschild, 1997) may also dampen the positive effects of education on career advancement. Along similar lines, members of racial minorities may be victims of racial stereotypes that leave them with fewer opportunities for training and development and poorer appraisal ratings (Ragins, 1997; Sidanius & Pratto, 1999; Williams & O’Reilly, 1998). Therefore, we predict that:

**Hypothesis 6:** The relationships between educational level and the dimensions of job performance are moderated by both gender (Hypothesis 6a) and race (Hypothesis 6b). The relationships will be stronger for men than for women and stronger for Caucasians than for non-Caucasians.

**Method**

**Literature Search**

We performed a comprehensive search for those field studies published in or before 2007 that examined the relationship between education level and job performance (core task performance, citizenship performance, and counterproductive performance). We also searched for unpublished studies and dissertations (Rosenthal, 1979) and utilized numerous research databases, including Dissertation Abstracts International, EBSCOHost, Emerald, Factiva, JSTOR, Oxford Journals, Proquest, PsycINFO, ScienceDirect, Sage Full-Text Collections, and several Wiley InterScience databases. In addition, the reference lists of recent meta-analyses that focused on core task performance, citizenship performance, or counterproductive performance were examined to locate other relevant articles (e.g., Berry, Ones, & Sackett, 2007; Hoffman, Blair, & Meriac, 2007; Judge, Thoresen, Bono, & Patton, 2001; LePine, Erez, & Johnson, 2002).

Our search yielded a total of 293 empirical studies, which contained 332 independent samples. Fourteen were unpublished dissertations and studies. The list of studies is provided in the Appendix. Two researchers (the first author and a research assistant) were responsible for coding
the meta-analysis, including measures used in individual studies, effect sizes, reliability information, sample characteristics, and job complexity. Interrater agreement was 93%.

Measures of Key Constructs

**Education level.** All studies we identified measured self-reported education level in one of the following three ways: as a binary variable (e.g., bachelor degree vs. no bachelor degree), as an ordinal variable (e.g., 1 = grade school, 2 = some high school . . . 7 = graduate work), or as a continuous variable (e.g., years of schooling).

**Performance dimensions.** Nine specific groups of behaviors representing the three performance dimensions discussed above were identified in this search. They include core task performance, performance in training programs, citizenship behavior, creativity, counterproductive work behaviors, workplace aggression, substance use, tardiness, and absenteeism.

**Core task performance.** Most previous studies examining educational level and job performance have focused on task performance. Four sources of task performance ratings were included in the current meta-analysis: ratings by supervisors, ratings by others (peers, subordinates, and customers), self-ratings, and objective measures.

**Performance in training programs.** Performance in training programs can be viewed as an additional indicator of core task performance because the purpose of most organizational training programs is to enhance the skill levels of employees on core tasks (Tracey, Tannenbaum, & Michael 1995). Here, we focused on studies that involved training of adults on tasks that have at least some relevance in organizational contexts. Furthermore, only studies that had an explicit training intervention and had measured post-training performance, competence, or learning were included. Studies that assessed employees’ participation in computer usage training programs are representative of the kinds of research articles included in this regard.

**Organizational citizenship behaviors (OCB).** We included two types of OCB in the meta-analysis. The first set of studies examined general OCB and did not differentiate among beneficiaries of those citizenship behaviors. The second set of studies examined OCB targeted at three specific beneficiaries: other people on the job, the employer organization as a whole, and the tasks themselves. Within each of these three subtypes, we differentiated self-ratings, ratings by supervisors, and ratings by peers or others. These behaviors are equivalent to the citizenship performance dimension in Rotundo and Sackett’s (2002) framework and have been identified by previous researchers as reasonable groupings of behaviors in this domain (LePine et al., 2002).
Creativity. Creativity is also considered as an indicator of citizenship performance here (Welbourne et al., 1998). In fact, in many organizations, creativity is used as a separate criterion in performance appraisals because employee creativity contributes to organizations’ ability to adapt to rapidly changing business environments (De Jonge & De Ruyter, 2004; Johnson, 2001). It should be noted that we did not differentiate between creativity and innovation (Anderson, De Dreu, & Nijstad, 2004); both types of measures are included in our study. In previous studies, creativity has been measured either via self-ratings or ratings by others; we used these two categories in our meta-analysis as well (Janssen, 2001).

General counterproductive work behaviors. This category of behaviors is equivalent to the counterproductive performance dimension of Rotundo and Sackett’s (2002) framework. Most studies have measured general counterproductive work behaviors without differentiating targets, that is, without specifying the target of the counterproductive behavior. A sample item here would be: “I get some pleasure out of causing a little confusion at work once in a while” (Gottfredson & Holland, 1990).

A few studies have differentiated between counterproductive work behaviors directed at specific others and those directed at the organization as a whole (e.g., Liao, Joshi, & Chuang, 2004). Because of the small number of studies making this distinction, we did not differentiate between these two categories of studies here. In those few studies that reported both interpersonal and organizational counterproductive work behaviors, we averaged the correlations to obtain an estimate of general counterproductive work behavior. Here, too, we differentiated self-ratings of counterproductive work behavior from ratings by others.

Workplace aggression. In addition to general counterproductive work behaviors, we also examined four specific forms of counterproductive work behavior that have been discussed separately and extensively in the organizational literature. The first of these is workplace aggression, which consists of employees’ efforts to harm coworkers and the reputations of their current employers (Lapierre, Spector, & Leck, 2005). Measures of workplace aggression typically ask respondents to indicate the frequency of occurrence of aggressive behaviors, such as swearing at others, damaging others’ property, and fighting (Glomb & Liao, 2003). All the studies we located utilized self-reported measures.

On-the-job substance use. On-the-job substance use involves drinking alcohol or taking illegal drugs at work or during work time (Lehman & Simpson, 1992). Measures of on-the-job substance use typically ask respondents to indicate the frequency of on-the-job use of alcohol or drugs (Frone, 2003). Here, too, all the studies identified utilized self-ratings.

Tardiness. Tardiness is lateness for work (Blau, 1994; Koslowsky, Sagie, Krausz, & Singer, 1997). It is typically measured in two ways.
In the first, employees are asked self-report questions like: “How often are you late from work? (never to constantly)” (Hanisch & Hulin, 1990). In the second, archival measures of lateness are obtained directly from personnel records (Conte & Jacobs, 2003). We included both types of measures in this meta-analysis.

Absenteeism. Skipping work has also been conceptualized as a form of employee counterproductive behavior (Bennett & Robinson, 2000; Harrison & Martocchio, 1998; Martocchio, 1989). Absenteeism has been measured in three different ways in previous research (Johns & Xie, 1998; Xie & Johns, 2000). The first group of studies measure general absenteeism; these studies do not differentiate between when employees are absent due to sickness or for purely discretionary reasons. Other studies in this line of research measure either the number of days absent from work in a given period (absence duration) or the frequency of absence spells in a given period (absence frequency). Because these indices are all closely related (Conte & Jacobs, 2003), they are aggregated together in the present meta-analysis.

A second research stream includes studies that measure sickness absenteeism. As an example, De Jonge, Ruevers, Houtman, & Kompier, (2000) computed sickness absence as the number of separate spells of sickness absence during one full calendar year.

The third, and last, group of absence studies consists of those that measure nonsickness-related absenteeism (Deery, Erwin, & Iverson, 1999). For instance, Vigoda (2001) asked respondents to report their estimates of days missed work for reasons other than sickness. In contrast to sickness-related absence, researchers have generally viewed nonsickness-related absence as an indicator of voluntary withdrawal behavior (Dalton & Todor, 1993).

Meta-Analytical Procedures

Raju, Burke, Normand, and Langlois’s (1991) meta-analysis technique, which includes corrections for range restriction, measurement error variance, and sampling error variance, was used. The Raju et al. procedures are optimally designed for the purpose of estimating appropriately defined standard errors for corrected correlations when sample-based and assumed (fixed) artifact values (e.g., sample-based reliability estimates) are incorporated into the corrections. More details and updated discussions of Raju et al.’s (1991) meta-analysis technique, particularly on the estimation of the standard errors for individually corrected correlations with sample-based and assumed (fixed) article values, can be found in Raju and Brand (2003) and Raju, Lezotte, and Fearing (2006). Burke and Landis (2003) provide equations to estimate the standard error of the
mean corrected correlation for both fixed and random effects models. In the present analysis, the standard errors (the square root of the quantity in Burke and Landis’s equation 10) and confidence intervals around the mean corrected effect were estimated for the random effects model. A mean corrected correlation was judged to be significant at $\alpha = .05$ when its 95% confidence interval did not include the value of zero. We note that corrections, as discussed in more detail below, were made for direct range restriction, criterion unreliability, and sampling error in order to estimate construct (as opposed to operational true validity) relationships between educational level and the various performance dimensions.

**Correction for range restriction.** We first corrected the observed correlations for range restriction in educational level. In many cases, organizations have a prespecified education criterion in hiring decisions (e.g., require a college degree to be hired as an accountant); this would directly result in range restriction. In other cases, organizations may hire employees based on the results of an aptitude test administered in the selection process, and those who score highly on these aptitude tests are frequently those who have more formal education. Such a scenario would indirectly result in range restriction. And, although range restriction often occurs in high-level jobs (like medicine), it can also occur in lower-level jobs as well. For example, fast food chains rarely hire college-educated workers into entry-level positions because new hires can be easily trained to do those jobs well. In any event, range restriction in educational level is likely to lower the observed correlation of educational level with other variables, including job performance (Hunter, Schmidt, & Le, 2006; Linn, Harnisch, & Dunbar, 1981).

In order to correct for range restriction in educational level, we needed to determine the standard deviation ($SD$) of education level, not only in the employee samples in the meta-analysis but in the broader population as well (Raju et al., 1991). Across the 85 studies that reported $SD$ of years of education associated with samples, the average $SD$ was 2.3 years. When we differentiated the average estimate of $SD$ by job complexity, we found that samples working in low-complexity jobs had an average $SD$ of 2.0 years, samples working in high-complexity jobs had an average $SD$ of 2.4 years, and heterogeneous samples in terms of job complexity had an average $SD$ of 2.3 years. Avolio and Waldman (1994) found similar estimates of $SD$ (1.8 years) in a large, heterogeneous sample of 25,000 American employees. Therefore, it is reasonable to estimate that, in our pooled employee samples, the average $SD$ of years of education is about 2 years.

It was much harder to gather information about the $SD$ of education level in the population as a whole because applicants who do not have the “right” educational qualifications are often screened out early in the
selection process (Sackett & Ostgaard, 1994). Therefore, we used U.S. government statistics to make our estimate (Hoffman, 1995). Specifically, the U. S. National Educational Center reported the highest educational attainments achieved by people aged 25 or above in the United States. The average $SD$ of years of education reported in 2007 was 2.94 years. This average $SD$ was quite consistent over time (3.01 years in 2006, 3.02 years in 2005, etc.). Therefore, it is reasonable to estimate that, in the unrestricted population, the average $SD$ of years of education is approximately 3 years.

Thus, the estimated ratio of the $SD$ of the years of education in the restricted population to the $SD$ of the years of education in the unrestricted employee samples is 2:3. We applied this ratio ($u$) to the correction formula proposed by Raju et al. (1991).

**Correction for measurement error variance.** The observed correlation between educational level and job performance required disattenuation so that the interpretation of effect sizes would not be confounded by measurement error variance. Even though some researchers have used *intrarater reliability* to correct for imperfect measurement when task performance is rated by others (Judge et al., 2001; Schmidt & Hunter, 1996; Viswesvaran, Ones, & Schmidt, 1996), other researchers have argued that measures of *intrarater reliability* (that is, alpha coefficients or internal consistency estimates) are more appropriate in this regard (Murphy & De Shon, 2000). Following Murphy and De Shon’s recommendation, therefore, we disattenuated the observed correlations for imperfect intrarater reliability.

The disattenuation procedures of the observed correlations between education level and subjective ratings of performance dimensions (e.g., creativity) were straightforward. We first corrected observed correlations for the lack of perfect intrarater reliability. This type of correction requires the use of alpha coefficients (i.e., internal consistency estimates) reported in individual studies. Similar to other researchers (Judge et al., 2001), if no alpha value was reported for a particular scale in a study, the average alpha value calculated from the rest of the studies using the same scale was taken as a substitute.

The disattenuation procedures of the observed correlations between education level and objective performance measures were different. We adopted Sturman, Cheramie, and Cashen’s (2005) estimate of test–retest reliability of objective task performance for disattenuation purpose for three reasons. First, studies included in our meta-analysis seldom reported any kind of reliability estimates for objective measures of task performance. Second, Sturman et al. (2005) argue that although the notion of intrarater reliability does not apply to objective measures of task performance, correlations based on objective measures are still likely to be
attenuated by error variance. Third, Sturman et al.’s estimates were based on multiple empirical studies of job performance rather than merely one single study (e.g., Judge & Cable, 2004) or a hypothetical artifact distribution (e.g., Roth, Huffcutt, & Bobko, 2003).

Based on 22 empirical studies, Sturman et al. assessed the test–retest reliability to be .50 for high-complexity jobs (e.g., managers) and .61 for low complexity (e.g., machine workers) jobs. We used those estimates here as well. For those studies that sampled mixed job complexity types, we used the average value of Sturman et al.’s two estimates as the proxy.

Objective measures of performance were also available for training test scores, lateness, and absence. Pearlman, Schmidt, and Hunter (1980), based on their review of the training literature and test manuals, estimated the expected value of the distribution of reliability values for training criterion to be .80. We, therefore, adopted this value in our procedures, too.

Regarding company record of absence, Martocchio’s (1989) meta-analysis of employee absenteeism reported an average reliability estimate across studies of .63 for both frequency and time-based measures of absence. Therefore, we adopted this value too in our diattenuation procedures involving objective measures of absence. Finally, there were no estimates of average reliability for objective indices of lateness, even in the two meta-analyses that had examined employee lateness (Koslowsky et al., 1997; Lau, Au, & Ho, 2003). Because organizations are likely to keep record of employee lateness the same way they document their absence, we used the estimates reported by Martocchio (1989) mentioned above (.63) as a proxy here.

**Corrections for sampling error variance.** The third artifact that we corrected for was sampling error due to sample size differences (Raju et al., 1991).

### Testing moderation effects.
In order to test for moderating effects, we adopted a regression procedure, recommended by Steel and Kammeyer-Mueller (2002), which has been found to be more reliable and robust than other moderation testing methods. An additional advantage of Steel and Kammeyer-Mueller’s (2002) method is that both categorical (e.g., gender) and continuous (e.g., job tenure) moderator variables can be included. These regression-based moderator tests have been used successfully in previous research studies (e.g., Wright & Bonett, 2002).
level and a dimension of job performance, then it would suggest that gender moderated that relationship.

The coding of demographic characteristics and research design characteristics of the studies is self-explanatory (e.g., percentage of Caucasians). The coding of job complexity requires some further explanation. Following previous authors (e.g., Avolio & Waldman, 1990; Salgado et al., 2003; Wood, Mento, & Locke, 1987), we classified each sample occupation into high and low job complexity according to the general intelligence, verbal ability, and numerical ability required to perform the job. The Dictionary of Occupational Titles (DOT) was used to assist the coding, too, because jobs in the DOT are classified according to several dimensions (e.g., data, people, and things) that reflect job complexity. Examples of “high-complexity” jobs are accountants, engineers, and IT professionals. “Low-complexity” jobs include clerks, restaurant workers, and receptionists.

Results

The meta-analysis results for the relationships between education level and the nine performance dimensions are presented in Table 1. Sixty-nine percent (69%) of criterion reliability data were sample-based.

Main Effects

Core task performance. Hypothesis 1 predicted that education level is positively related to task performance. We found support for this prediction. Education level was related to objective measures of task performance at .24, peer-rated task performance at .18, supervisor-rated task performance at .09, and self-rated task performance at .06.

However, we found that education level was very weakly related to performance in training programs (−.03). It should be noted, though, that many of the training performance studies involve computer training or computer-mediated learning, and employees have many opportunities to become excellent in information technology without attaining college.

Citizenship performance. Hypothesis 2 predicted that education level is positively related to citizenship performance. With respect to general OCB (OCB without differentiated targets), education level was related to ratings by supervisors at .17 and by oneself (.12). The relationship was only .03 when OCB was measured by peers.

With respect to interpersonal OCB, education level was weakly related to ratings by supervisors at .06, but largely unrelated to peer-ratings (.01) and self-ratings (.02). With respect to OCB directed at organizations, education level was related to ratings by supervisors at .12, ratings by
TABLE 1
Meta-Analytical Relationships Among Education Level and Task, Citizenship, and Counterproductive Performance

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>k</th>
<th>$r_u$</th>
<th>$SD_u$</th>
<th>AR</th>
<th>$r_c$</th>
<th>$SD_c$</th>
<th>95% CI</th>
<th>90% CrI</th>
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<tr>
<td><strong>Task performance</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Rated by supervisors</td>
<td>47,125</td>
<td>85</td>
<td>.06</td>
<td>.07</td>
<td>.88</td>
<td>.09</td>
<td>.07</td>
<td>(.08, .10)</td>
<td>(−.03, .21)</td>
</tr>
<tr>
<td>Rated by peers or others</td>
<td>1,562</td>
<td>7</td>
<td>.13</td>
<td>.18</td>
<td>.95</td>
<td>.18</td>
<td>.18</td>
<td>(.05, .31)</td>
<td>(−.12, .48)</td>
</tr>
<tr>
<td>Self-rated</td>
<td>18,184</td>
<td>43</td>
<td>.04</td>
<td>.10</td>
<td>.81</td>
<td>.06</td>
<td>.11</td>
<td>(.03, .09)</td>
<td>(−.21, .24)</td>
</tr>
<tr>
<td>Performance in training programs</td>
<td>4,348</td>
<td>16</td>
<td>−.01</td>
<td>.18</td>
<td>.80</td>
<td>−.03</td>
<td>.17</td>
<td>(−.11, .05)</td>
<td>(−.31, .25)</td>
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<td><strong>OCB</strong></td>
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<td></td>
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<td>Rated by supervisors</td>
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<td>10</td>
<td>.11</td>
<td>.04</td>
<td>.89</td>
<td>.17</td>
<td>.04</td>
<td>(.15, .19)</td>
<td>(−.10, .24)</td>
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<td>.02</td>
<td>.05</td>
<td>.74</td>
<td>.03</td>
<td>.05</td>
<td>(−.02, .08)</td>
<td>(−.05, .11)</td>
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<td>.11</td>
<td>.75</td>
<td>.12</td>
<td>.13</td>
<td>(−.09, .33)</td>
<td>(−.10, .21)</td>
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<tr>
<td>Directed at others</td>
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<td></td>
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<tr>
<td>Rated by supervisors</td>
<td>6,024</td>
<td>22</td>
<td>.04</td>
<td>.08</td>
<td>.87</td>
<td>.06</td>
<td>.09</td>
<td>(.02, .10)</td>
<td>(−.09, .21)</td>
</tr>
<tr>
<td>Rated by peers or others</td>
<td>2,063</td>
<td>14</td>
<td>.00</td>
<td>.06</td>
<td>.82</td>
<td>.01</td>
<td>.07</td>
<td>(−.03, .05)</td>
<td>(−.11, .13)</td>
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<tr>
<td>Self-rated</td>
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<td>.01</td>
<td>.06</td>
<td>.76</td>
<td>.02</td>
<td>.07</td>
<td>(−.02, .06)</td>
<td>(−.10, .14)</td>
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<tr>
<td>Directed at organization</td>
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<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Rated by supervisors</td>
<td>5,601</td>
<td>21</td>
<td>.07</td>
<td>.08</td>
<td>.82</td>
<td>.12</td>
<td>.11</td>
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<td>(−.06, .30)</td>
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<tr>
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<td>1,811</td>
<td>8</td>
<td>.08</td>
<td>.09</td>
<td>.88</td>
<td>.13</td>
<td>.09</td>
<td>(.07, .19)</td>
<td>(−.02, .28)</td>
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<tr>
<td>Self-rated</td>
<td>5,290</td>
<td>20</td>
<td>.07</td>
<td>.09</td>
<td>.73</td>
<td>.11</td>
<td>.11</td>
<td>(.06, .16)</td>
<td>(−.07, .29)</td>
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<tr>
<td>Directed at tasks</td>
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<tr>
<td>Rated by supervisors</td>
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<td>4</td>
<td>.14</td>
<td>.12</td>
<td>.87</td>
<td>.23</td>
<td>.14</td>
<td>(.09, .37)</td>
<td>(−.00, .46)</td>
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<td><strong>Creativity</strong></td>
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<td>Rated by supervisors</td>
<td>4,278</td>
<td>22</td>
<td>.17</td>
<td>.14</td>
<td>.90</td>
<td>.25</td>
<td>.15</td>
<td>(.19, .31)</td>
<td>(−.00, .50)</td>
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<td>.17</td>
<td>.16</td>
<td>.86</td>
<td>.27</td>
<td>.17</td>
<td>(.14, .40)</td>
<td>(−.01, .55)</td>
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</table>

continued
TABLE 1 (continued)

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<tr>
<th></th>
<th>$N$</th>
<th>$k$</th>
<th>$r_u$</th>
<th>$SD_u$</th>
<th>AR</th>
<th>$r_c$</th>
<th>$SD_c$</th>
<th>95% CI</th>
<th>90% CrI</th>
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<tr>
<td>Rated by supervisor or peers</td>
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<td>7</td>
<td>-.02</td>
<td>.14</td>
<td>.71</td>
<td>-.04</td>
<td>.18</td>
<td>(-.17, .09)</td>
<td>(-.34, .26)</td>
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<td>3,529</td>
<td>12</td>
<td>.01</td>
<td>.06</td>
<td>.77</td>
<td>.01</td>
<td>.08</td>
<td>(-.04, .06)</td>
<td>(-.12, .14)</td>
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<tr>
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<td>1,801</td>
<td>9</td>
<td>-.05</td>
<td>.03</td>
<td>.81</td>
<td>-.09</td>
<td>.04</td>
<td>(-.12, -.06)</td>
<td>(-.16, -.02)</td>
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<td>Self-rated on-the-job substance use</td>
<td>11,515</td>
<td>10</td>
<td>-.17</td>
<td>.10</td>
<td>.71</td>
<td>-.28</td>
<td>.11</td>
<td>(-.35, -.21)</td>
<td>(-.46, -.10)</td>
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<tr>
<td><strong>Tardiness</strong></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
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<tr>
<td>Objective measures</td>
<td>645</td>
<td>4</td>
<td>.02</td>
<td>.16</td>
<td>.63</td>
<td>.03</td>
<td>.15</td>
<td>(-.12, .18)</td>
<td>(-.22, .28)</td>
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<tr>
<td>Self-rated</td>
<td>6,117</td>
<td>12</td>
<td>.02</td>
<td>.08</td>
<td>.76</td>
<td>.04</td>
<td>.23</td>
<td>(-.09, .17)</td>
<td>(-.34, .42)</td>
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<tr>
<td><strong>Absenteeism</strong></td>
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<tr>
<td>General absence (undifferentiated causes)</td>
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<td></td>
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<tr>
<td>Objective measures</td>
<td>70,003</td>
<td>23</td>
<td>-.11</td>
<td>.10</td>
<td>.63</td>
<td>-.22</td>
<td>.09</td>
<td>(-.26, -.18)</td>
<td>(-.37, -.07)</td>
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<tr>
<td>Self-rated</td>
<td>4,962</td>
<td>12</td>
<td>-.06</td>
<td>.06</td>
<td>.78</td>
<td>-.10</td>
<td>.06</td>
<td>(-.13, -.07)</td>
<td>(-.20, .00)</td>
</tr>
<tr>
<td>Sickness absence</td>
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<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Objective measures</td>
<td>3,730</td>
<td>12</td>
<td>-.08</td>
<td>.07</td>
<td>.63</td>
<td>-.16</td>
<td>.05</td>
<td>(-.19, -.13)</td>
<td>(-.24, -.08)</td>
</tr>
<tr>
<td>Self-rated</td>
<td>33,622</td>
<td>5</td>
<td>-.02</td>
<td>.01</td>
<td>.78</td>
<td>-.04</td>
<td>.01</td>
<td>(-.05, -.03)</td>
<td>(-.06, -.02)</td>
</tr>
<tr>
<td>Nonsickness-related absence</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Objective measures</td>
<td>1,372</td>
<td>6</td>
<td>-.03</td>
<td>.07</td>
<td>.63</td>
<td>-.07</td>
<td>.04</td>
<td>(-.10, -.04)</td>
<td>(-.14, .00)</td>
</tr>
<tr>
<td>Self-rated</td>
<td>957</td>
<td>3</td>
<td>.02</td>
<td>.05</td>
<td>.78</td>
<td>.04</td>
<td>.06</td>
<td>(-.03, .11)</td>
<td>(-.06, .14)</td>
</tr>
</tbody>
</table>

Notes. $N =$ cumulative sample size; $k =$ number of studies cumulated; $r_u =$ sample-size weighted uncorrected (observed) correlation; $SD_u =$ standard deviation of $r_u;$ AR = average or assumed criterion reliability value; $r_c =$ sample-size weighted (fully) corrected correlation; $SD_c =$ standard deviation of $r_c;$ CI = confidence interval for $r_c;$ CrI = credibility interval for $r_c.$
peers at .13, and ratings by oneself at .11. With respect to OCB directed at tasks, education level was related to ratings by supervisors at .23.

As noted earlier, employee creativity can be viewed as an additional dimension of OCB. We found that education level was related to employee creativity rated by supervisors or measured objectively at .25 and to self-reported creativity (.27). Overall, then, the results provide some support for Hypothesis 2. All the results are in the predicted direction.

Counterproductive performance. Hypothesis 3 predicted that education level is negatively related to counterproductive performance. We found that education level was largely unrelated to general counterproductive work behaviors (those without differentiated targets). Education level was very weakly related to supervisors/peers’ ratings (−.04) and unrelated to self-ratings.

However, education level is inversely related to the first two specific counterproductive work behaviors we investigated, namely, workplace aggression and on-the-job substance use. Education level was negatively related to workplace aggression at −.09 and negatively related to on-the-job substance use at −.28.

Education level was very weakly related to the third specific indicator of counterproductive work behavior, namely, tardiness (.03 for objective measures and .04 for self-ratings). The fourth specific counterproductive work behavior we examined was absenteeism. Here, the effect sizes of education level depended on the type of absence measure utilized. When general measures of absence were used (i.e., absence measures that did not differentiate among causes for absence), education level was negatively related to objective measures at −.22. The effect size of education level on general absenteeism by self-ratings was only −.10. A similar pattern of results emerged for sickness-related absence; education level was negatively related to objective measures at −.16 but to self-ratings only at −.04. In contrast, education level had little relationship with nonsickness absence; the effect size was −.07 for objective measures and .04 for self-ratings.

Hypothesis 3, then, received partial support. Education is inversely related to workplace aggression, substance abuse, and objective measures of absence. On the other hand, education is unrelated to general counterproductive behaviors and tardiness.

Moderator Effects

Table 2 presents the results of the moderator regression analyses. Two points, in particular, are worth noting about these results. First, moderator searches were conducted on only those subsets of studies that we used for calculating the corrected correlations presented in Table 1 and had complete sample descriptions. In these cases, we used a regression-based
TABLE 2
Moderators of the Education Level-Job Performance Relationship

<table>
<thead>
<tr>
<th>Relationship</th>
<th>$k^*$</th>
<th>$\beta$</th>
<th>Explained Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Education level-Core task performance (rated by supervisors, peers, or others)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average job tenure</td>
<td>24</td>
<td>.02</td>
<td>.00</td>
</tr>
<tr>
<td>Average organizational tenure</td>
<td>72</td>
<td>.04</td>
<td>.00</td>
</tr>
<tr>
<td>Proportion of managers</td>
<td>46</td>
<td>.10</td>
<td>.01</td>
</tr>
<tr>
<td>Job complexity (low vs. high)</td>
<td>77</td>
<td>.15†</td>
<td>.02</td>
</tr>
<tr>
<td>Proportion of women</td>
<td>91</td>
<td>−.20*</td>
<td>.04</td>
</tr>
<tr>
<td>Proportion of racial minority</td>
<td>36</td>
<td>−.22†</td>
<td>.05</td>
</tr>
<tr>
<td>Education level-General OCB (rated by supervisors, peers, or others)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average job tenure</td>
<td>17</td>
<td>−.20</td>
<td>.04</td>
</tr>
<tr>
<td>Average organizational tenure</td>
<td>68</td>
<td>−.11</td>
<td>.01</td>
</tr>
<tr>
<td>Proportion of managers</td>
<td>39</td>
<td>−.31*</td>
<td>.10</td>
</tr>
<tr>
<td>Job complexity (low vs. high)</td>
<td>44</td>
<td>.07</td>
<td>.01</td>
</tr>
<tr>
<td>Proportion of women</td>
<td>72</td>
<td>.11</td>
<td>.02</td>
</tr>
<tr>
<td>Proportion of racial minority</td>
<td>28</td>
<td>−.30†</td>
<td>.09</td>
</tr>
<tr>
<td>Education level-Counterproductive work behavior (self-rated)$^b$</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Average organizational tenure</td>
<td>22</td>
<td>.11</td>
<td>.01</td>
</tr>
<tr>
<td>Job complexity (low vs. high)</td>
<td>15</td>
<td>.38†</td>
<td>.14</td>
</tr>
<tr>
<td>Proportion of women</td>
<td>34</td>
<td>.02</td>
<td>.00</td>
</tr>
<tr>
<td>Proportion of racial minority</td>
<td>22</td>
<td>.00</td>
<td>.00</td>
</tr>
</tbody>
</table>

$^†p < .10$ *$p < .05.$

Note. $k = \text{number of studies cumulated; } \beta = \text{standardized beta weight for the respective moderator.}$

$^a$Only relationships that involved 15 or more studies with complete sample descriptions were examined.

$^b$This category of performance included self-rated general counterproductive work behaviors, workplace aggression, on-the-job substance use, and tardiness.

moderator search solely for the purpose of detecting the existence and direction of moderator effects. Second, the moderator search focused on three relationships that had the largest number of cumulative samples (k): (a) education-core task performance (rated by supervisors or others); (b) education-general OCBs (rated by supervisors or others); (c) education-counterproductive work behaviors (self-rated).

Hypothesis 4 predicted that the relationship between educational level and job performance is moderated by job tenure (Hypothesis 4a) and organization tenure (Hypothesis 4b). Contrary to expectations, we found that average job tenure and average organizational tenure did not moderate any of the education-performance relationships. Thus, Hypothesis 4 was not supported.
Hypothesis 5a predicted that the education-performance relationship would be stronger for managerial jobs than for nonmanagerial jobs. Contrary to our expectations, we found that the relationship between education level and OCB was more positive for nonmanagers than for managers. Hypothesis 5a, then, was not supported.

Hypothesis 5b predicted that the education-performance relationship would be stronger for high-complexity jobs than for low-complexity jobs. Providing support for our prediction, the education-task performance relationship was more positive for high-complexity jobs. However, contrary to our expectations, we found that the relationship between education level and counterproductive work behavior was less negative for high-complexity jobs than for low-complexity jobs. Hypothesis 5, then, received mixed support.

Finally, Hypothesis 6 predicted that the education-performance relationship will be stronger for men (vs. women; Hypothesis 6a) and for Caucasians (vs. non-Caucasians; Hypothesis 6b). With respect to the relationship between education level and task performance, we found that the relationship was more positive for Caucasians than for other racial groups and for men than for women. Further, we found that the relationship between education and OCB was more positive for Caucasians than for other racial groups. These results provide some support for Hypothesis 6a and Hypothesis 6b.

Discussion

In this article, we suggest that the range of effects of education extend beyond core task performance to include citizenship and counterproductive performance too. Highly educated workers are likely to contribute more effectively to noncore activities at work as well (Pennings, Lee, & van Witteloostuijn, 1998). Further, in “weak situations” where performance demands or role expectations are not strong, the effect of one’s human capital may be particularly evident. For example, the meta-analysis shows that highly educated workers tend to display greater creativity and to demonstrate more citizenship behaviors than do less educated workers. Moreover, highly educated workers appear to engage in fewer counterproductive work behaviors like workplace aggression, workplace substance use, and absenteeism.

Limitations of Current Research and Implications for Research Designs

The meta-analytical results presented highlight the need for new approaches to studying the education-performance relationship in the future. From researchers’ initial design decisions through their conclusions about
their findings, we identify several specific issues that need to be addressed before robust conclusions about this relationship can be drawn.

**Longitudinal studies.** The positive effect of human capital investments on individuals’ career earnings may be more observable in the long run (Quiñones et al., 1995; Sweetland, 1996). For instance, college graduates may not be able to fully apply what they have learned in school to the work setting during the stressful school-to-work transition (Ng & Feldman, 2007). Once they become fully comfortable with the work environment, though, the beneficial effects of education on productivity might become more observable. In our pool of studies, only 11% used longitudinal designs. Additional longitudinal studies, then, are certainly needed.

**Mediating mechanisms.** We suggest that the process of human capital acquisition evokes a number of cognitive and emotional changes in individuals that may help explain more precisely why and how human capital is related to career success. For instance, educational level can enhance cognitive ability, increase job-relevant knowledge, and promote the development of a strong work ethic, all of which can strengthen job performance in turn. Furthermore, college education may also help build stronger social ties in the profession, thereby promoting job success (Ng et al., 2005). Conceptualizing and measuring mediating processes may be one of the most effective ways to help researchers explain why education matters to career success, not only that education matters to career success.

In particular, it is vital to examine the extent to which the processes of human capital acquisition cause changes in the levels of mediating variables. If the argument is being made, for example, that the reason why education promotes job performance is that it enhances individuals’ work ethic, then multiple measurements of the presumed mediating variable (work ethic) need to be gathered, too.

**Operationalization of education.** The focus of this study is largely on education level. However, there are other aspects of the educational experience that also warrant greater attention. For instance, very few studies have considered differences in college majors (indeed, only 3% of the studies here reported information about employees’ college major) or compared the effects of vocational and nonvocational education on job performance. It may be that vocational or technical schools directly promote high levels of core task performance, but the broad development focus of bachelor’s education is more likely to enhance individuals’ citizenship and counterproductive performance. In an excellent example of using multiple ways to operationalize education qualifications, Howard (1986) measured five college education experiences, including level of education, grades, quality of undergraduate institution, major field of study,
and participation in extracurricular activities, and the authors correlated these measures with job performance. She found that education level, college major, and participation in extracurricular activities were most strongly related to job performance.

Operationalization of performance. One of our key findings is that whether education matters to job performance partially depends on the definition of job performance. For instance, if counterproductive work behavior is defined very specifically as level of tardiness, education might have no effect whatsoever. On the other hand, if performance is defined in terms of absence or workplace aggression, the influence of education may be stronger. Thus, in order to obtain a more complete picture of the broad effects of education on worker productivity, we also recommend researchers to collect at least two kinds of performance measures in each study.

Our results also indicate that who evaluates job performance may affect the strength of the education-performance relationship. For instance, we found that supervisors and employees themselves have quite similar ratings of creativity (.25 vs. .27) and that supervisors, peers, and employees themselves share quite similar views of the level of OCB directed at organizations (.12, .13, and .11, respectively). On the other hand, there is much greater disparity among these raters when it comes to evaluating core task performance. Therefore, we also recommend future studies to collect performance measures from multiple sources and consider more fully why there is convergence or divergence in multisource ratings.

Sample characteristics. We found general support for our moderator hypothesis that the education-performance relationship is weaker for women than for men and for racial minority than for Caucasian employees (Maume, 1999; Ohlott, Ruderman, & McCauley, 1994; Stroh et al., 1992). Either due to selection bias or higher performance standards set for these groups, the investments of women and racial minorities into education may have less impact on their job performance. Thus, studies that are not heterogeneous or representative on important sample characteristics may yield nongeneralizable results.

As noted earlier, we found that years of work experience (operationalized as job and organizational tenure) did not moderate the education-performance relationship. One possible explanation is that these proxies capture the quantity but not the quality or variety of work experience (Quiñones et al., 1995). Another possibility is that work experience has a curvilinear relationship with performance, with its positive effects being stronger for the early- and midcareer groups and lower for the late career cohorts (Sturman, 2003). A third possibility is that work experience and education have somewhat similar predictive power on some dimensions of
performance, such as objective ratings of task performance (cf. Quiñones et al., 1995).

Indeed, the exact relationship of work experience to formal education—and their joint impact on job performance—needs further study. In some cases, work experience may partially offset or compensate for lower levels of formal education; in fact, in its visa application procedures, the U.S. government equates 3 years of work experience to 1 year of formal education. For example, in skilled trade jobs, one could easily see how work experience might offset or even dominate the contributions of education to job performance. In other cases, work experience may be an accelerator of work performance. For instance, in middle-management positions, work experience may not fully substitute for having the content knowledge gained in an MBA program, but it might accelerate the performance of middle managers who have completed their MBAs.

Along similar lines, future research should examine the factors that prompt individuals to choose obtaining more education over more work experience and vice versa. It is equally important for researchers to investigate the factors that affect organizations’ preferences (in both hiring and promotion decisions) for years of education or educational degrees over years of work experience. In some studies (e.g., Singer & Bruhns, 1991), researchers have found that interviewers weight applicants’ work experience more heavily than academic qualifications in hiring decisions. Undoubtedly, industry and organizational preferences come in to play here as well and warrant further attention, too.

The set of unexpected results in this study revolved around the moderating effects of job complexity and job type on the education-performance relationship. Contrary to expectations, highly educated workers in highly complex jobs were more likely to engage in counterproductive behavior. One possibility is that high stress levels among educated workers on complex jobs give rise to more counterproductive behavior. Along the same lines, we found that the relationship between education level and OCB was more positive for nonmanagers than for managers. One reason for this result may be that OCBs (such as promoting the organization to outsiders) are more often viewed as part of a manager’s core job than as part of a nonmanager’s core job; another is that highly educated nonmanagers may have greater incentives to demonstrate OCBs if they want to get promoted (Hui, Lam, & Law, 2000). Here, too, sample characteristics can strongly influence research results.

Use of meta-analyses. Although meta-analyses provide a robust picture of accumulated research findings, they also have some limitations. For instance, because of unreported data, we were not able to search for moderators for all education-performance relationships of interest here. A second limitation is the relatively small number of aggregated studies
for some of the relationships investigated. Even though meta-analysis can be executed with as few as two studies (Hunter & Schmidt, 1990), the cumulated effect sizes are more stable when the number of cumulative studies increases. Third, due to the data contained in individual studies, we had to use proxy variables in some of our moderator analyses (such as the percentage of women for the effect of gender). As the quality of empirical research in this area is strengthened, the inherent restrictions imposed by meta-analyses will be lessened as well.

Managerial Implications

To effectively contain hiring costs, managers frequently use job applicants’ educational level as a screening criterion (Kroch & Sjoblom, 1994; Maglen, 1990). At the aggregate level, the results of this study suggest that using education level as a screening device has quite robust validity. In many cases, then, the higher recruitment costs and wage costs that typically accompany hiring highly educated workers are justifiable.

However, hiring highly educated workers requires managers to attend to other HR issues more carefully as well. For example, hiring educated workers does not necessarily lead to better performance in training programs; as the results here suggest, education level is largely unrelated to performance in training programs. Workers with more education may be more confident about their skills and therefore take training less seriously, or workers with less education may be more motivated to take advantage of this opportunity. In either event, though, using education level as the screen for entry into training programs may be less important than ensuring that recipients of training are fairly homogeneous in terms of skill levels.

In this study, we presented evidence that educated employees, as a group, perform more effectively at task, citizenship, and counterproductive performance, and that certainly augurs well for the fulfillment of managers’ expectations of highly educated workers. At the same time, given the variance among self-evaluations, peer evaluations, and supervisor evaluations reported here, highly educated workers may especially need and benefit from the use of 360-degree feedback systems that include citizenship and counterproductive performance dimensions (Welbourne et al., 1998).

In the final analysis, the benefits of a highly educated workforce extend beyond core task performance to include several facets of citizenship and counterproductive performance. The relationships between education and performance dimensions, though, are not uniformly strong, not uniformly consistent across employee groups, and not consistently observed by different groups of raters. For these reasons, then, a finer-grained, strategic
approach is needed to ensure that the premium paid to hire more educated workers results in the specific outcomes most valued by organizations.

REFERENCES


APPENDIX

Empirical studies included in the meta-analysis.


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