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Experts are born, then made: Combining prospective and retrospective longitudinal data shows that cognitive ability matters

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ABSTRACT

Does cognitive ability matter in the development of expertise in educational and occupational domains? Study 1 reviewed prospective longitudinal data from the top 1% in ability within two cohorts of the Study of Mathematically Precocious Youth (SMPY; Total N = 1975) and examined four cohorts of a stratified random sample of America's population (Project Talent; Total N = 1536) to see whether ability differences at a younger age made a difference in the attainment of a higher percentage of educational degrees and specifically doctorates (e.g., JDs, MDs, or PhDs) at a later age. Compared to the general population, the top 1% in ability earned a much higher percentage of educational degrees at each level. And even within the top 1% of ability, ability differences made a difference in obtaining a doctorate degree. Study 2 reviewed retrospective longitudinal data from five groups of America's elite (Total N = 2254)—Fortune 500 CEOs, federal judges, billionaires, Senators, and members of the House of Representatives—to determine what percentage of each group was in the top 1% of general ability at a younger age. A large percentage of individuals within each of these areas of occupational expertise were found to be in the top 1% of ability. By combining multiple samples of both prospective and retrospective longitudinal data, cognitive ability was found to matter in the acquisition of educational and occupational expertise.

1. Introduction

A popular phrase today about people who have achieved greatly in any field is that they are "made, not born" (Ericsson, Prietula, & Cokely, 2007). This phrase is meant to convey that what really matters in the making of an expert is not inherent talent but years of deliberate practice (Ericsson, Krampe, & Tesch-Romer, 1993; Howe, Davidson, & Sloboda, 1998). And, in part, this is most certainly true because cognitive abilities do not come fully formed at birth but are developed over time (Lohman, 2006). Additionally, many factors other than ability play an important role in the development of talent or expertise, such as interests, personality, and willingness to work (Lubinski, 2004; Simonton, 1999).

This phrase has come to represent what some researchers have described as "absurd environmentalism," (Detterman, Gabriel, & Ruthsatz, 1998)—the idea that anyone can become an expert in any field as long as they put in the time and effort. Yet a large body of research has demonstrated that there are wide individual differences in general intelligence (g) in the population (Jensen, 1998), g is highly heritable (Bouchard, 2004; Neisser et al., 1995), and g is highly related to the acquisition of expertise in educational and occupational domains (Kuncel, Hezlett, & Ones, 2004; Schmidt & Hunter, 2004). Therefore, if we wish to appropriately represent the full network of evidence surrounding the acquisition of expertise, the phrase "made, not born" really should be changed to "born, then made."

Given that one third of the ability range exists within the top 1% alone (Lubinski & Benbow, 2000), this segment of the distribution provides the opportunity to test the idea that ability matters in the development of expertise. Therefore,

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this paper draws upon multiple sources of longitudinal data to examine the issue. Study 1 reviewed prospective data from the Study of Mathematically Precocious Youth (SMPY; Lubinski & Benbow, 2006) and introduced data from Project Talent (Wise, McLaughlin, & Steel, 1979) to examine whether ability differences within the top 1% assessed in youth make a difference in educational outcomes such as earning a bachelor's, master's, or doctorate degree at a later age. Study 2 reviewed retrospective data drawn from five groups of experts among "America's Elite" (Wai, 2013)—Fortune 500 CEOs, federal judges, billionaires, Senators, and members of the House of Representatives—and examined whether they were in the top 1% of cognitive ability in their youth. To the extent that the link between ability and expertise can be made using multiple sources of prospective and retrospective data would support the idea that ability matters in the development of expertise in educational and occupational domains, even within the top 1%.

2. Study 1 samples

2.1. The Study of Mathematically Precocious Youth (SMPY)

The two SMPY cohorts reviewed in this study were identified before age 13 in 1972–1974 (Cohort 1: top 1%) and 1976–1979 (Cohort 2: top 0.5%) and were followed up 20 years later at age 33. All participants were drawn from the top 1% of math ability as assessed by the math subtest of the Scholastic Assessment Test (SAT) given to gifted students in the 7th grade. The participants with 20-year follow-up data were included in this study (Cohort 1: N = 1383; Cohort 2: N = 592; Total N = 1975). Summary data on bachelor's, master's, and doctorate degrees was taken from Table 1 of Benbow, Lubinski, Shea, and Eftekhari-Sanjani (2000, p. 475), and data on doctorate degrees was taken from Table 1 of Wai, Lubinski, and Benbow (2005, p. 486). For more description of the SMPY samples, see Lubinski and Benbow (2006).

2.2. Project Talent

This is a stratified random sample of America's high school population (Total N ≈ 400,000) that was initially identified in 1960 and followed up 11 years after high school graduation. Project Talent includes four cohorts: 9th, 10th, 11th, and 12th graders who took a number of ability tests and were surveyed extensively (initially at ages 15 through 18). For this study I utilized the math ability composite which was also used in Wai, Lubinski, and Benbow (2009) to examine the top 1%. The participants with 11-year follow-up data on bachelor's, master's, and doctorate degrees were included in this study (9th grade: N = 420; 10th grade: N = 379; 11th grade: N = 388; and 12th grade: N = 349; Total N = 1536). For detailed description of the mathematical ability composite used see Wai et al. (2009). For more description of the Project Talent samples see Wise et al. (1979).

3. Study 1 method

Study 1 examines the importance of talent by using prospective longitudinal data in two phases. First, it examines the percentage of individuals earning bachelor's, master's, and doctorate degrees (e.g., JD, MD, or PhD) within the top 1% and 0.5% of math and general (math + verbal) ability in the SMPY sample (male and female data were combined for this study) and examines whether this pattern of findings is similar within the 9th, 10th, 11th, and 12th grade cohorts of Project Talent. Second, it examines whether differences in ability make a difference within the top 1% of math and general ability by comparing the top quartile of the top 1% to the bottom quartile of the top 1% and examining whether there are differences in

Table 1
Percent within the top 1% and top 0.5% in Math and general ability that earned bachelor's, master's, and doctorate degrees in SMPY and four cohorts of Project Talent.

	SMPY	PT 9th grade	PT 10th grade	PT 11th grade	PT 12th grade
Top 1% in math ability					
Bachelor's	1216/1383 = **87.9%**	358/420 = **85.2%**	339/379 = **89.5%**	346/388 = **89.2%**	330/349 = **94.6%**
Master's	505/1383 = **36.5%**	216/420 = **51.4%**	193/379 = **50.9%**	203/388 = **52.3%**	204/349 = **58.5%**
Doctorates	332/1383 = **24.0%**	97/420 = **23.1%**	90/379 = **23.8%**	90/388 = **23.2%**	97/349 = **27.8%**
Top 0.5% in math ability					
Bachelor's	568/592 = **95.9%**	188/222 = **84.7%**	191/208 = **91.8%**	176/193 = **91.2%**	191/199 = **95.9%**
Master's	250/592 = **42.2%**	123/222 = **55.4%**	120/208 = **57.7%**	114/193 = **59.1%**	137/199 = **68.8%**
Doctorates	185/592 = **31.3%**	60/222 = **27.0%**	67/208 = **32.2%**	60/193 = **31.1%**	74/199 = **37.2%**
Top 1% in general ability					
Bachelor's		362/421 = **86.0%**	342/378 = **90.5%**	350/384 = **91.1%**	336/353 = **95.2%**
Master's		214/421 = **50.8%**	198/378 = **52.4%**	209/384 = **54.4%**	205/353 = **58.1%**
Doctorates	**23%**	90/421 = **21.4%**	99/378 = **26.2%**	91/384 = **23.7%**	97/353 = **27.5%**
Top 0.5% in general ability					
Bachelor's		181/209 = **86.6%**	184/201 = **91.5%**	176/191 = **92.1%**	170/177 = **96.0%**
Master's		113/209 = **54.1%**	110/201 = **54.7%**	106/191 = **55.5%**	108/177 = **61.0%**
Doctorates	**30%**	56/209 = **26.8%**	55/201 = **27.4%**	53/191 = **27.7%**	53/177 = **29.9%**

Note. SMPY = Study of Mathematically Precocious Youth. PT = Project Talent. General ability was determined by adding math and verbal ability scores from PT. Summary data from SMPY for general ability was not available, with the exception of data on doctorates. The percentages in bold indicate the percentages within each sample that earned a particular degree.

Table 2
Percent earning doctorates within the top and bottom quartiles of the top 1% in math and general ability in SMPY and four cohorts of Project Talent.

	SMPY	PT 9th grade	PT 10th grade	PT 11th grade	PT 12th grade
Math ability					
Top 1% (Q4)	97/329 = **29.5%**	30/109 = **27.5%**	34/97 = **35.1%**	35/97 = **36.1%**	42/103 = **40.8%**
Top 1% (Q1)	63/361 = **17.5%**	17/117 = **14.5%**	12/85 = **14.1%**	18/98 = **18.4%**	13/87 = **14.9%**
95% CI around proportion differences	(0.06, 0.18), *significant*, RR = **1.69**	(0.03, 0.24), *significant*, RR = **1.89**	(0.09, 0.33), *significant*, RR = **2.48**	(0.05, 0.30), *significant*, RR = **1.96**	(0.14, 0.38), *significant*, RR = **2.73**
General ability					
Top 1% (Q4)		34/102 = **33.3%**	35/99 = **34.5%**	29/99 = **29.3%**	32/94 = **34.0%**
Top 1% (Q1)		14/99 = **14.1%**	21/79 = **26.6%**	20/99 = **20.2%**	24/87 = **27.6%**
95% CI around proportion differences		(0.08, 0.31), *significant*, RR = **2.36**	(−0.05, 0.22), *ns*, RR = **1.33**	(−0.03, 0.21), ns, RR = **1.45**	(−0.07, 0.20), *ns*, RR = **1.23**

Note. SMPY = Study of Mathematically Precocious Youth. PT = Project Talent. Q4 = top quarter of the top 1%. Q1 = bottom quarter of the top 1%. RR = relative risk. General ability was determined by adding math and verbal ability scores from PT. Summary data from SMPY for general ability was not available. The percentages in bold indicate the percentages within each sample that earned a doctorate degree.

the percentage earning doctorate degrees. Findings within SMPY will again be compared to findings within each cohort of Project Talent.

4. Study 1 results

Table 1 presents the percentage of participants earning bachelor's, master's, and doctorate degrees from SMPY and Project Talent in the top 1% and 0.5% of math ability and general ability (math + verbal), respectively. Within the top 1% of math ability of SMPY, roughly 88% earned bachelor's degrees, 37% earned master's degrees, and 24% earned doctorates. Within the top 1% of math ability of Project Talent, findings were replicated across all four cohorts with 85% to 95% having earned bachelor's degrees, 51% to 58% earned master's degrees, and 23% to 28% earned doctorate degrees. Findings within the top 0.5% were slightly higher than the top 1% and also replicated across SMPY and Project Talent. Findings for general ability within Project Talent were nearly identical to those for math ability. Summary data for SMPY was not available, with the exception of the data for doctorates: 23% of the top 1% and 30% of the top 0.5% (Lubinski & Benbow, 2006), and directly aligned with the Project Talent data. This shows that higher educational attainment within the top 1% of ability is markedly above the base rate of the general population and that as ability increases, so does the percentage of degrees obtained. For example, the base rate in the general U.S. population for earning a doctorate in 2012 was 1.6%, for master's degree was 8.1% and for bachelor's degree was 19.8% (U.S. Census Bureau, 2012a). Statistical tests were conducted comparing the top 1% in general ability to the general population regarding educational attainment. With all cohorts combined, the findings for bachelor's (top 1%: 90.5%, general population: 19.8%; 95% confidence interval around proportion differences: 0.69, 0.72; relative risk = 4.57), master's (top 1%: 53.8%, general population: 8.1%; 95% CI PD: 0.43, 0.48; RR = 6.64), and doctorates (top 1%: 24.5%, general population: 1.6%; 95% CI PD: 0.21, 0.25; RR = 15.31) were all significant. Within Project Talent, the top 1% in general ability were roughly 4.57 times as likely to earn a bachelor's degree, 6.64 times as likely to earn a master's degree, and 15.31 times as likely to earn a doctorate degree.[1]

Table 2 presents the analyses within SMPY and four cohorts of Project Talent that examined whether there were differences in doctorate attainment when comparing the top quartile of the top 1% to the bottom quartile of the top 1%. The findings demonstrate that even within the top 1% of math ability, more ability makes a difference in the attainment of doctorates. Confidence intervals around the differences between proportions were computed and all five of the comparisons were significant (see Table 2 for test statistics). Within SMPY, the top quartile was about 1.69 times as likely to earn doctorates as the bottom quartile. Within Project Talent, the top quartile was about 1.89 to 2.73 times as likely to earn doctorates as the bottom quartile. The pattern of findings for general ability in Project Talent was similar to the findings for math ability, however, only one of the four comparisons was statistically significant (see Table 2 for test statistics). When combining all four cohorts, however, the findings were significant (Q4: 33.0%, Q1: 21.7%; 95% CI PD: 0.05, 0.18; RR = 1.52). Within Project Talent, the top quartile was about 1.23 to 2.36 times as likely to earn doctorates as the bottom quartile.

Taken together, these findings show that ability identified at an earlier age (SMPY: age 12, Project Talent: ages 15 through 18) predicts higher educational attainment later in life.

5. Study 2 samples

5.1. America's Elite

Summary data (total N = 2254) was taken from Table 2 of Wai (2013) on Fortune 500 CEOs (N = 500), active federal

[1] Educational data from participants in Project Talent was collected in the mid 1970s; therefore using the base rates for higher educational degrees in 2012 likely gives higher values and these findings are likely an underestimate. For example, in 1979 (U.S. Census Bureau, 1979) 16.4% of the general population earned a bachelor's degree, which is slightly lower than the 19.8% found in 2012. Despite this, 2012 values were used because data on master's and doctorate degrees in the U.S. Census were not available in the 1970s.

judges (N = 789), American billionaires (N = 424), Senators (N = 100), and members of the House of Representatives (N = 441) in 2012. These groups were considered part of “America's Elite” as they are in positions with power to shape American society. Whether an individual was in the top 1% of general ability (math + verbal ability) was assessed retrospectively from average SAT and American College Test (ACT) scores of the colleges and universities these individuals attended for undergraduate and graduate schools (America's Best Colleges, 2013). For more description of these samples such as the colleges attended by participants and associated ability scores see Wai (2013).

6. Study 2 method

Study 2 examined the importance of talent by using retrospective longitudinal data. These sources included Fortune 500 CEOs, federal judges, billionaires, Senators, and members of the House of Representatives. Information on the college and university these individuals attended for undergraduate or graduate schools was used as a reasonable proxy for their general intelligence level (Murray, 2012) because standardized test scores on the SAT or ACT are required for admission and measure general intelligence or IQ to a large degree (Frey & Detterman, 2004; Koenig, Frey, & Detterman, 2008). The percentage attending an “Elite School” that had average standardized test scores on the combined SAT Math and Verbal subtests (or equivalent on the ACT) in the top 1% was examined, as well as the percentage independent of this top 1% that attended graduate school, college, or did not report or did not attend college. For more detail regarding the method including a list of the colleges and universities that had average test scores in the top 1%, see Table 1 of Wai (2013).

7. Study 2 results

Table 3 presents the percentage of each group who—according to high school standardized test scores—were in the top 1% of general ability. “Elite School” indicates the percentage that attended one of the schools with average test scores that placed them in the top 1% of ability. “Graduate School” indicates the percentage that attended graduate school independent of the Elite school category and represents a group likely in the top percentiles of ability. “College” indicates the percentage that attended college but not Graduate School or an Elite School. “NR/NC” indicates the percentage that did not report any education or had no college. These four categories are independent of one another and sum to 100%. Table 3 shows that CEOs (38.6%), judges (40.9%), Senators (41.0%), and billionaires (45.0%) had similarly high percentages within the top 1%. The exception was the House of Representatives (20.6%). These findings show that a large percentage of the groups of people who had reached the pinnacle of occupational attainment within America (average age ranging from 56 to 66) were highly able when retrospectively assessed at age 17.

8. Discussion

8.1. Cognitive ability matters even within the top one percent

These findings illustrate that cognitive ability matters even within the top 1%. The idea that ability no longer matters after a certain point—or the existence of an ability threshold (e.g., Gladwell, 2008)—is not supported by the analyses in Tables 1 and 2 within SMPY and across four cohorts of Project Talent. Additionally, when experts in various elite occupational positions within America were examined, a large fraction of them was within the top 1% of ability. Taken together, these findings support the idea that cognitive ability (and especially math ability) is linked to educational and occupational success, even within the top 1%. The fact these educational findings within a sample explicitly drawn from only the top 1% (SMPY) were replicated within a stratified national random sample (Project Talent) shows that at least at the level of higher educational outcomes (e.g., earning a doctorate) there is sufficient ceiling on the ability measures used within the top 1% and 0.5% for population level samples such as Project Talent.

8.2. Retrospective data may not give the same picture as prospective data

Using prospective longitudinal data from SMPY and Project Talent showed that groups in the top 1% had educational outcomes at a level markedly above the general population and that ability is important even within the top 1% for earning a doctorate. However, findings from SMPY (e.g., Benbow et al., 2000; Lubinski & Benbow, 2006; Wai et al., 2005) have also demonstrated that even within the top 1% and 0.5% the educational and occupational achievements are at a high level across multiple domains. For example, ability differences within the top 1% have been shown to make a difference not only in the attainment of doctorates, but also income, patents, publications, and even tenure at a top university (Park, Lubinski, & Benbow, 2007; Wai et al.,

Table 3
General ability and education level among Fortune 500 CEOs, federal judges, billionaires, Senators, and members of the House of Representatives.

	Sample size (N)	Elite school (Top 1%)	Graduate school	College	NR/NC
Fortune 500 CEOs	500	38.6%	28.4%	27.2%	5.8%
Federal judges	789	40.9%	59.1%	–	–
Billionaires	424	45.0%	11.6%	31.4%	12.0%
Senators	100	41.0%	42.0%	16.0%	1.0%
House of Representatives	441	20.6%	47.5%	30.8%	0.9%

Note. Table adapted from Wai (2013). Elite school = person attended one of the top schools for either undergraduate or graduate school according to the *U.S. News* rankings which reasonably indicates top 1% in ability status. Graduate school = percentage that attended graduate school. College = percentage that attended college. NR/NC = percentage that did not report any education or had no college. The Elite School, Graduate School, College, and NR/NC categories are independent of one another and sum to 100%. No information was available in the College and NR/NC categories for federal judges because all had obtained a JD.

2005). In particular, findings within the top 0.01% (Kell, Lubinski, & Benbow, 2013) document that many of these participants have reached levels of achievement near the level of America's elite examined in Study 2, but in multiple areas at a younger age. For example, Kell et al. (2013, Table 2) report participants becoming CEO's and vice presidents of companies, high level attorneys and physicians, professors at top universities, senior engineers, and other directors. Because the participants from SMPY were selected only on ability at a young age, other factors such as ability pattern, interests, drive, and other characteristics became influential in determining which area they chose to achieve within (Robertson, Smeets, Lubinski, & Benbow, 2010). Using prospective data with groups selected on ability alone therefore results in expertise attainment spread across multiple domains. And this achievement may not be at the very top of those domains unless you examine only the group at the pinnacle of ability (i.e., the top 0.01%; Kell et al., 2013).

Using retrospective longitudinal data on groups of experts such as those in Study 2 showed a different picture. Many of the people who end up as Fortune 500 CEOs, federal judges, billionaires, Senators, and House members are extraordinary on multiple traits, not just cognitive ability. This is important to keep in mind because those individuals retrospectively found to be in the top 1% of ability were already highly selected for other traits such as motivation and willingness to work and were not necessarily representative of the roughly three million other American individuals in the top 1% of ability in 2012.[2] What this shows is that when you select solely on specific domains of elite achievement or expertise, you end up getting ability levels that appear somewhat different than when you examine them prospectively. As Gardner (1984, pp. 64–65) has pointed out, "Performance in later life places rather heavy emphasis on precisely those attributes not measured by scholastic aptitude and achievement tests—zeal, character, judgment, staying power, and so on." Despite this, in four of the five groups, people in the top 1% in ability were roughly 40 times overrepresented among these groups, and billionaires who earned their wealth in multiple domains exhibited a similar pattern as the other groups. This shows general intelligence is central to many forms of talent and expertise acquisition (Humphreys, 1998; Jensen, 1998; Lubinski, 2004).

9. Limitations of this study

Ericsson and Charness (1995, p. 803) have stated "We prefer to attribute the development of even such prerequisite abilities to extensive prior experience and relevant activities. Such engagement may be sufficient to account for any individual differences prior to the start of training." Although it could be argued that abilities measured at an early age like those reported in this study are due to extensive prior experience or training, at least in part, it is not likely that these abilities are entirely due to prior experience, for the following reasons. First, the heritability of *g* (Bouchard, 2004; Neisser et al., 1996), math ability (Benbow, 1988; Petrill, Kovas, Hart, Thompson, & Plomin, 2009), and reading ability (Plomin, Shakeshaft, MacMillan, & Trzaskowski, 2013) is consistently high and these estimates are based on large samples and have been replicated many times. Second, individual differences in *g* cannot be reasonably attributed to deliberate practice, because such practice must occur in a specific domain. However, other traits, parent or tutor involvement, or even social class effects, cannot be entirely ruled out as contributing to the development of the abilities measured at an early age in this paper. Therefore, the most reasonable conclusion is that these abilities are developed over time (Lohman, 2006) and are due to both genetics and the environment.

It could also be argued that the outcomes in Study 1 (the earning of doctorates in SMPY and Project Talent) are not really measures of expert performance and therefore this study is not relevant to the discussion of expert performance. However, it is likely that problems with the validity of indices such as earning a doctorate should lead to an underestimate of the importance of cognitive ability. For example, someone with a relatively lower level of general ability may earn a PhD because of a good advisor; whereas someone with a relatively higher level of general ability may fail to do so because of a bad advisor. Thus, the true relationship between cognitive ability and earning a doctorate may even be stronger than Study 1 suggests. Findings from SMPY have also demonstrated that cognitive ability predicts more rarified outcomes such as patents, publications, and university tenure (Park et al., 2007; Wai et al., 2005), and Kell et al. (2013, see Figs. 1, 2, and 3) show the multifaceted areas of occupational expertise that people in the top 0.01% of cognitive ability end up in. Finally, the earning of a doctorate is a critical first step in the development of expertise in many domains.

The data on doctorates obtained in Project Talent were self-report. However, the data on doctorates and many other outcome variables were both self-report and independently verified using online search engines (see Park et al., 2007). Given that the patterns of findings across SMPY and Project Talent are nearly identical, it is highly unlikely that the self-report data is inaccurate.

Finally, Study 2 used average standardized test scores of a college or university according to the *U.S. News & World Report* (America's Best Colleges, 2013) as an approximation for ability level. Although this method did not rely on individual cognitive ability scores which were not publicly available, average test scores reasonably placed individuals that attended one of these elite schools (see Table 1 of Wai, 2013) within the top 1% of ability. However, using this method may give an underestimate because extremely smart people may not have chosen to attend a top school for multiple reasons (e.g., financial limitations, scholarship, and staying close to home). Alternatively, this method may also give an overestimate because there were likely some legacies, athletic admits, and those with political connections or others who were admitted with lower than typical test scores and academic metrics (Espenshade & Radford, 2009; Golden, 2006). Overall, the method appears reasonable as factors in both directions likely counterbalance one another.

10. Conclusion: talent matters, but so does practice

Ericsson and Charness (1994, p. 730) noted that in domains of expertise requiring thinking (e.g. chess) the

[2] According to the U.S. Census Bureau (2012b), in July 2012 the U.S. population was 313,914,040. One percent of this is 3,139,140 people within the top 1% of ability.

average IQ of experts was higher on average compared to the general population. However, they went on to argue that "IQ does not reliably discriminate the best adult performers from less accomplished adult performers in the same domain." However, a number of authors have found that IQ reliably discriminates the best from the rest in the same domain (Grabner, Stem, & Neubauer, 2007; Luce, 1965; Salis, 1977; see Hambrick et al., 2013 for a review). This study adds to this body of evidence by using prospective sources of longitudinal data, showing that even ability differences within the top 1% discriminate between the best adult performers in the educational domain (which requires a great deal of thinking). However, the conclusions reached by Ericsson and Charness (1994) may be due in part to what Humphreys (1998, p. 418) has pointed out: "Hard work and practice do become relatively more important in populations drastically restricted in range of talent or intelligence." Given that the majority of the expertise literature relies on retrospective data that may often be restricted in intelligence range, perhaps it is not surprising that researchers (Ericsson & Charness, 1994; Ericsson et al., 1993, 2007; Howe et al., 1998) who emphasize the importance of deliberate practice have concluded that cognitive ability plays little to no role (Detterman et al., 1998). Of course, although cognitive ability is central to many forms of talent and expertise acquisition, its relative importance likely varies depending upon the domain. This paper shows that combining multiple samples of prospective and retrospective longitudinal data helps provide a more complete picture regarding the role of talent and deliberate practice in the acquisition of expertise. Using this methodology, along with accounting for the large body of evidence documenting that we are not simply products of our environments (Benbow, 1988; Bouchard, 2004; Epstein, 2013; Neisser et al., 1996; Petrill et al., 2009; Plomin et al., 2013), can help us recognize the obvious fact that it is true that every expert is developed or made. But first, they are born.

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References

America's Best Colleges (2013). Retrieved March, 2013 from. http://www.usnews.com/rankings

Benbow, C. P. (1988). Sex differences in mathematical reasoning ability among the intellectually talented: Their characterization, consequences, and possible explanations. *The Behavioral and Brain Sciences*, *11*(169–183), 225–232.

Benbow, C. P., Lubinski, D., Shea, D. L., & Eftekhari-Sanjani, H. (2000). Sex differences in mathematical reasoning ability at age 13: Their status 20 years later. *Psychological Science*, *11*, 474–480.

Bouchard, T. J., Jr. (2004). Genetic influence on human psychological traits: A survey. *Current Directions in Psychological Science*, *13*, 148–151.

Detterman, D. K., Gabriel, L. T., & Ruthsatz, J. M. (1998). Absurd environmentalism. *The Behavioral and Brain Sciences*, *21*, 411–412.

Epstein, D. (2013). *The sports gene: Inside the science of extraordinary athletic performance.* New York, NY: Penguin Group.

Ericsson, K. A., & Charness, N. (1994). Expert performance: Its structure and acquisition. *American Psychologist*, *49*, 725–747.

Ericsson, K. A., & Charness, N. (1995). Expert performance: Its structure and acquisition: Reply. *American Psychologist*, *50*, 803–804.

Ericsson, K. A., Krampe, R. T., & Tesch-Romer, C. (1993). The role of deliberate practice in the acquisition of expert performance. *Psychological Review*, *100*, 363–406.

Ericsson, K. A., Prietula, M. J., & Cokely, E. T. (2007). The making of an expert. *Harvard Business Review*, 1–8.

Espenshade, T. J., & Radford, A. W. (2009). *No longer separate, not yet equal: Race and class in elite college admission and campus life.* Princeton, NJ: Princeton University Press.

Frey, M. C., & Detterman, D. K. (2004). Scholastic assessment or g? The relationship between the SAT and general cognitive ability. *Psychological Science*, *15*, 373–378.

Gardner, J. W. (1984). *Excellence: Can we be equal and excellent too?* New York: W. W. Norton & Company.

Gladwell, M. (2008). *Outliers: The story of success.* New York: Little, Brown & Co.

Golden, D. (2006). *The price of admission.* New York, NY: Three Rivers Press.

Grabner, R. H., Stem, E., & Neubauer, A. C. (2007). Individual differences in chess expertise: A psychometric investigation. *Acta Psychologica*, *124*, 398–420.

Hambrick, D. Z., Oswald, F. L., Altmann, E. M., Meinz, E. J., Gobet, F., & Campitelli, G. (2013). Deliberate practice: Is that all it takes to become an expert? *Intelligence*.

Howe, M. J. A., Davidson, J. W., & Sloboda, J. A. (1998). Innate talents: Reality or myth? *The Behavioral and Brain Sciences*, *21*, 399–442.

Humphreys, L. G. (1998). General intelligence is central to many forms of talent. *The Behavioral and Brain Sciences*, *21*, 418.

Jensen, A. R. (1998). *The g factor: The science of mental ability.* Westport, CT: Praeger.

Kell, H., Lubinski, D., & Benbow, C. P. (2013). Who rises to the top? Early indicators. *Psychological Science*, *24*, 648–659.

Koenig, K. A., Frey, M. C., & Detterman, D. K. (2008). ACT and general cognitive ability. *Intelligence*, *36*, 153–160.

Kuncel, N. R., Hezlett, S. A., & Ones, D. S. (2004). Academic performance, career potential, creativity, and job performance: Can one construct predict them all? *Journal of Personality and Social Psychology*, *86*, 148–161.

Lohman, D. F. (2006). *Identifying academically talented minority students.* Draft of a monograph prepared for the National Research Center on the Gifted and Talented (Retrieved March 21, 2013 from http://development.education.uiowa.edu/facultywebsite/docs/dlohman/Identifying_Academically_Talented.pdf)

Lubinski, D. (2004). Introduction to the special section on cognitive abilities: 100 years after Spearman's (1904) "'general intelligence', objectively determined and measured". *Journal of Personality and Social Psychology*, *86*, 96–111.

Lubinski, D., & Benbow, C. P. (2000). States of excellence. *American Psychologist*, *55*, 137–150.

Lubinski, D., & Benbow, C. P. (2006). Study of mathematically precocious youth after 35 years: Uncovering antecedents for the development of math–science expertise. *Perspectives on Psychological Science*, *1*, 316–345.

Luce, J. R. (1965). Sight-reading and ear-playing abilities as related to instrumental music students. *Journal of Research in Music Education*, *13*, 101–109.

Murray, C. (2012). *Coming apart: The state of white America, 1960–2010.* New York: Crown Forum.

Neisser, U., Boodoo, G., Bouchard, T. J., Boykin, A. W., Brody, N., Ceci, S. J., et al. (1996). Intelligence: Knowns and unknowns. *American Psychologist*, *51*, 77–101.

Park, G., Lubinski, D., & Benbow, C. P. (2007). Contrasting intellectual patterns predict creativity in the arts and sciences. *Psychological Science*, *18*, 948–952.

Petrill, S. A., Kovas, Y., Hart, S. A., Thompson, L. A., & Plomin, R. (2009). The genetic and environmental etiology of high math performance in 10-year old twins. *Behavioral Genetics*, *39*, 371–379.

Plomin, R., Shakeshaft, N. G., MacMillan, A., & Trzaskowski, M. (2013). Nature, nurture, and expertise. *Intelligence*.

Robertson, K. F., Smeets, S., Lubinski, D., & Benbow, C. P. (2010). Beyond the threshold hypothesis: Even among the gifted and top math/science graduate students, cognitive abilities, vocational interests, and lifestyle preferences matter for career choice, performance, and persistence. *Current Directions in Psychological Science*, *19*, 346–351.

Salis, D.L. (1977). The identification and assessment of cognitive variables associated with reading of advanced music at the piano (unpublished doctoral dissertation). Pittsburgh, PA: University of Pittsburgh.

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Schmidt, F. L., & Hunter, J. E. (2004). General mental ability in the world of work: Occupational attainment and job performance. *Journal of Personality and Social Psychology*, *86*, 162–173.

Simonton, D. K. (1999). Talent and its development: An emergenic and epigenetic model. *Psychological Review*, *104*, 66–89.

U.S. Census Bureau (1979). Table 2. Years of school completed by persons 18 years old and over, by single years of age, race, Spanish origin and sex: March 1979. Retrieved August 23, 2013 from. http://www.census.gov/hhes/socdemo/education/data/cps/1979/tab-02.pdf

U.S. Census Bureau (2012a). Table 2. Educational attainment of the population 25 years and over, by selected characteristics: 2012. Retrieved August 23, 2013 from. http://www.census.gov/hhes/socdemo/education/data/cps/2012/tables.html

U.S. Census Bureau (2012b). Population of the United States as of July 2012. Retrieved March 26, 2013 from. http://quickfacts.census.gov/qfd/states/00000.html

Wai, J. (2013). Investigating America's elite: Cognitive ability, education, and sex differences. *Intelligence*, *41*, 203–211.

Wai, J., Lubinski, D., & Benbow, C. P. (2005). Creativity and occupational accomplishments among intellectually precocious youths: An age 13 to age 33 longitudinal study. *Journal of Educational Psychology*, *97*, 484–492.

Wai, J., Lubinski, D., & Benbow, C. P. (2009). Spatial ability for STEM domains: Aligning over fifty years of cumulative psychological knowledge solidifies its importance. *Journal of Educational Psychology*, *101*, 817–835.

Wise, L. L., McLaughlin, D. H., & Steel, L. (1979). *The Project TALENT data bank*. Palo Alto, CA: American Institutes for Research.

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