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The plateauing of cognitive ability among top earners

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Are the best-paying jobs with the highest prestige done by individuals of great intelligence? Past studies find job success to increase with cognitive ability, but do not examine how, conversely, ability varies with job success. Stratification theories suggest that social background and cumulative advantage dominate cognitive ability as determinants of high occupational success. This leads us to hypothesize that among the relatively successful, average ability is concave in income and prestige. We draw on Swedish register data containing measures of cognitive ability and labour-market success for 59,000 men who took a compulsory military conscription test. Strikingly, we find that the relationship between ability and wage is strong overall, yet above €60,000 per year ability plateaus at a modest level of +1 standard deviation. The top 1 per cent even score slightly worse on cognitive ability than those in the income strata right below them. We observe a similar but less pronounced plateauing of ability at high occupational prestige.

Introduction

Scholars of cultural consecration and commemoration document how the most successful members of our society are commonly attributed exceptional talents in documentaries, biographies, and hall-of-fame elections (Bourdieu, 1984; Lang and Lang, 1988; Allen and Lincoln, 2004; Allen and Parsons, 2006; Watts, 2011; van de Rijt *et al.*, 2013). Experiments show that people readily infer the possession of extreme skill from the achievement of extreme success (Baron and Hershey, 1988; Gilbert and Malone, 1995; Denrell and Liu, 2011). Academics themselves have also explained extremely successful careers in terms of the superior intelligence of the individuals involved (Pareto, 1916; Domhoff, 1967; Rosen, 1981; Neal and Rosen, 2000; Murray, 2003; Rahman Khan, 2012; Mankiw, 2013). But do the highest earners and those with the most prestigious jobs indeed have the greatest minds?

Elite jobs are of special interest, for two reasons. First, income distributions have strong right skew. In all Western countries, top income shares have been steadily rising since the 1980s, with the 1 per cent highest earners receiving 9 per cent of national income in Sweden and even 20 per cent in the United States—excluding capital gains (Piketty, 2014; Alvaredo *et al.*, 2017; Statistics Sweden, 2020). This extremity of top incomes as well as their public salience render it crucial that they be earned by very capable individuals. Second, those with the most prestigious jobs wield the greatest economic and political power, and the intelligence of their decisions is consequential.

While scholars debate the origins and measurement of cognitive ability as well as the causal mechanisms linking it to labour-market success, there is a broad theoretical and empirical consensus that expected wages and occupational prestige monotonically increase in cognitive ability. But how, conversely, average ability varies with job success has not been systematically investigated. The present paper departs from prior work by swapping the axes, focusing on the relative intelligence of those with better jobs.

Drawing on arguments from the sociological literatures on stratification and cumulative advantage we propose that the ability—success relationship attenuates at high levels of success. In other words, we hypothesize that there are starker ability differences

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between adjacent ranks at moderate levels of income and prestige than at the highest levels. Our argument draws on the role of two key non-meritorious determinants of occupational success: Family resources and luck. The class- and network-advantages of those with elite family backgrounds are assumed instrumental for gaining access to the most privileged and best-paying jobs (Bourdieu, 1984; Lamont, 1994; Rivera, 2015; Friedman and Laurison, 2020). Second, rich-get-richer processes are assumed to allow inequalities in job success to grow between those who got a lucky break early in the career and those who did not (Merton, 1968; DiPrete and Eirich, 2006; Salganik, Dodds and Watts, 2006; Bol, de Vaan and van de Rijt, 2018). Our argument relies on these two determinants of occupational success, family resources and luck, having distributions in which extremely high values are common (Denrell and Liu, 2011; Frank, 2016). Because extreme ability is rare, extreme occupational success is more likely driven by family resources or luck than by ability. Hence, at higher levels of occupational success additional degrees of success will be less and less associated with greater ability. We illustrate this argument using a model by Denrell and Liu (2011).

While past studies have shown positive direct and indirect effects of cognitive ability on wage earnings (Coward and Sackett, 1990; Herrnstein and Murray, 1994; Ng *et al.*, 2005; Strenze, 2007; Ganzach *et al.*, 2013; Lubinski, 2016; Jokela *et al.*, 2017; Gensowski, 2018), they have not systematically studied the relative ability of top earners. This gap in the literature is mostly driven by data restrictions: examining the precise cognitive ability levels at all levels of labour-market success requires a representative and comprehensive dataset that has good coverage also of very successful individuals—especially top income data is often missing in survey data. In this article, we analyse Swedish register data on 59,000 men who took a mandatory cognitive-ability test at age 18–19, allowing detection of minute average ability differences between adjacent levels of occupational success with representative data. Our focus on men is an issue of data availability because only men took the conscription-related ability test. We discuss this limitation in the concluding section and invite further research that includes all members of society.

Literature

The empirical relationship between cognitive ability and job success

While 'cognitive ability' lacks a generally agreed upon definition, it is broadly used to indicate the capacity of the brain to perform a variety of cognitive tasks, including verbal understanding, technical comprehension, spatial ability, and logic (Borghans *et al.*, 2016). Such skills are thought to be partly learned, partly genetically determined, and partly acquired through interaction between genes and social environments. A sizeable literature has explored how wages are correlated with measures of cognitive ability (for overviews, see Ng *et al.*, 2005; Strenze, 2007). Among the relatively few studies that use direct measures of cognitive ability, the consistent result is that individuals with greater cognitive ability earn on average higher wages. In their book *The Bell Curve*, Herrnstein and Murray (1994) find that general cognitive ability is positively correlated with various indicators of labour-market success. Jensen (1998) also finds a positive correlation between test scores on a cognitive aptitude test and wage earnings. A meta-study by Strenze (2007) finds an average bivariate correlation of 0.23 on the basis of a large number of datasets containing labour-market earnings and cognitive ability measures. Achievement tests such as the Armed Forces Qualifications Test (AFQT) have been found to correlate more strongly with wages than tests of general intelligence (IQ) as the former capture closely related personality characteristics also relevant for job-market success (Fischer *et al.*, 1996; Borghans *et al.*, 2016). Several studies (Lubinski, 2016; Gensowski, 2018) have examined the popular claim by Gladwell (2008) that above some threshold level of cognitive ability further increases in ability would not matter for job success. Predicting occupational success from cognitive ability in multivariate regression they reject this thesis, finding a strictly monotonic relationship, with the very smartest being the most successful.

To the best of our knowledge, there are no empirical studies that systematically probe cognitive ability at different levels of occupational success. Several studies have looked at traits of highly successful people. Wai (2013) uses elite US college attendance as a proxy for extraordinary intelligence based on the logic of very high SAT score requirements for elite college entry. He finds that roughly 40 per cent of Fortune 500 CEOs, federal judges, billionaires, and Senators have elite college degrees. However, high school grades and achievement tests have been found to be significantly impacted by other factors besides cognitive ability such as family background and personality traits (e.g. Borghans *et al.*, 2016). Several studies find that top jobs in the private sector are not characterized by excessive cognitive ability. Bihagen, Nermo and Stern (2013), using direct measures of cognitive ability provided by Swedish register data, find a relatively minor role of cognitive ability in the explanation of elite-position occupancy in business firms. Adams, Keloharju and Knüpfer (2018), also using Swedish register data, find that the median

CEO of a large company ranks in the 83rd percentile of cognitive ability. Antonakis, House and Simonton (2017) find a mean IQ of 111 (less than a standard deviation above average) among mid-level executives from various Western countries.

To sum up, existing empirical studies find that labour-market success monotonically increases with cognitive ability. As far as we know, no prior study has systematically evaluated how cognitive ability expectations vary with labour-market success.

Theoretical mechanisms linking wage to family background

A vast body of work in the sociology of stratification finds that individuals in the right tail of the wage distribution often come from advantageous social backgrounds (Breen and Jonsson, 2007; Grusky, 2019). Sociologists have emphasized the relatively important role of parental socio-economic background vis-à-vis cognitive ability as wage determinant. Most prominently, in a reaction to *The Bell Curve*, Fischer *et al.* rejected the unidimensional focus on intelligence for explaining inequality in society, and argued that Herrnstein and Murray 'err in asserting that [intelligence] largely determines how people end up in life' (Fischer *et al.* 1996: p. 10). In contrast, the authors argue that, while genetic traits are important, the most important factor is the 'social milieux in which people grow up and live' (Fischer *et al.*, 1996: p. 9). More recent research has theorized and sought to evidence a variety of pathways through which social background and cognitive ability may co-determine occupational success.

A primary pathway through which socio-economic background impacts occupational success is education. In the human capital literature, wage differences are assumed to be driven by variation in human capital (Mincer, 1958). Wage is typically assumed to be a log-linear function of education and experience (Mincer, 1958; Heckman, Stixrud and Urzua, 2006; Jones and Schneider, 2006; Lemieux, 2006; Gensowski, 2018). Also in studies on social reproduction, education is a key mechanism. Educational credentials are more easily observed than ability, and several studies show that employers select strongly on the former (Collins, 1979; Barone and Van de Werfhorst, 2011; Di Stasio and Van de Werfhorst, 2016). It is well-known that the educational system does not grant all children equal opportunities for attaining high qualifications (Breen and Jonsson, 2007; Brand and Xie, 2010; Torche, 2011; Jackson, 2013; Bernardi, 2014). In a conflict-sociological perspective, educational degrees serve as crucial instruments in maintaining class barriers (Collins, 1979). Often these barriers become institutionalized, and educational degrees are formally required to enter occupations (Weeden, 2002). Studying Sweden, Erikson (2016) finds that cognitive ability accounts for about one third of the variance in educational attainment, whereas parental background explains about 20 per cent. Social background plays an important role in determining who ends up where in the education system (Breen and Jonsson, 2007), and thereby also where in the wage distribution. In a similar vein, Bowles and Gintis (2002) argue that cognitive skills only play a minor role in explaining the relation between education and earnings (about 20 per cent). In their cross-national study, Barone and Van de Werfhorst (2011) find that this portion is larger (32–60 per cent), but nevertheless argue that income differences are driven by factors unrelated to ability. In a field experiment, Gaddis (2015) finds that students from elite universities obtain a labour market premium for their educational degree. Wealthy families may thus be able to reproduce their advantage across generations by being able to pay for enrolment in elite institutions.

Wage may also be impacted by socio-economic background through an increase in cognitive ability, which in turn impacts education. Some have found a heritability factor in intelligence (Bowles and Gintis, 2002; Nisbett *et al.*, 2012), with part of the socio-economic inequality in educational and labour-market outcomes driven by inequality in genetic factors (Conley and Fletcher, 2017; Belsky *et al.*, 2018). However, only a small portion of parent-child correlations in education may be due to genetic transmission (Conley *et al.*, 2015). It has also been suggested that genetic endowments have larger effects on cognition for children born into higher socio-economic classes (Scarr-Salapatek, 1971; Rowe *et al.*, 1999), but evidence is equivocal (Fischbein, 1980; Guo and Stearns, 2002; Figlio *et al.*, 2017; Baier and Lang, 2019; Gottschling *et al.*, 2019). Yet differently, being raised in a poor neighbourhood has been found to impact one's cognitive ability (McCulloch and Joshi, 2001) and that of one's children (Sharkey and Elwert, 2011). Wealthy parents prevent such adverse effects on their children by living in better neighbourhoods.

Family background may also impact occupational success net of education (Torche, 2011, 2018; Falcon and Bataille, 2018; Oh and Kim, 2020). Laurison and Friedman (2016) and Friedman and Laurison (2020) show that individuals with a higher class background obtain higher wages than those from a lower class background, keeping their educational level constant. Bernardi and Gil-Hernández (2021) find that this direct effect of social origin is stronger among those with higher levels of education. One mechanism through which socio-economic background may impact occupational success net of education is the cultural capital that individuals gain from home (Bourdieu, 1984). Those from privileged backgrounds are thought to be more likely to occupy privileged positions themselves because their cultural backgrounds provide a leg up in the educational system and subsequently the labour market (Bourdieu and Passeron, 1979; Lareau, 2011). The acquisition of high-status positions would require mastering the right tastes, behaviours, and customs. Such subtle and elaborate displays of sophistication are naturally taught during upbringing in some families. Cultural capital might thus push children from higher social classes into steeper career trajectories (Lamont, 1994). Cultural tastes may also indirectly affect careers through the ability to build more extensive networks to important others (Lizardo, 2006).

An accelerator of social-capital effects on job success is the fact that skill requirements and recruitment processes for top jobs are less transparent and objective than those for intermediate-level jobs. Some note that in top management, hiring, and wage setting is often done by peers (Bebchuk, Fried and Walker, 2002; DiPrete, Eirich and Pittinsky, 2010; Piketty, 2014: pp. 331–332). Such lack of transparency and objectivity provides room for factors unrelated to cognitive ability to determine appointment decisions (Clauset, Arbesman and Larremore, 2015; Rivera, 2015; Laurison and Friedman, 2016). In a case study of hiring practices for elite positions, Rivera (2012) finds that decisions are only rarely based on competence assessments but largely on cultural tastes. Similarly, Friedman and Laurison (2020) argue that access to elite positions in the United Kingdom is to a large extent explained by having the right tastes and right connections.

In sum, then, while the causal pathways through which family background and cognitive ability may co-determine career success are varied, the literature suggests that net of cognitive ability, the resources elite families provide play an important role in the attainment of top jobs.

Theoretical mechanisms linking wage to cumulative advantage

Earning an extremely high wage may also be a telltale sign of luck. Frank (2016) illustrates the relative importance of luck in competitive labour markets using a simulated hiring tournament in which individuals' ability and luck are independently drawn numbers (from the same 0 to 100-interval), and their weighted sum determines a contestant's chance to land a scarce high-income job. Even under a strongly performance-based calibration of the model in which ability accounts for 98 per cent of individuals' achievement and luck accounts for the remaining 2 per cent, most winners (78 per cent) do not have the highest ability scores.

The role of luck may be enhanced through a process of cumulative advantage (Coleman, 1964; Allison, 1980; DiPrete and Eirich, 2006), whereby an initial resource advantage of one individual over another skews also the subsequent allocation of successes in favour of that individual. As a result, small initial success differences between individuals are not cancelled out over time but instead grow into winner-take-all distributions characterized by extreme inequalities. When individuals with great talent compete in a market that can only sustain a few winners, cumulative advantage processes following chance events may determine the difference between moderate and great success (Adler, 1985; Salganik, Dodds and Watts, 2006; Keuschnigg, 2015). In its most problematic form, cumulative advantage is capable of perpetuating a random advantage of a less able over a more able individual (Arthur, 1994; Lynn, Podolny and Tao, 2009). This may for example happen when labour market contexts vary in the degree to which they enable chance and cumulative advantage to determine outcomes, so that extreme success becomes a marker of luck (Denrell and Liu, 2011).

Empirically, cumulative (dis-)advantage has been investigated as temporal relationships between various career and health outcomes (e.g. Heckman and Borjas, 1980; O'Rand, 1996; Dannefer, 2003; Gangl, 2004; Willson *et al.*, 2007; Mazoni *et al.*, 2014; Birkelund *et al.*, 2017; Huckfeldt, 2022). Studies generally find a positive effect of past on future unemployment and a negative effect on future wages. Cumulative advantage has also been investigated in specific sectors such as academic careers. Early work looked for growing cohort inequality in citations and publications, with mixed results (Allison *et al.*, 1982). More recent studies have employed quasi-causal designs to identify cumulative advantage effects (Azoulay *et al.*, 2014; Bol, de Vaan and van de Rijt, 2018; Wang *et al.*, 2019).

Theoretical expectations

The model proposed by Denrell and Liu (2011) from which we derive our main hypothesis linearly relates generic notions of performance P_i, skill u_i and noise e_i for individuals i:

$$P_i = u_i + e_i$$

Of interest is how expected skill changes with performance. Denrell and Liu vary how common extremely high and extremely low values of skill and noise are (i.e. the kurtosis and thus fat-tailedness of the respective distributions). They do so by assuming that an individual's skill u_i and noise e_i are drawn from normal distributions with zero mean and individual-specific standard deviations. The more varied these standard deviations are across individuals, the more common extreme values are. Specifically, an individual's standard deviation of the skill distribution is drawn from a gamma distribution with a shape parameter $s > 0$ and scale parameter

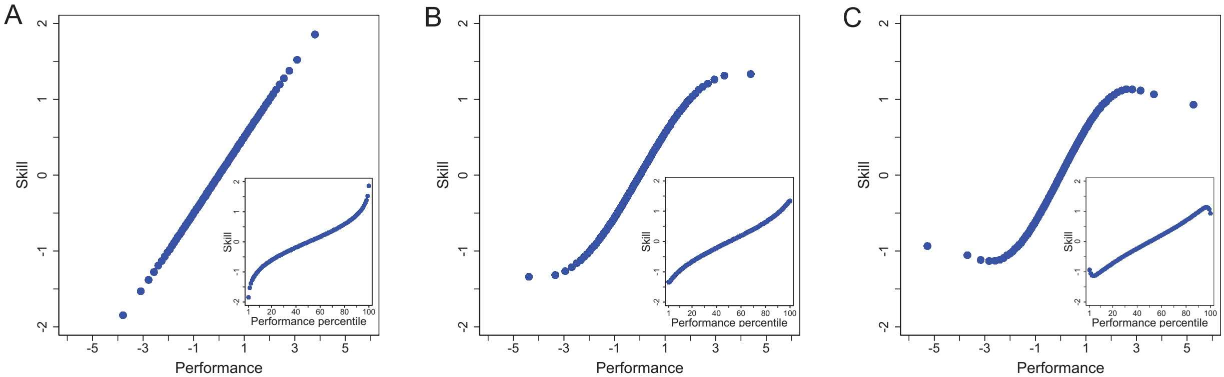

Figure 1 Expected skill by performance. One hundred blue dots represent the mean skill and mean performance of each performance percentile of a population of 59,387 agents, averaged across 100 simulation runs of the Denrell and Liu model with $s = 100$. The insets show the same results but with the horizontal axis rescaled to measure performance percentiles. (**A**) Results when extreme values of noise happen rarely ($n = 100$). (**B**) Results when extreme values of noise happen occasionally ($n = 5$). (**C**) Results when extreme values of noise happen often ($n = 2$).

$1/s$. Similarly, an individual's standard deviation of the noise distribution is drawn from a gamma distribution with a shape parameter $n > 0$ and scale parameter $1/n$. Lower values of s and n correspond to greater heterogeneity in respectively skill and noise. This method for varying the prevalence of extreme values through individual heterogeneity permits the natural interpretation that the importance of skill and noise depend on contextual factors specific to individuals' environments. For example, skill may play a greater role in sports and research, while inherited wealth and luck may play a larger role in the determination of success in business and investment. Alternatively, we can interpret the model to implement the sharing of a single environment by all individuals in which s and n determine how common outliers in skill and noise are.

Denrell and Liu find that the more outliers the noise distribution has relative to the skill distribution, the less top performance is indicative of extraordinary skill. In Figure 1 we fix s at 100, so that outliers are rare. The distribution of skill is then approximately standard normal, and skill is conveniently measured in z-scores. Across panels A, B, C we reduce n, thereby increasing the role of noise in the production of extreme performance values. In panel A, n equals 100 so that the distribution of noise is also approximately normal and outliers in noise are as rare as outliers in skill. In this scenario, skill monotonically increases with performance. The 1 per cent best performers, denoted by the right-most blue dot, are superstars who are on average nearly two standard deviations more skilled than the average person (Rosen, 1981). The inset of panel A shows how, when the horizontal axis is rescaled to represent performance percentiles, the relationship is convex on the right: The difference in average skill between adjacent percentiles increases at the top.

As n decreases, top performance is increasingly the product of extreme luck rather than extreme skill. In panel B, for example, where n equals 5, so that outliers in noise are more common, at intermediate levels, performance is as indicative of skill as it was in panel A. However, there is now a point beyond which further increases in performance no longer indicate noticeably greater skill. (And similarly, there is a point below which further decreases in performance do not indicate a further lack of skill.) Skill peaks at somewhat over one standard deviation above the mean.

In panel C, where n equals 2, and outliers in noise are even more common, the correspondence between performance and skill at intermediate levels of performance is again as strong as before, but at high levels of performance skill now *declines* as performance rises. The 1 per cent best performers have a moderate skill level that falls short of a standard deviation above the mean.

We then arrive at our hypothesis by considering income and job prestige to represent performance, cognitive ability to represent our key skill variable, and privilege and luck together to constitute the noise variable. We take the literature reviewed in the previous sections to indicate that cognitive ability is approximately normally distributed, suggesting a high value of s, while privilege and luck are characterized by common outliers, implying lower n: Family resources are concentrated in high quantities among a small fraction of elite families (e.g. McDonald and Ransom, 2008) and models of cumulative (dis-)advantage render extreme forms of success and failure common (Coleman, 1964; Allison, 1980; Adler, 1985; DiPrete and Eirich, 2006). Assuming a sufficiently high level of s relative to n it then follows that average cognitive ability ceases to increase beyond a certain job success level.

The Denrell and Liu model was not formulated with our specific application in mind. It assumes that skill and noise are uncorrelated. When applied to our context of interest this is untenable as this, for example, implies that family background and cognitive ability are uncorrelated, which the past evidence we have reviewed before suggests is false. It is to be seen in the empirical analysis whether this simplification is consequential. Another discrepancy is that the performance variable takes on negative values, creating a mismatch with income and prestige which are always positive. We address this by considering performance ranks. Performance ranks are invariant under any monotonic transformation of the performance variable. The insets of Figure 1 show that also the relationship between expected skill and performance *rank* becomes concave as n decreases.

In sum, we have taken a generic model of performance and used theoretical arguments about outliers in the distributions of family resources and luck to derive the result that above some level of occupational success cognitive ability ceases to detectibly increase, and perhaps even decreases. This yields the following hypothesis:

Hypothesis: At high levels of occupational success, cognitive ability is concave in occupational success.

We test this hypothesis both for the wage–ability and the prestige–ability relationship.

Data and measures

Statistics Sweden, the country's central statistical office, assembled micro-data on cognitive ability, socio-economic background, education, wage, and occupational prestige for us by merging administrative population registers. The data are collected and directly reported by government agencies, including tax authorities, educational institutions, and the military. Missing data are virtually non-existent and—unlike in population surveys in which most captured households locate in the middle of the wage distribution—the register data are not truncated but cover the entire wage distribution.

Our analysis includes men who joined the labour force between 1991 and 2003 (median 1993). In total, 670,203 men, aged 18–60, entered the labour market in this period to be fully employed for at least 1 year. Cognitive-ability scores are available only for Swedish men who had the obligation to undergo military conscription. We subset on men who took a compulsory conscription test at age 18–19 during 1971–1977 or 1980–1999, years in which ≥90 per cent of each cohort enlisted (94 per cent on average). Enlistment became less comprehensive after 1999 and dropped substantially until its abolition in 2010. We focus on multi-year career success for those men for which we observe 11 years of labour market participation centred around the age of 40 (see below). This leaves us with a full census of 59,387 Swedish-born men for whom we observe a balanced 11-year panel of annual labour-market success.

Cognitive ability

We draw on standardized test results of cognitive ability among male conscripts (see Figure 2A and Table 1 for a description). The Swedish military enlistment procedure consisted of a series of physical, psychological, and intellectual tests all men had to take at age 18–19. Motivation for participation in military service was not a factor for evaluation as avoiding enlistment by obtaining low-ability scores was not possible (Lindqvist and Vestman, 2009). Early-life measurement of cognitive ability circumvents endogeneity problems which may arise when using ability scores measured after job market entry (e.g. Aldén, Hammarstedt and Neuman, 2017): One can plausibly assume that learning on the job is steeper in highly paid jobs and that these learning effects may reduce the role of innate ability in later-life cognitive skills. The enlistment procedure included an assessment of cognitive ability similar to the AFQT used in the United States (Carlsson *et al.*, 2015), which was found a better predictor of wages than IQ test scores (Borghans *et al.*, 2016). There were separate paper and pencil tests for verbal understanding, technical comprehension, spatial ability, and logic. Each test consisted of 40 items presented in order of increasing difficulty and speed (Carlstedt and Mårdberg, 1993) and grades from each dimension were combined into a normally distributed stanine scale ranging from 1 to 9 (Lindqvist and Vestman, 2009). This measure has been frequently used in medical studies (e.g. Åberg *et al.*, 2009) and in the social sciences, for example for assessing managers' intelligence (Adams, Keloharju and Knüpfer, 2018), entrepreneurs' balance in skill sets (Aldén, Hammarstedt and Neuman, 2017), the importance of social origin in achieving promotions to managerial positions (Bihagen, Nermo and Stern, 2013), and the effect of smart teachers on student performance (Grönqvist and Vlachos, 2016). With only minor revisions implemented over the years, this procedure evaluated the same four underlying dimensions of ability throughout the full observation period.

Labour-market success

We consider two success measures, individuals' average annual wage and their average occupational prestige during a 11-year career window (age 35–45)

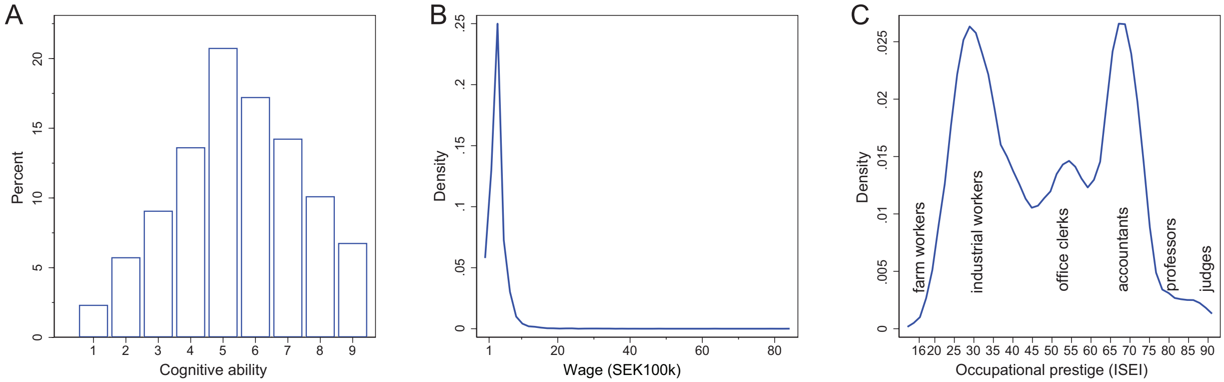

Figure 2 Distributions of cognitive ability, wage, and occupational prestige. (**A**) Relative frequencies of cognitive-ability scores (1–9) measured at age 18–19 in our target population of 59,387 Swedish men. (**B**) Kernel density distribution of multi-year average gross annual wage in 100k Swedish krona (SEK). (**C**) Kernel density distribution of occupational prestige (ISEI); exemplary occupations highlighted for orientation.

Table 1 Description of variables

	Mean	SD	Median	Min	Max	N
Cognitive ability (1–9)	5.45	1.98	5	1	9	59,387
Annual wage (SEK100k)	3.33	2.66	2.89	0	84.40	59,387
Occupational prestige (ISEI)	48.88	17.94	49	16	88	49,022

centred on the age of 40 (Haider and Solon, 2006). We measure annual gross wage—directly reported by employers to the Swedish tax authorities—in hundreds of thousands of Swedish krona (roughly equivalent to units of 10,000 present-day Euros). We include years of part-time employment and of zero-income, and our measure includes bonuses paid out as additional, directly taxable wage income. We adjust annual wages for inflation (using an OECD consumer price index for Sweden, with base year 2012) to make wages comparable between individuals who entered the labour market in different calendar years where the same nominal incomes represent different levels of purchasing power. See Figure 2B and Table 1 for descriptives of the wage variable. To demonstrate the robustness of our findings, we change to snapshot annual wages in individuals' 2nd, 10th, and 20th year of labour-market participation in Appendix A. Because these snapshots do not require a balanced panel of individuals with 11 years of labour-market participation, we can include up to 238,000 earners in these analyses. Our second measure of labour-market success is occupational prestige, measured on the International Socio-Economic Index (ISEI) scale, where higher values indicate occupations with greater social status (Ganzeboom, De Graaf and Treiman, 1992). We obtain ISEI scores from employees' registered occupation which are available for 49,022 employees. Following the above operationalization, we measure individuals' multi-year average occupational prestige (see Appendix A for prestige in the 2nd, 10th, and 20th career year). Ranging from 16 (farm workers) to 90 (judges), ISEI averages 48.9 and density peaks at low (e.g. industrial workers, construction workers), intermediate (e.g. office clerks, policemen), and sub-top levels (e.g. accountants, engineers; see Figure 2C).

Analysis strategy

Our theoretical analysis yielded a hypothesis about the bivariate relationship between labour-market success and expected ability. Accordingly, our analysis strategy is to evaluate the bivariate relationships between wage and occupational prestige on the one hand and average ability on the other. We examine the variables of labour-market success both as absolute scores and, to avoid the problem of different results for different distributional transformations, also as ranks. We exploit the size of our dataset and partition the income distribution into percentile bins, each containing 594 (wage) respectively 490 (prestige) cases.

Results

Figure 3A shows the conditional mean, geometric mean, and median wage for each cognitive-ability score. The figure reproduces the positive effect of ability on wage identified in earlier work (Coward and Sackett, 1990;

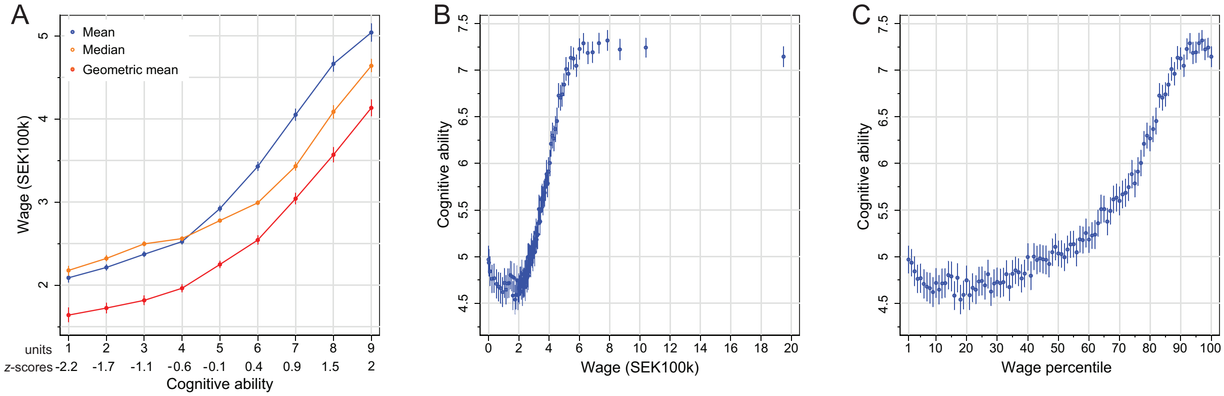

Figure 3 Ability and wage. (**A**) Mean wage (and 95 per cent confidence intervals) by ability units 1–9 and corresponding *z*-scores. (**B**) Mean ability (and 95 per cent confidence intervals) by mean wage per wage percentile. (**C**) Mean ability by wage percentile.

Herrnstein and Murray, 1994; Ng *et al.*, 2005; Strenze, 2007; Jokela *et al.*, 2017). The rank correlation between ability and wage equals $\rho = 0.400$ ($P < 0.001$; $N = 59{,}387$). The monotonicity of the relationship in Figure 3A is consistent with previous studies (Lubinski, 2016; Gensowski, 2018) rejecting the claim that past a certain threshold having even higher cognitive ability does not matter (Gladwell, 2008). The most able Swedish men can expect to make more money than less able others. The substantive magnitude of the relationship is, however, modest, as the worst scoring men on average still earn more than a third of the salary of the best scoring men. The most cognitively able individuals clearly cannot expect outlandish labour-market returns (Rosen, 1981; Frank and Cook, 1995; Borghans and Groot, 1998; Neal and Rosen, 2000; Brynjolfsson and McAfee, 2011; Mankiw, 2013).

Figure 3B flips the axes, conditioning ability on wage to allow an evaluation of the comparative intelligence of top earners. Each dot represents the average ability level for a wage percentile. The figure reveals a marked contrast between the body and the tail of the wage distribution, with a strong correspondence at intermediate wage levels, while above a certain wage level average ability plateaus at an average of around 7.25. This plateauing of the wage–ability relation occurs at approximately SEK600,000 annual wage (about €60,000). In the three top wage percentiles, that earn between SEK800,000 and SEK8,400,000 annually, the relationship even slightly reverses. As in our model simulations (Figure 1C), there are no significant differences in ability between the three top income percentiles, despite there being 594 cases in each percentile bin and despite those in the 100th percentile earning more than double the wage of those in the 98th percentile. This result supports our hypothesis, and it suggests that the inverse of Gladwell's (2008) claim *does* hold: Past a certain wage threshold, having a higher wage is no longer telling of cognitive ability. The average score individuals in the top percentile achieved as adolescents on the cognitive-ability test is 7.15 ± 0.11 (95 per cent confidence interval). On a stanine scale this amounts to less than a standard deviation (+0.86) above average.

Figure 3C shows the same 100 cognitive ability levels but this time expressed with wage percentiles on the horizontal axis. The upper part of the distribution exhibits the predicted concave pattern, just as it does in Figure 3B. This lends further support to our hypothesis.

Figure 4 shows results when using occupational prestige instead of wage as measure of career success. Results are similar as for wage: Figure 4A shows that expected prestige monotonically increases in cognitive ability, with extremely intelligent people having the best job-market prospects. Yet when ability is conditioned on occupational prestige in Figure 4B, we find no systematic pattern in how average cognitive ability varies between those with ISEI scores 70 and above. Individuals in these professions (judges, lawyers, professors, and doctors) achieved an average cognitive-ability test score of 7.13 ± 0.04, which is less than a standard deviation (+0.80) above the mean.

Figure 4C, however, shows that when average cognitive ability levels are expressed with prestige percentiles on the horizontal axis, the upper end of the relationship is neither clearly convex nor clearly concave. The evidence for our hypothesis in the case of occupational prestige is thus weaker than for income.

Appendix A shows that the pattern of plateauing skill at high job success displayed in Figures 3 and 4 is robust when wage and prestige are measured in specific years after entering the job market (2, 10, 20 years) rather than as multi-year averages. An additional analysis in Appendix B shows that the share of men with a maximum ability score of 9 is strictly lower among the 1 per cent than among the percentiles below them,

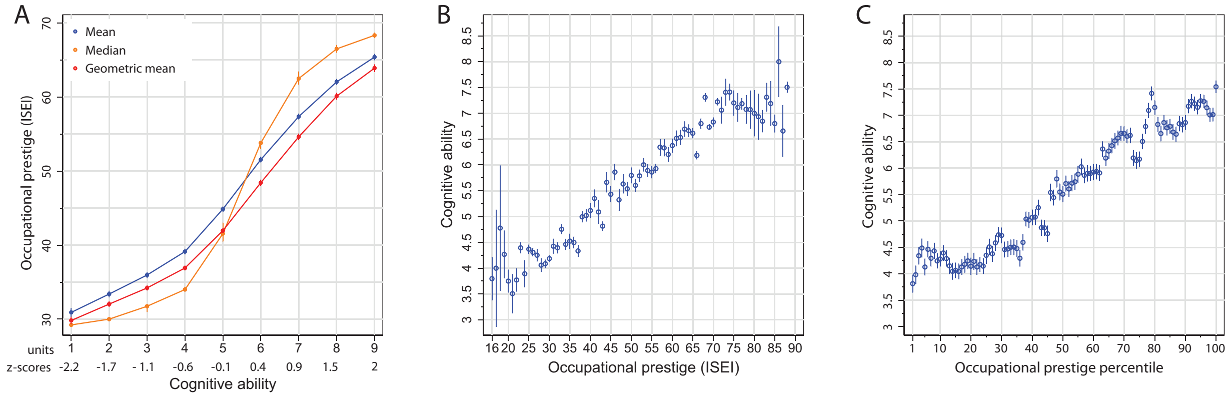

Figure 4 Ability and occupational prestige. (**A**) Mean prestige (and 95 per cent confidence intervals) by ability units 1–9 and corresponding *z*-scores. (**B**) Mean ability (and 95 per cent confidence intervals) by prestige score. (**C**) Mean ability by prestige percentile.

rendering it implausible that a ceiling effect is preventing cognitive ability levels that are off-the-charts from showing up at high levels of job success.

Discussion

The empirical results lend support to our argument that cognitive ability plateaus at high levels of occupational success. Precisely in the part of the wage distribution where cognitive ability can make the biggest difference, its right tail, cognitive ability ceases to play any role. Cognitive ability plateaus around €60,000 at under a standard deviation above the mean. In terms of occupational prestige, it plateaus at a similar level above a job prestige of 70: The differences in the prestige between accountants, doctors, lawyers, professors, judges, and members of parliament are unrelated to their cognitive abilities.

A limitation of our study is that we do not account for effort or non-cognitive capacities—motivation, social skills, creativity, mental stability, and physical ability (Borghans *et al.*, 2016). Cognitive ability is more relevant for some occupations than for others, and academia, for which it is arguably most relevant, is neither the best-paid nor the most prestigious professional field. Our results thus raise the question to what degree top wages are indicative of other, unobserved dimensions of ability. However, omission of effort and non-cognitive ability from the analysis is only problematic for our conclusions about the relationship between ability and success if there are theoretical arguments to be made that their effects dominate luck in the production of top income and prestige, either because their distributions have many extreme values or if there are strongly increasing returns.

Our analysis, further, is limited to a single country. Sweden may be seen as a conservative testing ground. In countries where higher education is less inclusive, one would expect an overall weaker relationship between labour-market success and ability (Breen and Jonsson, 2007). Namely, less income redistribution and steep tuition barriers to elite colleges may impede the flow of gifted individuals from lower classes into top jobs. On the other hand, higher net wages and greater social status at the top may attract more talent, and greater differentiation in college prestige elsewhere may allow firms to select on cognitive skills among those with a college degree by using elite affiliations as a proxy. Future research on different countries may seek to evaluate to what extent our findings generalize.

Third, we limit our analyses to native-born men. This is an unavoidable restriction of the data (women and immigrants were not enrolled in the military), and it is important to learn whether our findings generalize to the full working population. We invite further research that includes women and citizens from different ethnic backgrounds, and we call for careful adjustments in measuring occupational success for different cohorts in light of marked increases in female labour-force participation over time as well as in the share of the immigrant workforce and the varying disadvantages they face along different career paths in many countries. Such research could also explore potential variation in meritocracy regimes across social groups, connecting debates on gender equality and integration to quantitative studies of the relationship between success and ability.

Finally, our analysis was descriptive in nature and did not assess the proposed theoretical mechanism. An additional mechanism that may drive the plateauing of the success–ability relation at high wages is that brighter individuals select into more poorly remunerated occupational groups, even if within these groups the brightest are rewarded the highest wages. If these worse-paying jobs are of higher prestige, this could explain the weaker patterns we observed for the relationship between wage and occupational prestige. While we could not effectively explore the operation of this possible mechanism, future studies may be able to disentangle competing mechanisms through longitudinal analysis of educational and labour market trajectories.

Recent years have seen much academic and public discussion of rising inequality (e.g. Mankiw, 2013; Piketty, 2014; Alvaredo *et al.*, 2017). In debates about interventions against large wage discrepancies, a common defence of top earners is the superior merit inferred from their job-market success using human capital arguments (Murray, 2003; Mankiw, 2013). However, along an important dimension of merit—cognitive ability—we find no evidence that those with top jobs that pay extraordinary wages are more deserving than those who earn only half those wages. The main takeaway of our analysis is thus the identification, both theoretically and empirically, of two regimes of stratification in the labour market. The bulk of citizens earn normal salaries that are clearly responsive to individual cognitive capabilities. Above a threshold level of wage, cognitive-ability levels are above average but play no role in differentiating wages. With relative incomes of top earners steadily growing in Western countries (Alvaredo *et al.*, 2017), an increasing share of aggregate earnings may be allocated under the latter regime.

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Data Availability

The Swedish register data come from administrative and tax records and can therefore not be shared; access may be requested from Statistics Sweden. The code used for the empirical analysis as well as for the simulation analysis is available from the authors upon request.

References

Åberg, M. A. *et al.* (2009). Cardiovascular fitness is associated with cognition in young adulthood. *Proceedings of the National Academy of Sciences*, **106**, 20906–20911.

Adams, R., Keloharju, M. and Knüpfer, S. (2018). Are CEOs born leaders? Lessons from traits of a million individuals. *Journal of Financial Economics*, **130**, 392–408.

Adler, M. (1985). Stardom and talent. *American Economic Review*, **75**, 208–212.

Aldén, L., Hammarstedt, M. and Neuman, E. (2017). All about balance? A test of the Jack-of-all-Trades Theory using military enlistment data. *Labour Economics*, **49**, 1–13.

Allen, M. P. and Lincoln, A. E. (2004). The cultural consecration of American films. *Social Forces*, **82**, 871–894.

Allen, M. P. and Parsons, N. L. (2006). The institutionalization of fame: achievement, recognition, and cultural consecration in baseball. *American Sociological Review*, **71**, 808–825.

Allison, P. D. (1980). Estimation and testing for a Markov Model of reinforcement. *Sociological Methods & Research*, **8**, 434–453.

Allison, P. D., Long, J. S. and Krauze, T. K. (1982). Cumulative advantage and inequality in science. *American Sociological Review*, **47**, 615–625.

Alvaredo, F. *et al.* (2017). Global inequality dynamics: new findings from WID.world. *American Economic Review*, **107**, 404–409.

Antonakis, J., House, R. J. and Simonton, D. K. (2017). Can super smart leaders suffer from too much of a good thing? The curvilinear effect of intelligence on perceived leadership behavior. *Journal of Applied Psychology*, **102**, 1003–1021.

Arthur, W. B. (1994). *Increasing Returns and Path Dependence in the Economy*. Ann Arbor: University of Michigan Press.

Azoulay, P., Stuart, T. and Wang, Y. (2014). Matthew: Effect or fable? *Management Science*, **60**, 92–109.

Baier, T. and Lang, V. (2019). The social stratification of environmental and genetic influences on education: new evidence using a register-based twin sample. *Sociological Science*, **6**, 143–171.

Baron, J. and Hershey, J. C. (1988). Outcome bias in decision evaluation. *Journal of Personality and Social Psychology*, **54**, 569–579.

Barone, C. and Van de Werfhorst, H. G. (2011). Education, cognitive skills and earnings in comparative perspective. *International Sociology*, **26**, 483–502.

Bebchuk, L. A., Fried, J. M. and Walker, D. I. (2002). Managerial Power and Rent Extraction in the Design of Executive Compensation. *University of Chicago Law Review*, **69**, 751–846.

Belsky, D. W. Domingue, B. W. *et al.* (2018). Genetic analysis of social-class mobility in five longitudinal studies. *Proceedings of the National Academy of Sciences*, **115**, E7275–E7284.

Bernardi, F. (2014). Compensatory advantage as a mechanism of educational inequality: a regression discontinuity based on month of birth. *Sociology of Education*, **87**, 74–88.

Bernardi, F. and Gil-Hernández, C. J. (2021). The social-origins gap in labour market outcomes: compensatory and boosting advantages using a micro-class approach. *European Sociological Review*, **37**, 32–48.

Bihagen, E., Nermo, M. and Stern, C. (2013). Class origin and elite position of men in business firms in Sweden, 1993–2007: the importance of education, cognitive ability, and personality. *European Sociological Review*, **29**, 939–954.

Birkelund, G. E., Heggebø, K. and Rogstad, J. (2017). Additive or multiplicative disadvantage? The scarring effects of unemployment for ethnic minorities. *European Sociological Review,* **33**, 17–29.

Bol, T., de Vaan, M. and van de Rijt, A. (2018). The Matthew effect in science funding. *Proceedings of the National Academy of Sciences*, **115**, 4887–4890.

Borghans, L. *et al*. (2016). What grades and achievement tests measure. *Proceedings of the National Academy of Sciences*, **113**, 13354–13359.

Borghans, L. and Groot, L. (1998). Superstardom and monopolistic power: why media stars earn more than their margin. *Journal of Institutional and Theoretical Economics*, **154**, 546–571.

Bourdieu, P. (1984). *Distinction: A Social Critique of the Judgment of Taste*. Cambridge: Harvard University Press.

Bourdieu, P. and Passeron, J.-C. (1979). *The Inheritors: French Students and Their Relation to Culture*. Chicago: University of Chicago Press.

Bowles, S. and Gintis, H. (2002). The inheritance of inequality. *Journal of Economic Perspectives*, **16**, 3–30.

Brand, J. E. and Xie, Y. (2010). Who benefits most from college? Evidence for negative selection in heterogeneous economic returns to higher education. *American Sociological Review*, **75**, 273–302.

Breen, R. and Jonsson, J. O. (2007). Explaining change in social fluidity: educational equalization and educational expansion in twentieth-century Sweden. *American Journal of Sociology*, **112**, 1775–1810.

Brynjolfsson, E. and McAfee, A. (2011). *Race Against The Machine: How the Digital Revolution is Accelerating Innovation, Driving Productivity, and Irreversibly Transforming Employment and the Economy*. Lexington: Digital Frontier Press.

Carlsson, M. *et al*. (2015). The effect of schooling on cognitive skills. *Review of Economics and Statistics*, **97**, 533–547.

Carlstedt, B. and Mårdberg, B. (1993). Construct validity of the Swedish enlistment battery. *Scandinavian Journal of Psychology*, **34**, 353–362.

Clauset, A., Arbesman, S. and Larremore, D. B. (2015). Systematic inequality and hierarchy in faculty hiring networks. *Science Advances*, **1**, e1400005.

Coleman, J. S. (1964). *Introduction to Mathematical Sociology*. New York: Free Press.

Collins, R. (1979). *The Credential Society*. New York: Academic Press.

Conley, D. *et al*. (2015). Is the effect of parental education on offspring biased or moderated by genotype? *Sociological Science*, **2**, 82–105.

Conley, D. and Fletcher, J. (2017). *The Genome Factor: What the Social Genomics Revolution Reveals about Ourselves, Our History, and the Future*. Princeton: Princeton University Press.

Coward, W. M. and Sackett, P. R. (1990). Linearity of ability-performance relationships: a reconfirmation. *Journal of Applied Psychology*, **75**, 297–300.

Dannefer, D. (2003). Cumulative advantage/disadvantage and the life course: Cross-fertilizing age and social science theory. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, **58**, S327–S337.

Denrell, J. and Liu, C. (2011). Top performers are not the most impressive when extreme performance indicates unreliability. *Proceedings of the National Academy of Sciences*, **109**, 9331–9336.

DiPrete, T. A. and Eirich, G. M. (2006). Cumulative advantage as a mechanisms for inequality: a review of theoretical and empirical developments. *Annual Review of Sociology*, **32**, 271–297.

DiPrete, T. A., Eirich G. M. and Pittinsky, M. (2010). Compensation benchmarking, leapfrogs, and the surge in executive pay. *American Journal of Sociology*, **115**, 712.

Di Stasio, V. and Van de Werfhorst, H. G. (2016). Why does education matter to employers in different institutional contexts? A vignette study in England and the Netherlands. *Social Forces*, **95**, 77–106.

Domhoff, G. W. (1967). *Who Rules America?* Englewood Cliffs: Prentice-Hall.

Erikson, R. (2016). Is it enough to be bright? Parental background, cognitive ability and educational attainment. *European Societies*, **18**, 117–135.

Falcon, J. and Bataille, P. (2018). Equalization or reproduction? Long-term trends in the intergenerational transmission of advantages in higher education in France. *European Sociological Review*, **34**, 335–347.

Figlio, D. N. *et al*. (2017). Socioeconomic status and genetic influences on cognition. *Proceedings of the National Academy of Sciences*, **114**, 13441–13446.

Fischbein, S. (1980). IQ and social class. *Intelligence*, **4**, 51–63.

Fischer, C. S. *et al*. (1996). *Inequality by Design: Cracking the Bell Curve Myth*. Princeton: Princeton University Press

Frank, R. H. (2016). *Success and Luck: Good Fortune and the Myth of Meritocracy*. Princeton: Princeton University Press.

Frank, R. H. and Cook, P. (1995). *The Winner-Take-All Society*. New York: Free Press.

Friedman, S. and Laurison, D. (2020). *The Class Ceiling: Why it Pays to be Privileged*. Bristol: Policy Press.

Gaddis, S. M. (2015). Discrimination in the credential society: an audit study of race and college selectivity in the labor market. *Social Forces*, **93**, 1451–1479.

Gangl, M. (2004). Welfare states and the scar effects of unemployment: a comparative analysis of the United States and West Germany. *American Journal of Sociology*, **109**, 1319–1364.

Ganzach, Y. *et al*. (2013). General mental ability and pay: nonlinear effects. *Intelligence*, **41**, 631–637.

Ganzeboom, H. B., De Graaf, P. M. and Treiman, D. J. (1992). A standard international socio-economic index of occupational status. *Social Science Research*, **21**, 1–56.

Gensowski, M. (2018). Personality, IQ, and lifetime earnings. *Labour Economics*, **51**, 170–183.

Gilbert, D. T. and Malone, P. S. (1995). The correspondence bias. *Psychological Bulletin*, **117**, 21–38.

Gladwell, M. (2008). *Outliers: The Story of Success*. New York: Little, Brown and Company.

Gottschling, J. *et al*. (2019). Socioeconomic status amplifies genetic effects in middle childhood in a large german twin sample. *Intelligence*, **72**, 20–27.

Grönqvist, E. and Vlachos, J. (2016). One size fits all? The effects of teachers' cognitive and social abilities on student achievement. *Labour Economics*, **42**, 138–150.

Grusky, D. (2019). Social Stratification. *Class, Race, and Gender in Sociological Perspective*, 2nd edn. New York: Routledge.

Guo, G. and Stearns, E. (2002). The social influences on the realization of genetic potential for intellectual development. *Social Forces*, **80**, 881–910.

Haider, S. and Solon, G. (2006). Life-cycle variation in the association between current and lifetime earnings. *American Economic Review*, **96**, 1308–1320.

Heckman, J. and Borjas, G. (1980). Does unemployment cause future unemployment? Definitions, questions and answers from a continuous time model of heterogeneity and state dependence. *Economica*, **47**, 247–283.

Heckman, J., Stixrud, J. and Urzua, S. (2006). The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor Economics*, **24**, 411–482.

Herrnstein, R. J. and Murray, C. (1994). *The Bell Curve: Intelligence and Class Structure in American Life*. New York: Free Press.

Huckfeldt, C. (2022). Understanding the scarring effect of recessions. *American Economic Review*, **112**, 1273–1310.

Jackson, M. (2013). *Determined to Succeed? Performance versus Choice in Educational Attainment*. Palo Alto: Stanford University Press.

Jensen, A. R. (1998). *The g Factor: The Science of Mental Ability*. Westport: Praeger Publishers.

Jokela, M. *et al.* (2017). Secular rise in economically valuable personality traits. *Proceedings of the National Academy of Sciences*, **114**, 6527–6532.

Jones, G. and Joel Schneider, W. (2006). Intelligence, human capital, and economic growth: a Bayesian Averaging of Classical Estimates (BACE) approach. *Journal of Economic Growth*, **11**, 71–93.

Keuschnigg, M. (2015). Product success in cultural markets: the mediating role of familiarity, peers, and experts. *Poetics*, **51**, 17–36.

Lamont, M. (1994). *Money, Morals and Manners: Culture of the French and the American Upper-Middle Class*. Chicago: University of Chicago Press.

Lang, G. E. and Lang, K. (1988). Recognition and renown: the survival of artistic reputation. *American Journal of Sociology*, **94**, 79–109.

Lareau, A. (2011). *Unequal Childhoods: Class, Race, and Family Life*, 2nd edn. Berkeley: University of California Press.

Laurison, D. and Friedman, S. (2016). The class pay gap in higher professional and managerial occupations. *American Sociological Review*, **81**, 668–695.

Lemieux, T. (2006). Postsecondary education and increasing wage inequality. *American Economic Review*, **96**, 195–199.

Lindqvist, E. and Vestman, R. (2009). The labor market returns to cognitive and noncognitive ability: evidence from the Swedish enlistment. *American Economic Journal: Applied Economics*, **3**, 101–128.

Lizardo, O. (2006). How cultural tastes shape personal networks. *American Sociological Review*, **71**, 778–807.

Lubinski, D. (2016). From Terman to today: a century of findings on intellectual precocity. *Review of Educational Research*, **86**, 900–944.

Lynn, F. B., Podolny, J. M. and Tao, L. (2009). A sociological (de)construction of the relationship between status and quality. *American Journal of Sociology*, **115**, 755–804.

Mankiw, N. G. (2013). Defending the one percent. *Journal of Economic Perspectives*, **27**, 21–34.

Manzoni, A., Härkönen, J. and Mayer, K. U. (2014). Moving on? A growth-curve analysis of occupational attainment and career progression patterns in West Germany. *Social Forces*, **92**, 1285–1312.

McCulloch, A. and Joshi, H. E. 2001. Neighbourhood and family influences on the cognitive ability of children in the British National Child Development Study. *Social Science & Medicine*, **53**, 579–591.

McDonald, J. B. and Ransom, M. (2008). The generalized beta distribution as a model for the distribution of income: estimation of related measures of inequality. In Chotikapanich, D. (Ed.), *Modeling Income Distributions and Lorenz Curves*. New York: Springer, pp. 147–166.

Merton, R. K. (1968). The Matthew effect in science. *Science*, **159**, 56–63.

Mincer, J. (1958). Investment in human capital and personal income distribution. *Journal of Political Economy*, **66**, 281–302.

Murray, C. (2003). *Human Accomplishment: The Pursuit of Excellence in the Arts and Sciences*. New York: Carper Collins.

Neal, D. and Rosen, S. (2000). Theories of the distribution of earnings. In Atkinson, A. B. and Bourguignon, F. (Eds.), *Handbook of Income Distribution*. Dordrecht: North-Holland, pp. 379–427.

Ng, T. W. *et al.* (2005). Predictors of objective and subjective career success: a meta-analysis. *Personnel Psychology*, **58**, 367–408.

Nisbett, R. E. *et al*. (2012). Intelligence: new findings and theoretical developments. *American Psychologist*, **67**, 129130–129129.

Oh, B. and Kim, C. H. (2020). Broken promise of college? New educational sorting mechanisms for intergenerational association in the 21st Century. *Social Science Research*, **86**, 102375.

O'Rand, A. M. (1996). The precious and the precocious: Understanding cumulative disadvantage and cumulative advantage over the life course. *The Gerontologist*, **36**, 230–238.

Pareto, V. (1916). *The Mind and Society: A Treatise on General Sociology*. New York: Dover.

Piketty, T. (2014). *Capital in the Twenty-First Century*. Cambridge: Harvard University Press.

Rahman Khan, S. (2012). The sociology of elites. *Annual Review of Sociology*, **38**, 361–377.

Rivera, L. A. (2012). Hiring as cultural matching: the case of elite professional service firms. *American Sociological Review*, **77**, 999–1022.

Rivera, L. A. (2015). *Pedigree: How Elite Students Get Elite Jobs*. Princeton: Princeton University Press.

Rosen, S. (1981). The economics of superstars. *American Economic Review*, **71**, 845–858.

Rowe, D. C., Jacobson, K. C. and Van den Oord, E. J. (1999). Genetic and environmental influences on vocabulary IQ: parental education level as moderator. *Child Development*, **70**, 1151–1162.

Salganik, M., Dodds, P. and Watts, D. (2006). Experimental study of inequality and unpredictability in an artificial cultural market. *Science*, **311**, 854–856.

Scarr-Salapatek, S. (1971). Race, social class, and IQ. *Science*, **174**, 1285–1295.

Sharkey, P. and Elwert, F. (2011). The legacy of disadvantage. *American Journal of Sociology*, **116**, 1934–1981.
Statistics Sweden. (2020). *Income and Tax Statistics: Income Inequality Indicators 1975–2018*. Örebro: SCB.
Strenze, T. (2007). Intelligence and socioeconomic success: a meta-analytic review of longitudinal research. *Intelligence*, **35**, 401–426.
Torche, F. (2011). Is a college degree still the great equalizer? Intergenerational mobility across levels of schooling in the United States. *American Journal of Sociology*, **117**, 763–807.
Van de Rijt, A. *et al*. (2013). Only fifteen minutes? The social stratification of fame in printed media. *American Sociological Review*, **78**, 266–289.
Wai, J. (2013). Investigating America's elite: cognitive ability, education, and sex differences. *Intelligence*, **41**, 203–211.
Wang, Y., Jones, B. F. and Wang, D. (2019). Early-career setback and future career impact. *Nature communications*, **10**(1), 1–10.
Watts, D. (2011). *Everything Is Obvious: How Common Sense Fails Us*. London: Atlantic Books.
Weeden, K. A. (2002). Why do some occupations pay more than others? Social closure and earnings inequality in the United States. *American Journal of Sociology*, **108**, 55–101.
Willson, A. E., Shuey, K. M. and Elder, Jr, G. H. (2007). Cumulative advantage processes as mechanisms of inequality in life course health. *American Journal of Sociology*, **112**, 1886–1924.

Appendix

A. Snapshots: 2nd, 10th, and 20th year of employment

In the main text, we report results for multi-year averages of labour-market success. Here, we look at snapshots of workers' 2nd, 10th, and 20th career year. We focus on those who were fully employed in the respective year. We chose year 2 to capture entry-level wages, because annual wage data is truncated in year 1 for all those who did not start their first employment in the month of January. Figure A1 shows the density distribution of log(wage) at tenure length t = 2, t = 10, and t = 20 with average inflation-adjusted wages rising from SEK2.89k in the 2nd career year to SEK4.28k in the 20th career year (panel A). Panels B and C demonstrate the robustness of our results based on early, mid, and late career wages. At each career stage there is a positive wage–ability relation for the vast majority of earners. Among the top earners, however, this positive association levels off. Panels D–F repeat a similar robustness analysis for occupational prestige.

B. A ceiling effect?

An alternative interpretation of the plateauing of cognitive ability at high job success levels is that a ceiling effect in measured ability prevents higher averages from showing up at the highest percentiles. To further explore this alternative explanation for the observed pattern, we compute—within each wage percentile—the share of those who reached a maximum ability score of 9 on the 1–9 stanine scale of cognitive ability. A large and increasing number of top smart individuals among the top percentiles would be particularly concerning. Figure A2 shows that the percentage of those scoring 9 in cognitive ability is highest among earners of relatively high wages (between SEK500,000 and SEK800,000). With 23.2 per cent it is highest in the 97th wage percentile. But among the top 3 percentiles, the percentage of top scorers declines to 18.4 per cent on average, for the top percentile it is 17.0 per cent. This suggests that our result is not driven by a ceiling effect.

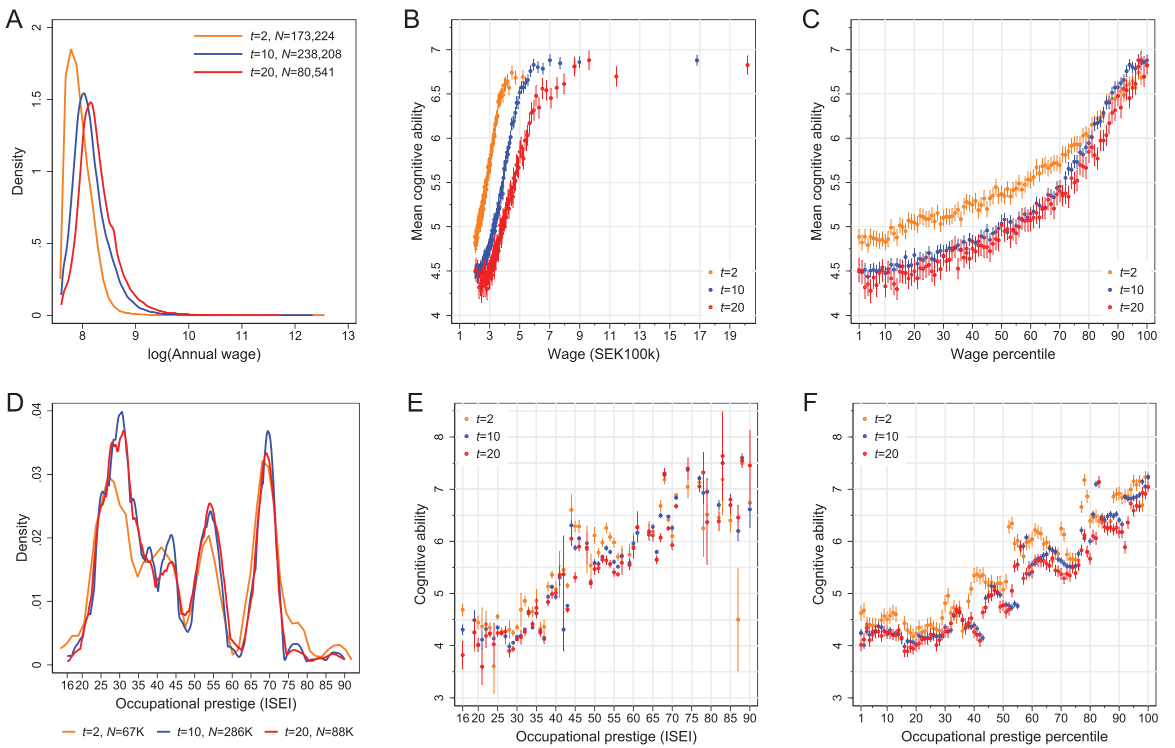

Figure A1. Labour market success in the 2nd, 10th, and 20th year of employment. (**A**) Kernel density distribution of log(annual wage) in SEK100k. Average inflation-adjusted wages rise from SEK2.89k (orange) to SEK3.73k (blue) and SEK4.28k (red). (**B**) Mean ability (and 95 per cent confidence intervals) by mean wage per wage percentile. (**C**) Mean ability by wage percentile. (**D**) Kernel density distribution of ISEI scores. (**E**) Mean ability (and 95 per cent confidence intervals) by prestige score. (**F**) Mean ability by prestige percentile.

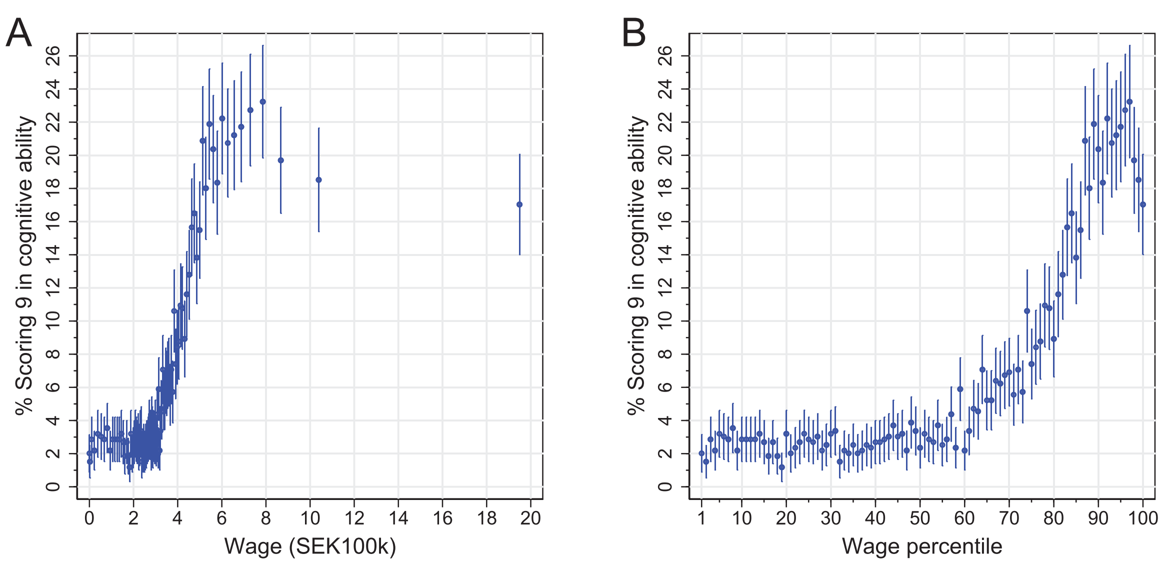

Figure A2. (**A**) Percentage of earners who received a maximum score of 9 in ability (and 95 per cent confidence intervals) by mean wage per wage percentile. (**B**) The percentage of top scorers by wage percentile.