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1. Introduction

So far the literature that has examined the relative effects of socioeconomic background (SEB) and intelligence on social success has taken what can be called a static approach, examining the main effects of these two variables on social success. In this approach, indicators of social success are regressed on SEB and intelligence, and the effects of these two variables are compared. This was the approach used by Herrnstein and Murray (1994) in their controversial book "The Bell Curve" and in the debate that it initiated (e.g., Arrow, Bowles, & Durlauf, 2000; Brody, 1997; Devlin, Fienbert, Resnick, & Roeder, 1997; Fischer et al., 1996; Jacoby & Glauberman, 1995; Ng, Eby, Sorensen, & Feldman, 2005; Schmidt & Hunter, 2004). The principles of this method drew very little criticism, if any, and the debate centered primarily on the measurement of SEB - whether its measurement appropriately captures the underlying concept of socioeco-

ABSTRACT

We compare the effects of socioeconomic background (SEB) and intelligence on wage trajectories in a dynamic growth modeling framework in a sample that had completed just 12 years of education. I show that the main difference between the two is that SEB affected wages solely by its effect on entry pay whereas intelligence affected wages primarily by its effect on mobility. I argue that a major issue that has been at the center of the debate about the roles of intelligence and SEB in social success — the difficulty in accurately measuring SEB — is to a large extent resolved by these results.

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nomic background (e.g., Dickens & Schulze, 1999; Fischer et al., 1996; Heckman, 1995; Levine & Painter, 1999; Nisbett, 2009).

In the current paper I take a *dynamic* approach (see Judge & Hurst, 2008; Judge, Klinger, & Simon, 2010; Warren, Hauser, & Sheridan, 2002) and examine the effect of SEB and intelligence on wages — perhaps the most important indicator of social success — by examining the way these two variables affect how wages develop and change over time throughout people's careers.

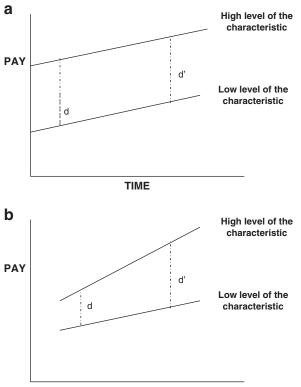
In the following discussion I treat both intelligence and SEB as individual characteristics that may affect wages in two ways. First they may affect the *initial* wage — the wage that people obtain when they enter the job market. And second, they may affect *changes* in wages, which at the early stages of people's careers could be conceptualized in terms of the pace at which wages increase as a function of time. Fig. 1a and b provides two possible patterns of trajectories by which SEB, intelligence, or for that matter any other individual characteristic, may affect wage dynamics. In each figure one trajectory is associated with people high on the characteristic and the other with people low on the characteristic. Fig. 1a portrays a pattern of *stable influence* with regard to the characteristic — the effect of the characteristic on pay, represented in the figure by the distance between the two trajectories, is constant over time; or



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TIME

Fig. 1. a: A pattern of trajectories of stable influence illustrated by the constant gap between the trajectories associated with low and high levels of the characteristic. b: A pattern of trajectories of increasing influence illustrated by the increased gap between the trajectory associated with low and high levels of the characteristic.

alternatively, the trajectory associated with high characteristic value and the trajectory associated with low characteristic value increase at the same pace. Note also that if these trajectories begin at the time people start their careers, the effect of the characteristic on one's pay during her career is due to its effect on initial pay. Such a pattern is likely to be found when a characteristic has an impact on entry to the job market, but does not affect mobility.

Fig. 1b portrays a pattern of *increasing influence* — the effect of the characteristic (the distance between the two trajectories) increases over time; or alternatively, the trajectory associated with high characteristic value increases at a faster pace than the trajectory associated with low characteristic value. In this figure the characteristic affects wages primarily by influencing the pace of their increase and less by influencing initial wages. Such a trajectory is likely to be found when the important effect of the characteristic is less on entry position and more on mobility. This pattern is likely to occur when people who are high on the characteristic, are able to navigate themselves in the job market to find better jobs and obtain better pay.

1.1. The difference between intelligence and SEB in their effects on job market mobility

Our main hypothesis is that a pattern of increasing influence is more likely to describe the effect of intelligence on wage trajectories whereas a pattern of stable influence is more likely to describe the effect of SEB. The reason is that one's social environment is relatively more important on entering the job market, whereas one's abilities are more important in determining her progress in the job market (Warren, 2001; Warren et al., 2002).

We argue that SEB is particularly important at entry, because job-market entry heavily depends on social capital, which in turn depends on SEB. Both parts of this argument are supported by empirical findings. First, entry depends on social capital because friends and relatives may supply useful information regarding the availability of jobs and where to look for them (Grieco, 1987), how to present oneself to employers, how to behave on the job, what wages to ask for and which jobs and worksites to avoid (Aguilera, 2002). And second, since the value of a specific source of social capital depends on the socioeconomic status of the source (e.g., Edwards & Foley, 1997), higher SEB is associated with more valuable social capital (e.g., the higher the SEB, the more valuable social connections are).

On the other hand, intelligence affects job-market mobility primarily through its role in gravitational processes - the processes by which people gravitate towards jobs that are commensurate with their abilities (Gottfredson, 2003; McCormick, DeNisi, & Shaw, 1979; McCormick, Jeanneret, & Mecham, 1972). A misfit between job requirements and ability prompts employees to move to a job that better fits their abilities: to more complex, higher paying, jobs if the employee is overqualified or to a less complex, less paying, jobs if she is under qualified (Wilk, Burris, & Sackett, 1995; Wilk & Sackett, 1996). Although such movements have been documented primarily with regard to job complexity (Ganzach, 2003), they are also likely to occur with regard to pay, since complexity is strongly associated with pay. Thus, I expect that changes in pay will be strongly related to ability. The wages of people with higher ability will increase at a faster pace than the wages of people with lower ability.¹

1.2. Relevant evidence from previous studies

Some empirical evidence for *dynamic* effects of intelligence on wages does exist in the literature. First, based on the NLSY data, Cawley, Heckman, Lochner, and Vytlacil (2000) reject the hypothesis that the effect of intelligence on wages is constant over different ages. However, they neither describe the nature of this interaction, nor suggest a theory to explain it. Second, in a meta-analysis of the effect of intelligence on occupational success, Strenze (2007) found that the higher the age at which success was measured, the stronger the relationship between intelligence and success. Finally, using the NLSY data as well, Judge et al. (2010) also find evidence for increasing influence of intelligence.

¹ There are a number of processes by which SEB may affect mobility. For example, it is possible that the jobs people get because of their SEB may be in areas less likely to award large pay increases. On the other hand, it is also possible that higher entry will be associated with higher mobility (Judge & Hurst, 2008) since early success affect later success (i.e., tournament mobility; Rosenbaum, 1979). Thus, we do not propose clear predictions regarding the effect of SEB on mobility.

However, these studies did not compare the influence of SEB to the influence of intelligence. In fact, they did not even control for SEB.

Highly relevant to our issue are results presented by Zax and Reese (2002). These authors examined the effect of intelligence and SEB based on the Wisconsin Longitudinal Survey (See, Sewell, Hauser, Springer, & Hauser, 2006). Although in their paper they did not attempt to compare the longitudinal effects of intelligence and SEB, and approached this issue within a static framework, they coincidentally report regressions of log earnings at two points in time - 1974 and 1992 — which allow for the examination temporal changes in the influence of both intelligence and SEB. I fully reproduce the results of these regressions in Table 1 here (Table 6 of Zax & Reese, 2002). It is clear from this table that whereas the effect of intelligence on earning increased with time, the effects of the background variables did not change much. As can be seen by the t-statistics in the table, except of intelligence, the effects of all the variables that were significant in 1974 (bold faced in the table) did not change much or even decreased in 1992. On the other hand, the effect of intelligence increased (the change in the t-statistics correspond to a highly significant change from 0.1 to 0.18 in partial r). Thus, although Zax and Reese (2002) do not discuss the differences between SEB and intelligence over time, their results are consistent with our hypotheses that the effect of intelligence increases, whereas the effect of SEB does not change much.

1.3. Dynamic analysis and the accuracy of SEB measurement

One of the main problems in comparing the effects of SEB and intelligence in the static approach is the difficulty in arriving at an accurate measure of SEB.² If SEB is not measured accurately, then any difference in the relative effects of SEB and intelligence may not be due to 'true' differences but to the error-ridden measure of SEB. However, a dynamic examination of the effect of SEB and intelligence may overcome this problem. In such an examination, the relative effects of SEB and intelligence at an earlier time, t1, serve as 'controls' for their relative effects at a later time, t2, since the same inaccuracy occurs at both measurement occasions. As I show below, the effect of intelligence and SEB are rather similar at t1, whereas the effect of intelligence is stronger at t2. In this case the difference in the relative effects of the two characteristics at t2 is not likely to be the result of differences in measurements' accuracy, because the same measures are used at both times, and is most likely to be a true difference.

A worthwhile methodological note here concerns the difficulty of comparing the effects of SEB (or environments in general) and intelligence as the measurements of the two are not independent. On the one hand, the variance associated with SEB may be attributed to some extent to intelligence

through the genetically influenced correlation between parents and children (e.g., Lubinski, 2009; Lynn, 2003; Sesardic, 2005. Jensen, 1998, labeled the tendency to ignore this effect "the sociologist's fallacy"). On the other hand, it was also argued that the variance attributed to intelligence is due to SEB because intelligence tests are "culturally biased". (See, Ceci, 1990; Irvine & Berry, 1988; Kamin, 1995 and Nisbett, 1995, for earlier discussions. See Helms-Lorenz, van de Vijver, & Poortinga, 2003, and Malda, van de Vijver, & Temane, 2010 for recent empirical demonstration. But see te Nijenhuisa & van der Flierb, 2003, for contradictory findings). In the current paper we take the middle-of-the-road approach used in the bell curve and in the literature that followed it (e.g., Fischer et al., 1996; Korenman & Winship, 2000; Levine & Painter, 1999), and associate both the effect of intelligence and the effect of SEB only to their unique variance.

1.4. High-school graduates and 'true' job-market mobility

Although it could be argued that a comparison between the effects of intelligence and SEB does not require controlling for education, as education is endogenous to intelligence and SEB, I chose Herrnstein and Murray's (1994) conservative approach and controlled for education by limiting the analysis to an educationally homogenous group of highschool graduates; that is, I kept schooling constant at 12 years of education. I did it for two main reasons. First, fixing education level at 12 years of education provides a natural control for the possibility that the effects of intelligence and SEB on pay are confounded with the effect of quality of education. Because students are selected to colleges based on both their success in standardized tests measuring intelligence³ (resulting in more intelligent students populating the more prestigious colleges and more lucrative departments), and their SEB (a voluntary selection process associated with students' financial background), the effects of these two characteristics on wages in an educationally heterogeneous group, and even in an educationally homogenous group with a higher level of education (i.e., college graduates), may be associated with their effects on education (see Tittle & Rotolo, 2000). Thus, for this group of high-school graduates the effects of intelligence and SEB are more closely related to the true role of these variables in job-market mobility than to selection processes in the educational system. Second, an analysis of high-school graduates allows for better isolation of the effect of entry from the effect of mobility, since the time at which this group starts its real job-market career is relatively clear – about the age of 19 (see Light, 1998 for a discussion of the ambiguity in identifying career start dates).

2. Method

2.1. Participants and procedure

The data were taken from the National Longitudinal Survey of Youth (NLSY), conducted with a probability sample

² There are a number of problems concerning both the validity and the reliability of the measurement of SEB (see for example Cirino et al., 2002; Ensminger et al., 2000) Among the problems that are more relevant to the current study is the difficulty in taking into account the large number of attributes associated with this concept; the ambiguity regarding the weights that should be assigned to the indicators of SEB; or low correlation between these indicators (Goldberger & Manski, 1995 and Fischer et al., 1996 for discussion of these problems).

³ In the US selection to colleges is based to a large extent on the Scholastic Aptitude Test (SAT), which is a measure of intelligence (Frey & Detterman, 2004).

Table 1

The determinants of labor market earnings in 1974 and 1972 (Zax & Reese, 2002, Table 6).

	1974		1992		
Explanatory variable	Coefficient	t-statistic	Coefficient	t-statistic	
Respondent characteristics					
Respondent IQ	0.00363	(4.81)	0.00898	(8.20)	
Respondent planning college	0.0867	(3.46)	0.116	(3.19)	
Household characteristics					
Household income	0.0287	(3.91)	0.0308	(2.89)	
(Household income) ²	- 0.000537	(2.97)	- 0.000597	(2.28)	
Father has white collar job	0.0355	(1.42)	0.0162	(0.48)	
Mother has white collar job	0.0348	(1.29)	-0.0322	(0.823)	
One or both natural parents absent	0.0519	(1.35)	0.156	(2.80)	
Number of siblings	0.00440	(1.06)	0.00911	(1.52)	
Father's education					
Missing	0.0137	(0.291)	0.00133	(0.0194)	
Graduated high school	-0.00561	(0.231)	0.0360	(1.02)	
Graduated college	-0.00497	(0.117)	0.0511	(0.827)	
Mother's education					
Missing	0.0236	(0.507)	0.0317	(0.470)	
Graduated high school	-0.00492	(0.209)	0.0570	(1.66)	
Graduated college	-0.00186	(0.0463)	0.128	(2.19)	
Parental attitude toward college					
Encouraged	0.0665	(2.63)	0.0600	(1.64)	
Discouraged or did not permit	0.0389	(0.632)	-0.108	(1.21)	
Community characteristics					
High school in town of <10,000 population	-0.00871	(0.304)	-0.0545	(1.31)	
High school in town of $>49,999$ population	-0.0309	(1.09)	-0.0297	(0.724)	
School characteristics					
Private	- 0.215	(2.36)	- 0.279	(2.11)	
Catholic	0.0622	(1.73)	0.0696	(1.33)	
Size of class (100s)	0.0105	(0.928)	0.00539	(0.330)	
Peer household characteristics				. ,	
Average household income (\$10,000s)	0.0220	(1.47)	-0.000667	(0.0306)	
% fathers graduated high school	-0.113	(1.12)	-0.0933	(0.632)	
% fathers graduated college	0.115	(0.707)	0.372	(1.58)	
Peer characteristics					
Average IO	0.00387	(1.49)	0.000425	(0.112)	
% planning college	- 0.0325	(0.324)	-0.0914	(0.628)	
% planning white collar	- 0.0708	(0.695)	-0.0264	(0.178)	
% planning military service	0.143	(0.675)	0.557	(1.81)	
% planning to farm	-0.278	(1.48)	-0.296	(1.09)	
Friends' characteristic		()		()	
Planning college	0.0606	(2.53)	0.0859	(2.47)	
Constant	9.66	(40.0)	9.47	(27.0)	
R ²	0.117	(10.0)	0.136	(27.0)	
Adjusted R ²	0.105		0.124		

The dependent variables are the natural logarithms of 1974 and 1992 annual wages and salaries, measured in 1992 dollars. The predictors were measured in 1957, when participants were 18 years old. The sample consists of 2264 men. The effects of all the variables that were significant in 1974 are in bold.

of 12,686 Americans (with an oversampling of Afro-Americans, Hispanics and economically disadvantaged whites) born between 1957 and 1964. Thus, the basic sampling was of a specific cohort, though there is some variability in age in the sample. As I show below, this variability allows us to examine the dynamic effects of SEB and intelligence in a cross-sectional design as well as a longitudinal design. Due to funding constraints, 1079 participants were dropped in 1984 and 1643 in 1990.⁴ Natural sample attrition was about 10% a year. The participants were first interviewed in 1979. Until 1994 they were interviewed annually, and from then on they were interviewed every two years. The current study used information from the 1979–2000 interviews.

For our analyses I selected only those 1996 participants who either by the beginning of the survey or by the age of 19 completed 12 years of education and did not obtain any more education at least by 2000 (participants who had GED but did not have 12 years of education were not included in the sample, nor were participants who completed 12 years of education and did not obtain a high school diploma).

2.2. Variables and measurement

2.2.1. Intelligence

The measure of intelligence in the NLSY is derived from participants' test scores in the Armed Forces Qualifying Test (AFQT). This test was administered to groups of five to ten

⁴ The original sample of 12,686 individuals included two random subsamples: (a) 5295 individuals who were oversampled from Hispanic, Black, and economically disadvantaged non-Black/non-Hispanic households; and (b) a military sample of 1280 individuals. Due to funding constraints, 1079 individuals from the military supplemental sample were dropped after 1984, and 1643 individuals from the economically disadvantaged non-Black/non-Hispanic supplemental sample were dropped after 1990.

participants of the NLSY during the period of June through October 1980. Respondents were compensated, and the overall completion rate was 94%. The intelligence score in the NLSY is the sum of the standardized scores of four tests: arithmetic reasoning, paragraph comprehension, word knowledge and mathematics knowledge, and is expressed as a percentile score on the basis of the US army scoring scheme aimed at achieving nationally representative standard scores (see addendum to attachment 106 of the NLSY user guide⁵).

2.2.2. Pay

The logarithm of the hourly rate of pay adjusted for the consumer price index was used as a measure of pay. The hourly rate of pay was calculated by the NLSY's staff based on participants' reports about their pay, the time unit by which they are paid, and the number of hours they work. Observations for which the hourly rate of pay was less than \$1 or more than \$200 were omitted from the analysis.

2.2.3. Socioeconomic background

I used two indices for socioeconomic background. The first is the common 'narrow' index (see Bradley & Corwyn, 2002; Hauser, 1994) used by Herrnstein and Murray (1994). This index includes four variables as indicators of SEB: education of the two parents, parent's family income, and occupational status of the parent holding the higher occupation. Parents' education was measured in terms of the highest grade completed by each of the parents. Family income was based on the net family income in 1979, as reported by the participant's parents (it was excluded if the reported income for this year referred to the respondent's own income). Parental occupational status was measured using the Duncan index, which assigns to each occupation a 0-100 score representing occupational prestige (Duncan, 1961). These four indicators were standardized and averaged to produce the narrow index of SEB. The narrow index has been criticized by a number of authors both on statistical grounds (i.e., assigning equal weights to the socioeconomic components) and as being too narrow in that it does not capture important environmental influences (Dickens & Schulze, 1999; Fischer et al., 1996; Heckman, 1995; Korenman & Winship, 2000). Therefore following previous work, in addition to this narrow SEB index, I also examined the effect of an extended background index that allowed for differential weights and included additional relevant variables. In calculating this index I followed Fischer et al. (1996) perhaps the most prominent critiques of the bell curve. Their index included, in addition to the four variables of the narrow index and four indicators for missing values for these four variables, the following additional variables: number of siblings, farm background (whether the participant lived in a farm at the age of 14), whether the participant lived in a two-parents home at age 14, a school composite variable averaging the percent of 10th graders who drop out of high school, the percent of economically disadvantaged students and percent of non-white students (obtained by the NLSY staff from the schools which the participants' attended), geographic region

(west, northeast, central or south), years of schooling while taking the AFQT. To construct this extended index I applied the Fischer et al. method (see also Korenman & Winship, 2000; Levine & Painter, 1999) by first estimating a model predicting pay as a function of these variables as well as intelligence, and then multiplying for each participant the coefficient vector by her background characteristics.

2.2.4. Age, cross-sectional age, gender and ethnic background

Date of birth, sex and ethnic background were collected in the first year of the survey. Ethnic background was coded as 0 for whites and 1 for non-whites. Sex was coded as 1 for male and 2 for female. Age was calculated for each participant at each time point based on date of birth. In addition to this *longitudinal age* I use in the analyses a *cross-sectional age* defined as the age of the participant at 1983.

2.3. Models

Most of our analyses were conducted within a longitudinal framework by estimating wage trajectories as a function of intelligence and SEB. Two parameters defined the effect of each of these two characteristic on wage trajectory. One, associated with the effect of the characteristic on the intercept of the trajectory, represents the characteristic's effect on initial pay. The other, associated with the effect of the characteristic on the slope of the trajectory, represents the characteristic's effect on mobility (a third parameter included in the model, representing the concavity of the trajectory, has statistical, but not theoretical, significance in the current work).

Within this longitudinal framework, it is instructive to think about the data in terms of 18 observations for each participant, one for each of the 18 years of the survey (participants who have missing values on some of these observations are retained in our analysis). In each observation there is one time-varying dependent variable (pay), two time-varying independent variable (age and age squared⁶), two time-invariant independent variables of interest (SEB and intelligence) and time-invariant control variables (sex, ethnicity and age in 1979, the beginning of the survey). For each of the participants, the observations for which any of these variables were missing or for which the participant was enrolled in school were omitted from the analyses.

To statistically examine the effects of SEB and intelligence within the growth modeling framework, I used a multi-levelanalysis (Bryk & Raudenbush, 1987). This analysis is defined by the following equations:

$$\ln(\text{HRP})_{ij} = \beta_{0j} + \beta_{1j} \cdot \text{AGE} + \beta_{2j} \cdot \text{AGE}^2 + r_{ij}$$
(1)

$$\beta_{0j} = \gamma_{00} + \gamma_{01} \cdot INT_j + \gamma_{02} \cdot SEB_j + Controls + u_{0j}$$
(2)

$$\beta_{1j} = \gamma_{10} + \gamma_{11} \cdot \text{INT}_j + \gamma_{12} \cdot \text{SEB}_j + u_{1j}$$
(3)

$$\beta_{2j} = \gamma_{20} + u_{2j} \tag{4}$$

⁵ http://www.nlsinfo.org/nlsy79/docs/79html/codesup/NLSY79% 20Attachment%20106,%20Profiles%20of%20American%20Youth.pdf.

⁶ The inclusion of the latter is the standard in empirical work involving pay trajectories (see for example, Ehrenberg & Smith, 1988) because it captures the concavity of pay trajectory, associated with the fact that the effect of age on changes in pay is stronger in earlier than later career stages.

	М	SD	1	2	3	4	5	6
1. Mean log pay	1.63	0.39	-					
2. Intelligence	0.00	1.00	0.31	-				
3. Narrow SEB	0.00	1.00	0.21	0.38	-			
4. Extended SEB	0.00	1.00	0.29	0.33	0.65	-		
5. Sex	1.53	0.50	-0.40	-0.08	-0.05	-0.06	-	
6. Ethnicity	0.48	0.50	-0.10	-0.44	-0.38	-0.41	-0.02	-
7. Cross-sectional age	22.62	2.31	0.12	0.09	0.14	0.02	-0.03	-0.01

Table 2Descriptive statistics and inter-correlations.

Males were coded as 1, females as 2. Ethnicity was coded as 0 for whites, otherwise 1. Intelligence and SEB were standardized. Correlations above 0.10 are significant at the 0.0001 level, above 0.08 at the 0.001 level. Cross-sectional age is the age at the 1983 survey. N ranges between 1933 and 1996 depending on missing values.

Where ln(HRP)_{ij} is the logarithm of the hourly rate of pay of participant j at age i, INT is intelligence and SEB is socioeconomic background. Cross-sectional age (as opposed to the time-varying longitudinal age), ethnicity and sex were used as controls. For convenience and without loss of generality I used the age in 1983 as the cross-sectional age (crosssectional ages in other years differ from it only by a constant).

The analysis could be viewed as consisting of two stages. At the first stage each individual's wages were regressed on her age and age squared (Eq. (1)). At the second stage the intercepts and the slopes of these individual regressions were regressed on SEB, intelligence and the time-invariant controls (Eqs. (2) and (3), respectively) to obtain estimates of the effects of the individual characteristic on the intercept and the slope. Eq. (4) is less important and was included to capture the concavity of wage trajectories associated with the slow-down in gravitational processes as age increases).

Finally, the dynamic effects of intelligence and SEB can also be examined within a cross-sectional framework on the basis of the variability in the cross-sectional age in our sample by estimating the following model for a specific point in time (i.e., specific survey year):

$$\begin{split} ln(HRP)_{j} &= \beta_{0} + \beta_{1} \cdot CSAGE_{j} + \beta_{2} \cdot CSAGE_{j}^{2} + \beta_{3} \cdot INT_{j} \\ &+ \beta_{4} \cdot SEB_{j} + \beta_{5} \cdot CSAGE_{j} \cdot INT_{j} + \beta_{6} \cdot CSAGE_{j} \cdot SEB_{j} \\ &+ Controls + r_{i} \end{split}$$
(6)

where CSAGE is the cross-sectional age and sex and ethnicity are the controls.

Although it is possible to estimate this model for each of the 18 survey years, I present below only the analysis of the 1983 survey. The reason is that, as a result of the slowdown in gravitational processes with age, the effects of cross-sectional age (both main effect and interaction with intelligence) became less important in later years when the participants were older (e.g., cross-sectional effects of age are stronger at ages 25–30 than 40–45).⁷

3. Results

Table 2 presents descriptive statistics and inter-correlations of the study variables. In this table pay was averaged across the 18 years analyzed in the paper. It is worthwhile noting in this table that the correlation between the extended SEB and pay is considerably higher than the correlation between the narrow SEB and pay, and it is almost as high as the correlation between intelligence and pay. These results are consistent with Fischer et al. (1996). However, below I show that in a dynamic analysis there are considerable differences between the effect of intelligence and the effect of SEB on pay, even when the extended index is used to measure SEB.

The left panel of Table 3 presents the results of a growth modeling analysis on pay using our narrow index of SEB. In this analysis age was transformed to have a value of 0 when actual age is 19, thus allowing the intercept to represent the value of pay at job-market entry. It is clear from these results that whereas the effect of intelligence on the slope was significant (p<0.0001), the effect of SEB was not (p>0.8). On the other hand, both intelligence and SEB had significant effects on the intercept (p<0.0001 for both).⁸ These results suggest that whereas both intelligence and SEB affected our participants' entry wages, only intelligence affected their mobility, or the pace of pay increases throughout their careers.

On the basis of the parameters estimated in the multilevel model, Fig. 2 provides a graphical representation of trajectories of participants high (one standard deviation above the mean) and low (one standard deviation below the mean) on intelligence and SEB, keeping the other timeinvariant variables constant at their means. It is clear from the figure that while the trajectories of high and low intelligence diverge, the trajectories of high and low SEB do not. This suggests that intelligence, but not SEB, affected the slope of wage trajectories.⁹ It also suggests that SEB affected entry wages, and that its effect was similar to the effect of intelligence.

⁷ We chose 1983 because at this year most of the participants of our sample of the NLSY were already working, but they were still young enough to exhibit a cross-sectional effect of age. This is indeed consistent with the pattern of results reported in footnote 7.

⁸ The effects of the two characteristics on the intercept, or entry level pay, are rather similar. On the basis of the multi-level parameters, one standard deviation increase in SEB [intelligence] leads to a 4.6% [5.4%] increase in entry pay.

⁹ We also examined models in which the slope, and not only the intercept, depends on the control variables, but this model revealed no significant effects of the control variables on the slope. In particular, this suggests that the effect of intelligence on mobility cannot be explained by ethnic differences in intelligence.

Table 3

	Based on narrow	SEB		Based on extended SEB		
Parameter	Estimate	SE	t ratio	Estimate	SE	t ratio
Intercept model						
Intercept	6.30	0.07	91.9**	6.40	0.06	93.5 **
Intelligence	0.053	0.010	6.0 **	0.051	0.009	5.9 **
SEB	0.043	0.010	4.9**	0.068	0.008	8.1 **
Sex	-0.236	0.014	18.1 **	-0.237	0.014	18.1 **
Ethnicity	0.0079	0.0164	0.5	0.023	0.016	1.9
Cross-sectional age	0.0061	0.0031	2.1	-0.0018	0.0031	0.5
Slope of age						
Intercept	0.036	0.002	18.1 **	0.036	0.002	17.6**
Intelligence	0.0034	0.0007	4.9**	0.0034	0.0008	4.9**
SEB	-0.0001	0.0008	0.9	0.0001	0.0008	0.8
Slope of age ²						
Intercept	-0.00074	0.00009	8.6**	-0.00073	0.00009	8.4**

Males were coded as 1, females as 2. Ethnicity was coded as 0 for whites, otherwise 1. Intelligence and SEB were standardized. Age was transformed to have a value of 0 when age is 19.

** p<0.0001.

3.1. Extended SEB-based analysis

Intelligence and SEB as predictors of growth in pay.

In the analyses below I use the extended SEB index, rather than the narrow index, as a measure for socioeconomic background. If our hypothesis that background characteristics in general, and not only those of our narrow index, influence pay through their effects on entry pay but not through their effects on the pace of pay progress, the effect of the extended SEB should be larger than the effect of the narrow SEB for all ages, though it should still stay stable over time. This will be expressed as an increase in the effect of the extended index on the intercept of the trajectory, but not on its slope.

The right panel of Table 3 reports the results of a growth modeling analysis of pay in which the extended index is used as a measure of SEB. The results are similar to the results based on the narrow index in that both intelligence and SEB had significant effects on the intercept of the trajectory (p<0.0001 for both), but only intelligence, and not SEB, had a significant effect on the slope (p<0.0001 and p>0.4, respectively). This analysis is even more impressive than the

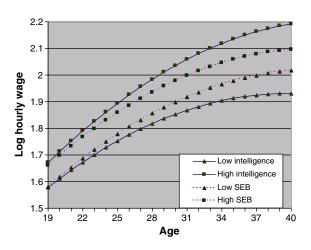


Fig. 2. Trajectories of log hourly wage (in 1983 US dollars) over time as a function of low (one SD below the mean) and high (one SD above the mean) levels of intelligence and narrow SEB.

narrow-index-based analysis in showing the differential effects of SEB and intelligence, since it suggests that whereas extended SEB had a negligible, non-significant, effect on mobility (slope), its effect on the entry (intercept) was larger than the effect of intelligence (on the basis of the multi-level parameters, the effect of SEB was about 50% larger than the effect of intelligence: one standard deviation increase in SEB [intelligence] leads to a 7.7% [5.2%] increase in entry pay).

The graphical representation of the multi-level-based trajectories of the extended-SEB model is presented in Fig. 3. This figure is similar to Fig. 2, which was based on the narrow SEB, in showing that intelligence, but not SEB, affected the slope of pay trajectories, but it is different from Fig. 2 in showing that on the average the effects of SEB and intelligence were rather similar.¹⁰

3.2. Cross sectional analysis

Table 4 presents the results of the cross-sectional analysis on the 1983 survey using the narrow index of SEB (the results for the extended index are similar, and are not presented here). To allow the intercept to represent the value of pay at job-market entry, the cross-sectional age was transformed to have a value of zero at the age of 19, the time of job-market entry, by subtracting 18 from participant's ages in 1983.

The results of the cross-sectional analysis in Table 4 are consistent with the results of the longitudinal analysis. The effect of SEB on entry pay was significant (p<0.01 for the main effect of SEB), but the effect of intelligence was not (p>0.3 for the main effect of intelligence). On the other hand, the effect of SEB on mobility was not significant (p>0.1 for

¹⁰ The extended-SEB analysis is biased towards higher predictive validity for SEB (and lower validity for intelligence) because it capitalizes on chance: the weights of the SEB index are estimated on the same sample for which the index is calculated. However, as the sample size is large, this is not likely to be a serious problem. Note that if anything, using the extended-SEB measure inflate the dynamic effect of SEB and deflate the effect of intelligence. Note also that the calculation of the narrow index as well as the calculation of the intelligence score do not rely on in-sample weight estimation, and therefore their effects are not affected by capitalization on chance.

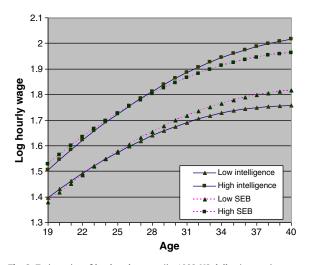


Fig. 3. Trajectories of log hourly wage (in 1983 US dollars) over time as a function of low (one SD below the mean) and high (one SD above the mean) levels of intelligence and extended SEB.

the interaction between SEB and CSAGE), whereas the effect of intelligence on mobility was significant (p<0.01 for the interaction between the cross-sectional age and intelligence).¹¹ Fig. 4 provides a graphical representation of the effect of cross-sectional age on pay for low and high levels of intelligence and SEB.¹²

4. Discussion

The current paper deals with an issue which has been intensely researched and debated in the literature — to what extent do SEB and intelligence affect job-market success. The focus of the current paper is somewhat different: less on the relative impact of these two characteristics on job-market success, and more on the processes by which they affect success. The results suggest that SEB affected wages solely by its effect on entry pay whereas intelligence affected wages primarily by its effect on mobility. The effect of intelligence on entry pay seems to be weaker than the effect of SEB.

One implication of these results is that they suggest that the important difference between the effect of SEB and intelligence is not that the former is measured inaccurately whereas the latter is not, but that they play different roles in the dynamic of job-market success, and in particular that intelligence, but not SEB, is what drives individuals' progress in the job market.

Given the differences in the effect of intelligence and SEB on wages, it seems that, no matter what SEB index is used, the

Table 4

Intelligence and SEB as predictors of pay in the cross-section analysis.

	Parameter	SE	t ratio
Intercept	6.19	0.05	130.6**
Cross-sectional age	0.152	0.019	8.2 **
Cross-sectional age squared	-0.013	0.002	5.4 **
Intelligence	-0.023	0.022	1.0
SEB	0.093	0.026	3.6*
Sex	-0.24	0.02	10.0 **
Ethnicity	-0.011	0.028	0.6
Cross-sectional age × Intelligence	0.016	0.005	3.1 *
Cross-sectional age × SEB	-0.0078	0.0053	1.5

 $N\!=\!1430,\,R^2\!=\!0.20.$ Males were coded as 1, females as 2. Ethnicity was coded as 0 for whites, otherwise 1. Intelligence and SEB were standardized. Cross-sectional age was coded to have a value of 0 when participants are 19. $^{**}\,\,p\!<\!0.0001.$

* p<0.01.

relative weight of these two characteristics as predictors of job-market success is age dependent. This pattern suggests that different conclusions about the relative impact of SEB and intelligence would emerge depending on the time (age) the analysis was made. This analysis suggests that had investigators in the bell curve controversy chosen earlier or later periods, they might have obtained different results. For example, on the basis of the 1990 survey, using a similar extended index to the one used here, Fischer et al. (1996) found in a static analysis that the effect of the extended SEB was larger than the effect of intelligence. Since their analysis was conducted on data obtained when the participants were about 29, these results are consistent with ours. However, conducting the analysis 10 years later may very well have led to different conclusions regarding the relative effects of the two characteristics (see Fig. 3). Similarly, had Herrnstein and Murray (1994) conducted their analysis a few years earlier, they might have found a smaller disparity between the effects of SEB and intelligence even by using their narrow index for SEB (see Fig. 2).

Since increasing influence of a characteristic could also be understood as representing an increase in return on this characteristic, an alternative explanation for our data is that the increasing influence observed for intelligence was not the result of age, but of time — the result of growing return on

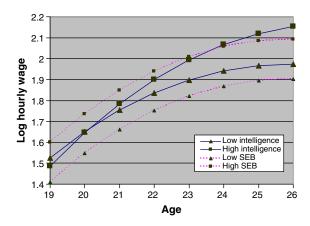


Fig. 4. The effect of cross-sectional age on log hourly wage (in 1983 US dollars) for low (one SD below the mean) and high (one SD above the mean) levels of intelligence and SEB.

¹¹ In examining other survey years we found that the main effect of crosssectional age on pay stays significant until the survey of 1985 and the interaction between cross-sectional age and intelligence until the survey of 1984

¹² Although a quadratic term is the standard method by which a decreasing positive (or, for that matter, decreasing negative) slope is modeled (e.g., Cohen & Cohen, 1983, pp. 223–230), in each specific case the exact power which best describes the data may be somewhat different. Indeed, in trying various power terms to depict the decreasing positive slope, I found that a power of 1.9 better describes the data than a power of 1.9. Therefore, the curvilinear trend is depicted in Fig. 4 using a power of 1.9.

ability in the second part of the 20th century (Blackburn & Neumark, 1993; Murnane, Willett, & Levy, 1995). However, this alternative explanation is not consistent with some of our findings. First our results indicated that the influence of intelligence increased until about the age of 30 (see Figs. 3 and 4), and remained at a plateau afterwards. This would suggest that in our data the return on ability increased until about 1990 (when our participants were about 30), but did not increase afterwards, which is inconsistent with a time-dependent increase in return on ability. Second, our cross-sectional analysis suggested that the effect of age on pay also existed when time is held constant.

That is not to say that our results are necessarily universal. Since the role of intelligence is likely to depend on the type of economy in which the study was conducted, in less developed economies, and in yet earlier periods, the role of intelligence in job-market success may have been less important. Furthermore, our measure of job-market success – wages – may not encompass all the dimensions of the concept under investigation. Thus, future research should encompass other dimensions of success such as occupational success or job-satisfaction. Furthermore, our results regarding job-market success may not be generalizable to measures of social success other than jobmarket success which may exhibit different dynamic patterns.

It also could be asked whether the current results, which were obtained from an analysis of a sample of people with 12 years of education, apply to other educational levels. There are a number of processes which may cause both SEB and intelligence to have different effects in other educational levels. Intelligence may be more important in affecting performance – and therefore pay - in more complex jobs, those largely held by college graduates (Hunter & Hunter, 1984), although it also could be argued that for some professional jobs income may vary in ways that have to do less with intelligence and more with the economics of the business area. Note, however, that, in order not to confound age effects with career stage effects, research on the effect of SEB and intelligence on job-market success requires data about cohorts that graduated college and entered the job market at about the same age. Given the relatively low percentage of NLSY participants that graduated from college at about the same age, it is doubtful whether this database allows for such an investigation.

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