Skills, Aspirations, and Occupations

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Abstract

It is well documented that children often "inherit" the occupations of their parents. This paper studies the role of early occupational aspirations in determining later life outcomes, a potentially important channel for intergenerational correlations in occupations. Using the Wisconsin Longitudinal Study, we estimate a lifecycle model of college choice and occupation choice to quantify the effect of aspirations on education and wages. We find that aspirations have a sizeable impact on educational attainment and wages, even conditional on latent skills that we recover from the choice model. We also simulate the importance of family background conditional on skills through the strong correlation between family background and aspirations. Our findings suggest that aspirations may be a valuable lever for reducing intergenerational inequality.

Key words: college choice, occupations, lifecycle wage growth, aspirations

JEL codes: I24, J24

1 Introduction

While occupational aspirations have received much attention in the sociology literature[1], there is much less work in economics examining its role in determining later life outcomes. This is due in part to the difficulty of modeling occupational choices. This paper exploits recent advances in conceptualizing occupations as *tasks* to examine the effect of occupational aspirations on education attainment and occupational choices later in life. The estimated effects are used to quantify the consequence of "mismatch" between aspirations and initial skills for education choice, lifecycle wages, and occupation choice.

We develop a model of occupation and education choices where workers begin with a set of latent initial skills and occupational aspirations. They make their college choice based on the expected utility from future career paths that depend on education level, aspirations, as well as education costs and initial skills. College attendance boosts skills both at job market entry and throughout the career of workers, and hence wages.

After schooling is complete, occupation choices are made each year. Occupations are characterized as a vector of task requirements (corresponding to each skill) that interact with the respective worker skills to determine wages. As workers gain experience in their jobs, they develop their skills, at faster or slower rates depending on how demanding the job is with respect to each task. They also update their occupational aspirations based on their current skill levels and past aspirations. Optimal occupation choice thus depends on skill level and aspirations, where skill level determines monetary returns on task requirements as well as non-pecuniary returns from performing tasks. It is less psychologically costly for skilled workers to work at task intensive jobs. Occupational aspirations only affect non-pecuniary returns from tasks.

[1] See for example, Duncan et al. (1968); Jecks et al. (1983); Marini and Greenberger (1978); Sewell et al. (1970, 1969)

Aspirations capture individual specific non-pecuniary returns to occupation choices that are distinct from the non-pecuniary returns to occupation choices associated with skills. It incorporates a broader notion of occupation choice that entails the social advantages associated with occupations such as social class, prestige, community expectations, etc.

We face three main challenges in studying aspirations. First, early aspirations are highly likely to correlate with early unobserved skills, which are in turn linked to later skills (Cunha and Heckman, 2007). To tackle this, we rely on the revealed occupation and education choices and lifecycle wages, along with the parametrization of skill growth over the careers of workers, to recover early skills. Second, aspirations are potentially measured with error given that there were only two points in time where subjects self-reported aspirations. Similar to latent skills, we build on revealed occupation and education choices as well as a parameterization of aspiration updating combined with self-reported aspirations to recover latent aspirations. Third, education choice may be endogenous even conditional on early initial skills. We use the presence of a college in the city of residence at age 18 as an instrument to identify the effect of college attainment on occupation choices and wages. We are thus able to decompose the effect of aspirations on wages into the indirect channel through college and the direct channel through occupation choice.

We use the Wisconsin Longitudinal Survey (WLS) to estimate the model. The survey follows a one-third sample of Wisconsin high-school seniors in 1957, capturing a state-administered IQ test, administrative life-cycle wages, self-reported early occupational aspirations, education attainment, occupation choice, and a rich set of family background variables. While the sample is specific to Wisconsin, it has been shown to be broadly representative of white Americans of the time period (Herd et al., 2014).

We include roughly 2800 white male high school graduates with a maximum education attainment of a bachelor's degree to estimate the model via the simulated method of moments. We focus on white males due to the demographic composition of the sample, as well as the lower numbers of females attending college and to abstract from the endogeneity of fertility. Lifecycle wages and occupation choices of respondents are recorded, as are early measures of IQ and educational attainment. We combine this with the Occupational Information Network data (O*NET), a comprehensive set of occupation-related questions that link occupational titles to task requirements.

The estimated model is used to quantify the role that early aspirations play in education and occupation choice. We show that the aspirations we capture do not exhibit direct labor market returns and are hence distinct from skills that are useful for generating earnings. We generate counterfactual simulations where aspirations do not affect occupation choice and compare the resulting wages, occupation choices, and education choices with baseline moments. Our results show that aspirations explain about 40% of wage variation over the lifecycle and about 10% of education attainment.

Given the importance of aspirations, we propose that it is a viable policy lever to reduce intergenerational inequality. In this paper, aspirations are a natural part of preferences and we do not explicitly model any underlying frictions (such as a lack of information or exposure) that drive differences in aspirations. However, to the extent that aspirations are malleable (as shown by Oyserman et al. (2006) and consistent with our estimates of the dynamic updating of aspirations) and related to self-esteem issues, it is plausible that early aspirations may be "mismatched" with worker abilities.

Consider a highly skilled high school senior who may, for reasons due to family background or social environment, have low levels of occupational aspirations for cognitive tasks. He therefore decides against going to college because he is more likely to choose occupations with low task requirements after graduation that yield lower returns to college. To show this effect, we generate counterfactual aspirations for workers with low-SES backgrounds conditional on skill, using mean aspirations for workers with high-SES backgrounds and similar initial skills. We find that after equating aspirations, wages and cognitive tasks increase significantly in the early career, fading out gradually as workers update their aspirations through their labor market experiences.

This paper contributes by offering a new and tractable way of incorporating the concept of aspirations as a form of individual-and-task specific latent heterogeneity in occupational preferences within a lifecycle model. We also endogenize education choice and allow it to be determined by expected occupational choice. This combination is, to the best of our knowledge, lacking in previous occupation choice models that conceptualize occupations as tasks (Costas Cavounidis and Malhotra, 2023; Deming and Kahn, 2018; Guvenen et al., 2020; Postel-Vinay and Lise, 2020; Sanders and Taber, 2012; Yamaguchi, 2012). As a result, we are able to demonstrate the importance of early aspirations and show that its effect on wages through occupation choice is particularly key.

This ties in to a larger literature estimating education choices and labor market choices jointly, starting with Keane and Wolpin (1997). Occupation choice was modeled as blue collar, white collar, or military, with workers accumulating skills within those categories. Modeling occupations as tasks provides a more nuanced view of skill accumulation, which is a function of task intensity, varying across occupations within the broader occupation categories typically used in occupation choice models. A similar argument can be made for wage growth where the heterogeneity in skill prices is now allowed to depend on task intensity instead of being held constant across all occupations within broader occupation categories. For instance, secretaries and managers, being both white-collared jobs, would have the same skill prices. Finally our model includes individual-specific heterogeneity in non-pecuniary task returns through aspirations, in contrast to occupation-specific non-pecuniary returns in Keane and Wolpin

(1997).

A more closely related recent literature includes Arcidiacono et al. (2020), Patnaik et al. (2022), and Wiswall and Zafar (2021). These papers elicit subjective wage expectations to recover individual-specific heterogeneity in non-pecuniary returns to occupations and majors. To the extent that aspirations capture beliefs about expected returns, our findings are related, although our model also includes direct preferences for occupations as well. Their findings also strongly suggest that college experiences shape beliefs and hence choices, a key source of motivation for allowing aspirations to vary over time.

Our paper also complements existing studies on aspirations, broadly defined. An extensive set of papers (e.g. Dalton et al. (2015); Durlauf et al. (2022); Genicot and Ray (2017, 2020); Haushofer and Salicath (2023); Kearney and Levine (2016); Lybbert and Wydick (2018); Mookherjee et al. (2010)) provide theoretical frameworks for understanding the role of aspirations in economic models, particularly with regard to inequality and poverty. Our contribution is to bring these ideas to data and show that aspirations matter empirically for lifecycle wages.

Other work document more general associations between aspirations and socioeconomic variables but stop short of quantifying lifecycle impacts on labor market outcomes (Guyon and Huillery, 2020; Hassani-Nezhad et al., 2021; Jacob and Linkow, 2011; Knight and Gunatilaka, 2012). We fill this gap in the literature by imposing structure on the problem and focusing on worker outcomes in a partial equilibrium setting.

This paper raises occupational aspirations as an alternative mechanism to explain lower education attainment among highly able children from less well-off families. This adds to our understanding of intergenerational (im)mobility. To the extent that these aspirations can be influenced either by career counseling during high school (Oyserman et al., 2006) or early exposure to peers, role models or information (Cools et al., 2022; Gonzalez Amador et al., 2022), this can have important policy implications. Indeed, in other settings, a growing number of experimental papers have shown that interventions targeting aspirations can be effective at improving socioeconomic outcomes (Carlana and La Ferrara, 2024; Galiani et al., 2021; Kate Orkin, 2023; Rojas Valdes et al., 2021).

The rest of the paper is organized as follows. Section 2 outlines the Wisconsin Longitudinal Study dataset. Section 3 describes empirical facts about the aspirations we capture. Section 4 details our model of aspirations, education, and occupations. Section 5 presents our main results. Section 6 concludes.

2 Data

We use the Wisconsin Longitudinal Study (WLS), a representative sample of men and women who graduated from Wisconsin high schools in 1957. Respondents were interviewed first in 1957 (at the age of 18), and tracked through 2011 with data collected in several waves (1975, 1992, 2004, and 2011). Information on employment and earnings come from administrative state tax records. Unfortunately, these administrative records do not include Information about occupations. We construct the occupation history of each individual using the information collected retrospectively in the different waves of the WLS, which allows to set the first occupation in 1964. That is, at the age of 26.

The key independent variables include early occupational aspirations, IQ scores, and a rich set of family background variables such as parental occupation and education. We also observe the presence of a college in the city of residence at age 18, our instrument for college attainment. Our outcomes of interest are college attendance, occupation choice, and wages.

During the first round, each respondent was asked to report his or her early occupational aspiration. Based on the answer to this question, coders assigned a three-digit 1970 Census occupational code to the original response. Table 1 shows the distribution of these answers, aggregated at the one-digit occupational category, for all men included in the sample. We observe that almost half declared an occupation within the professional category as their intended occupation. The second and third more important categories are craftsmen and operatives, with 11.4% and 11.2% of preferences, respectively.

To quantify aspirations and occupation choices, we combine the WLS with O*NET data to exploit the idea that occupations can be characterized as *tasks* rather than job titles. The advantage of this approach is to achieve a dimension reduction in the occupation choice space whilst preserving meaningful heterogeneity among occupational choices, particularly useful in the setting where we wish to recover interpretable latent skills from occupation choices.[2]

Occupations are typically reported using three-digit Census codes. The O*NET data contains roughly 1000 job titles, each corresponding to a three-digit Census code. Modeling an agent who chooses a specific occupation out of 1000 is not feasible. Instead, the literature often reduces this dimension by modeling the choice of 2–10 occupational categories, the chief assumption being that skill accumulation and skill prices are constant within the occupational categories. This approach is not conducive for understanding how occupational preferences affect educational attainment if there are substantial numbers of both education groups within each occupational category, for example. It is also difficult to construct meaningful categories that would capture the occupational differences between high school graduates and college-educated workers.

Instead, we construct a two dimensional factor representation of occupational task

[2]See Yamaguchi (2012) for a more in-depth discussion of this approach relative to modeling occupations as discrete choices based on one-digit or two-digit occupation classifications.

requirements: cognitive and interpersonal. These two factors are based on measures in the O*NET data where each measure captures the intensity of a specific task on the job on a scale of one to five. For example, workers and industry members belonging to a three-digit occupation code are asked how often they "process information" or "interact with computers". The O*NET data surveys a nationally representative sample of workers to elicit such responses.

These measures are then grouped into "natural" categories. For instance, "analyzing data", "interacting with computers", "making decisions and solving problems" can be categorized as cognitive tasks, while "assisting and caring for others" might be categorized as interpersonal. Using exploratory factor analysis, we use the strength of covariances between the measures to guide how they are categorized. Then, we estimate a factor model and construct factor scores for the two task factors. Any three-digit occupation can be represented as a two-dimensional vector comprising a score each for cognitive and interpersonal task intensities on the job. The scores are normalized to have mean 0.5 and standard deviation 0.1. For instance, the task score vector for mechanics is $(0.446, 0.426)$ for cognitive and interpersonal tasks, respectively. In contrast, the vector for accountants is $(0.560, 0.491)$.

The task-based definition of occupations extends to the conceptualization of occupational aspirations. Workers have aspirational preferences for tasks so that a worker with higher cognitive task aspirations receives a higher utility pay-off when he chooses a job which is cognitive task intensive. Similarly, the worker may have higher or lower task aspirations for interpersonal tasks.

3 Understanding Aspirations

In this section we present some stylized facts regarding the links between aspirations, background variables, education, and occupations.

Consistent with a large literature documenting the strong correlations between parental and child occupations, we find that aspirations are strongly correlated with father's occupational tasks and other background variables (see Table 2) Conditional on IQ scores, high-school rank, and family characteristics, an increase of 1 s.d. in the cognitive task intensity of the father's occupation is associated with an increase of 0.15 s.d. in the reported cognitive task aspiration. Similarly, an increase of 1 s.d. in the interpersonal task intensity is associated with an increase of 0.12 s.d. in the reported interpersonal task aspiration.

We also show that there is large variation in aspirations. Figure 1 shows the distribution of aspirations for each IQ quintile. Aside from the clear correlation between cognitive aspirations and IQ, we also see that even conditional on IQ quintile, aspirations can vary dramatically. As we would expect, the correlation between interpersonal aspirations and IQ is much weaker.

Regardless, the correlations between an observable proxy for cognitive skill (IQ) and aspirations strongly suggest that unobserved skill is also likely to correlate with aspirations. The subsequent descriptive statistics should thus be interpreted with this in mind. In the case where the policy intervention of interest is to alter aspirations without necessarily changing initial skills, the associations that follow are likely to be over-estimates of the impact of aspirations on college attendance. On the other hand, these estimates may still be of interest if we believe that interventions of aspirations would also improve skills upon high school graduation.[3]

[3]For example, the intervention documented by Oyserman et al. (2006) suggests that counseling to raise aspirations also improve school grades and behavior.

Next we show the strong link between early aspirations and college attendance, even conditional on IQ scores, high school rank, and family background controls (see Table 3). Given our normalizations, a 1 s.d. increase in cognitive task aspirations is associated with a 10 percentage points (p.p.) increase in the probability of attending college. As is true for the rest of our descriptive statistics, this coefficient is likely to encompass the correlation between cognitive aspirations and cognitive skills.

Aspirations also predict occupational choice, and hence are likely to be important for fully understanding the career paths of workers. We regress observed tasks and wages on early aspirations and college attendance over the lifecycle of the workers, first with college attendance entering naively (Table 4) and also using our proximity instrument for the presence of a college in the city of residence at high school graduation (Table 5). In terms of occupational choice, our OLS estimates show that an increase of 1 s.d. in cognitive or interpersonal aspirations associates with higher task complexity by around 0.11-0.15 s.d. The IV estimates show similar results but our estimates of cross-dimension are no longer statistically significant at the 10% level. For wages, our OLS estimates show that, conditional on college attainment and background characteristics, an increase of 1 s.d. in cognitive and interpersonal aspirations associate with a change of 3.8 p.p. and a reduction of 4.2 p.p. in wages, respectively. After using our proximity instrument, the estimate for cognitive aspirations reduces to 1.8 p.p., while the estimate for interpersonal aspirations is -5.6 p.p. Both coefficients remain statistically significant at the 5% level.

Finally, we show that aspirations change over time. Using two measures of aspirations (first in 1957 and second in 1975), we see that workers tend toward the mean in their aspirations (see Figure 2). We therefore incorporate dynamic aspirations into the model to capture this tendency.

Taken together, these descriptive statistics motivate the model we lay out in the next section. We will use the moments presented above to discipline the model during estimation and use the model to consider several policy-relevant counterfactuals.

4 Model

We augment a task-based occupational choice model with endogenous college choice and early aspirations. Figure 3 shows the timing of decisions and how variables are determined in every period. The model begins at high school graduation, where graduates decide whether to go to college or start working. If college is chosen, then occupation choice begins four years after high school graduation, where college boosts skills. If not, high school graduates begin their careers, choosing occupations based on skills and aspirations. Both are updated in every period depending on contemporaneous latent variables.

4.1 Education Choice Model

Consider a high school graduate facing the choice of pursuing college education or working. He has an initial endowment of skills, aspirations, and his college costs depend on initial skills and our instrument (college proximity). He maximizes the following expression:

$$V_0(\boldsymbol{\theta_0}, \boldsymbol{A_0}, \boldsymbol{X}, \kappa) = \max_{d \in \{0,1\}} \mathbb{E}\big[\sum_t V_t(\boldsymbol{\theta_t}, \boldsymbol{A_t}, \boldsymbol{\tilde{\nu}_t}, d)\big] + \mathbf{1}\{d = 1\}(\gamma_0 \kappa + \gamma_1 \theta_{0,C} + \gamma_2 \theta_{0,I} + \zeta) \tag{1}$$

Where $\boldsymbol{\theta_0}$ and $\boldsymbol{A_0}$ correspond to the set of initial latent skills and aspirations, respectively. d is a college attendance indicator, κ is an indicator for the geographic availability of college (graduate attended high school in city with college/university) and ζ is a normal preference shock with standard deviation σ_ζ.

High school graduates form expectations over their future utility which depends on the vectors of skills $\boldsymbol{\theta_t}$, aspirations $\boldsymbol{A_t}$, and skill shocks $\boldsymbol{\tilde{\nu}_t}$. College potentially affects their labor market experiences by boosting initial skills, improving the rate of skill growth, and reducing the psychological cost of task intensive jobs. The last point serves to capture the fact that cognitive task intensive jobs are often accompanied by education requirements. Their college choice also depends on their aspirations through its influence on occupation choice.

Importantly, the key threat to identification is captured by latent initial skills that depend on background variables:

$$\theta_{0,k} = \boldsymbol{X'\alpha_k} + \eta_{\theta,k} \tag{2}$$

We normalize $\boldsymbol{\theta_0}$ to have mean 0 and standard deviation 1. These skills enter into early aspirations $\boldsymbol{A_0}$:

$$\mathrm{A}_{0,k} = \boldsymbol{X'\beta_k} + \lambda^p_{1k}\theta_{0,k} + \eta_{A,k} \tag{3}$$

where k takes on values of C and I representing "cognitive" and "interpersonal", respectively. The vector $\boldsymbol{X}$ includes standardized IQ, high-school rank, and a socioeconomic index constructed using parents' occupation, parents' education, and family income in 1957. The parameter λ^p_{1k} corresponds to the weight assigned to the initial skill in how initial aspirations are determined. We allow for heterogeneity by letting this parameter vary by socioeconomic status. In practice, we divide individuals in quartiles according to an index based on family income and parents' education. $\boldsymbol{A_0}$ is normalized to have mean 0.5 and standard deviation 0.1. Equation (3) shows that we restrict initial skills to only affect their respective aspirations. This assumption can be relaxed to allow for cross-dimension correlations between skills and aspirations, although we do not find strong evidence in favor of this in the data.

4.2 Occupation Choice Model

Expanding on the occupation choice part of the model, we have workers choosing a vector of two-dimensional tasks ($\boldsymbol{x_t}$) in each period, representing their chosen occupation. They do this given their early aspirations, their current skills, and their education attainment. For each individual, the Bellman equation is given by:

$$V_t(\boldsymbol{\theta_t}, \boldsymbol{A_t}, \boldsymbol{\tilde{\nu}_t}; d) = \max_{\boldsymbol{x_t}} w(\boldsymbol{x_t}, \boldsymbol{\theta_t}) + g(\boldsymbol{x_t}, \boldsymbol{\theta_t}, \boldsymbol{A_t}) + \beta \mathbb{E} V_{t+1}(\boldsymbol{\theta_{t+1}}, \boldsymbol{A_{t+1}}, \boldsymbol{\tilde{\nu}_{t+1}}; d) \tag{4}$$

Where $w(\boldsymbol{x_t}, \boldsymbol{\theta_t})$ is the log-wage function, and $g(\boldsymbol{x_t}, \boldsymbol{\theta_t}, \boldsymbol{A_t})$ is a function of job preferences. Wages are a function of tasks and skills:

$$\begin{aligned} w(\boldsymbol{x_t}, \boldsymbol{\theta_t}) =& p_0 + p_{1,C} x_{t,C} + p_{1,I} x_{t,I} + p_{2,C}\theta_{t,C} + p_{2,I}\theta_{t,I} \\ & + p_{3,C} x_{t,C}\theta_{t,C} + p_{3,I} x_{t,I}\theta_{t,I} + \eta_t \end{aligned} \tag{5}$$

While job preferences are a quadratic function of task choices:

$$\begin{aligned} g(\boldsymbol{x_t}, \boldsymbol{\theta_t}, \boldsymbol{A_t}) =& (\Sigma_{0,C} + \Sigma_{1,C} d + \Sigma_{2,C}\theta_{t,C} + \tilde{\nu}_{t,C}) x_{t,C} - \Sigma_{3,C} x_{t,C}^2 - \Sigma_{4,C}(x_{t,C} - A_{t,C})^2 \\ & + (\Sigma_{0,I} + \Sigma_{1,I} d + \Sigma_{2,I}\theta_{t,I} + \tilde{\nu}_{t,I}) x_{t,I} - \Sigma_{3,I} x_{t,I}^2 - \Sigma_{4,I}(x_{t,I} - A_{t,I})^2 \end{aligned} \tag{6}$$

$w(\boldsymbol{x_t}, \boldsymbol{\theta_t})$ captures the pecuniary returns to occupation choice and skills, while $g(\boldsymbol{x_t}, \boldsymbol{\theta_t}, \boldsymbol{A_t})$ captures the non-pecuniary returns. Note that the non-pecuniary returns depend on education attainment, aspirations, and skill level. The squared term captures the cost of choosing occupations that demand high task levels, while the interactions between task levels and the other variables capture the notion of a good "match" between one's preferences/skills and the tasks required by the occupation chosen. Aspirations can also thus have a negative impact on earnings if they are significantly higher than skill levels.[4]

Finally, the technology of skill growth is given as:

$$\theta_{t+1,k} = s_{0,k} + s_{1,k}d + s_{2,k}x_{t,k} + s_{3,k}\theta_{t,k} + \epsilon_{t,k} \tag{7}$$

Equation (7) implies that skills evolve as a function of current period's skill levels, college, and tasks. For aspirations, we adopt a more flexible parametrization that allows different updating patterns by socioeconomic status, depending on college attainment:

$$\mathrm{A}_{t+1,k} = q_{0,k} + q_{1,k}d + q_{2,k}\theta_{t,k} + q_{3,k}\mathrm{A}_{t,k} + q_{4,k}\mathrm{SES} + q_{5,k}(d \times \mathrm{SES}) + \varepsilon_{t,k} \tag{8}$$

As before, equations (7) and (8) show that skills and aspirations do not affect next period cross-dimension objects. We assume that all shocks are i.i.d. and normally distributed with mean 0.

As shown in Yamaguchi (2012), the linear parametrization of the wages, non-pecuniary task preferences, and skill growth give rise to a linear policy function (in terms of state variables). We show in section A.1 in the Appendix that the parametrization of the model allows to write the optimal task choice as:

$$x^*_{t,k} = b_{0,t,k} + b_{1,t,k}d + b_{2,t,k}\theta_{t,k} + b_{3,t,k}A_{t,k} + b_{4,t,k}\tilde{\nu}_{t,k} \tag{9}$$

where b's are the time-varying reduced-form coefficients that are functions of underlying structural parameters. The model solution suggests the intuition that optimal task choices are noisy measures of underlying skills and aspirations. Together with wages and the structure imposed by the technology of skill growth, they facilitate the recovery of latent skills.

[4]This negative effect has been documented in other settings, for instance McKenzie et al. (2022).

5 Results

We estimate the model using indirect inference. We match education-specific mean wages and tasks over the lifecycle, which reflect skill growth and aspirations for workers in each education category (college versus high school graduates). We match covariances between wages, tasks, and reported aspirations across multiple years of work history to capture the role of aspirations. The covariances between wages and tasks in each period reflect latent skills in that period, while the cross-time covariances capture skill growth. To identify the effect of education, we exploit the proximity of college instrument. The wedge between the IV and OLS estimates for the effect of college on labor market outcomes reflect the importance of initial skills at high school graduation. Section A.2 in the Appendix summarizes the moments we employ. Overall, we use 318 moments to estimate 77 parameters in our model.

The estimated model parameters are reported in Appendix Section A.3.[5] Here, we present statistics showing our model fit in Figure 4. Our model does reasonably well matching the wage profiles of both high school and college graduates, as well as their respective occupation task profiles. As described in the data section, the WLS allows to track occupations only starting in 1964. For this reason, we can match task intensities starting in the fourth and eighth year after the individual has finished college or high school, respectively. Finally, the last two plots show how our model replicates the distribution of college enrollment by IQ and socioeconomic status quartiles.

The model also replicates the dynamic moments closely. In Appendix Section A.4 we include an extended list of tables detailing the sample and simulated moments.

[5] We compute standard errors using a bootstrap procedure. We randomly sample with replacement from our original sample and re-estimate the model. We do this 50 times and calculate the standard deviation of each parameter across bootstrap samples.

5.1 Skills vs Aspirations

We use the model to simulate latent initial skills and estimate the contribution of latent skills in the correlation between aspirations, education, and labor market outcomes. We show that the model plays a crucial role in parsing out the effect of aspirations on later life outcomes conditional on latent initial skills, relative to the naive association that omits initial skills.

First, we simulate the labor market trajectories for each individual 10 times using the estimated parameters of our model. Starting from the vector of individual characteristics X_i we simulate initial skills θ_i, college choice d_i, tasks, and wages. Then, we use the pooled simulated across individuals and simulations and run regressions on each of the outcomes controlling for initial skills and aspirations.

Table 6 shows that both cognitive and interpersonal aspirations continue to matter for college choice even after including latent initial skills $\boldsymbol{\theta_0}$, although their coefficients decline substantially for cognitive aspirations. For interpersonal aspirations, the decline is smaller.

Similarly, for tasks, Table 7 shows that aspirations continue to matter for occupation choice conditional on initial skills. For cognitive tasks, columns (1) and (2) show that the inclusion of initial cognitive skills reduces the importance of cognitive aspirations by 0.03σ. For interpersonal tasks, the reduction is substantially larger. Finally, Table 8 shows the effect of aspirations on wages conditional on education attainment. Columns (1) and (2) show that the importance of cognitive aspirations on wages decreases by around 1.1σ after accounting for initial skills, while the effect of interpersonal aspirations becomes negative. This pattern is similar when we include controls for tasks in columns (3) and (4).

Finally, to see if our conception of aspirations can be distinguished from labor market skills, we use the model to test whether aspirations have a direct effect on wages in addition to the effect through occupational choice. We augment equation (5) to include aspirations and re-estimate the model. We find a null effect of aspirations and minimal changes in the other parameters.[6]

5.2 Decomposition

We next use the model to decompose the impact of aspirations on education and labor market outcomes. We calculate the total impact by simulating the model after setting the parameters of aspirations in the optimal task function to zero for all workers, *ceteris paribus*.[7] We quantify the effects on education by comparing the fraction of individuals attaining college in the benchmark and counterfactual scenarios. For tasks and wages, we compare the variances across all periods in each case.

Figure 5 shows the changes in educational attainment by IQ and cognitive aspiration quartiles after simulating choices relative to the benchmark levels. At baseline, 32% of the sample attends college. When we shut down aspirations in the optimal task choice, this fraction decreases to 29%. In terms of IQ quartiles, we find a similar decrease across different groups, while for cognitive aspirations the figure shows decreases in all groups except the top quartile.

For labor market outcomes, Table 9 shows how the variance of each outcome changes when we set the role of aspirations to zero. Columns (1) and (2) show the variances in the benchmark and counterfactual scenario, respectively. We find a large reduction in the variance of cognitive tasks across all periods, column (3) shows that the ratio is 0.11 in this case. By contrast, the change in the variance of interpersonal tasks

[6]Specifically, we model the wage equation as:

$$w(\boldsymbol{x_t}, \boldsymbol{\theta_t}, \boldsymbol{A_t}) = p_0 + \boldsymbol{p_1 x_t} + \boldsymbol{p_2 \theta_t} + \boldsymbol{p_3 x_t} \cdot \boldsymbol{\theta_t} + \boldsymbol{p_4 A_t} + \eta_t \tag{10}$$

Our estimates of $p_{4,C}$ and $p_{4,I}$ are $9 \cdot 10^{-5}$ and $2 \cdot 10^{-5}$, respectively.

[7]That is, we fix $b_{3,t,k} = 0\ \forall t, k$ in equation (9)

is substantially smaller. Both effects combined imply a reduction in the variance of log-wages across all periods of around 40%.

Together, our decomposition results suggest that cognitive aspirations matter significantly for explaining both education attainment and labor market outcomes, while interpersonal aspirations are less consequential. These results are consistent with the descriptive correlations in the data.

5.3 Changing Aspirations

We consider aspirations as a potential lever for reducing intergenerational inequality. In the following simulation, we focus on workers with similar initial cognitive and interpersonal skills but different socioeconomic status (SES).[8] We analyze how the labor market trajectories of low-SES individuals change after equating their observed aspirations to the average levels of comparable (in terms of skills) high-SES individuals. First, we classify each individual as high-skilled or low-skilled according to their estimated value of θ_0^C and θ_0^I. For each skill, cognitive and interpersonal, the high-skilled group corresponds to the subset of people whose initial skill θ_0^k is above the average. Therefore, each individual will be classified in one of the following groups: (High Cog, High Inter), (High Cog, Low Inter), (Low Cog, High Inter), and (Low Cog, Low Inter).

Then, we compute the average value of A_{i0}^C and A_{i0}^I separately for high-skill and low-skill individuals in the top quartile of the SES distribution, and input these values for the bottom quartile in the respective skill group. We denote the vector of updated aspirations as $\boldsymbol{A_0^*}$. Using the updated individual characteristics for low-SES individuals, $(\boldsymbol{A_0^*}, \boldsymbol{\theta_0})$, we simulate the model using our estimated parameters.

On average, the increase for high-skilled individuals is 1σ and 0.4σ for cognitive and interpersonal aspirations, respectively. For low-skilled, the increases are 0.8σ and

[8]SES is defined by an index constructed from our family background variables.

1.1σ for cognitive and interpersonal, respectively.

Table 10 shows the differences in aspirations between high-SES and low-SES individuals with comparable skills. The first two columns show the gap for individuals with skill levels above the average, while columns 3 and 4 show the difference for the sub-group below the average. The first row shows both gaps for cognitive aspirations. For the subgroup with cognitive skills above the average, the gap across socioeconomic groups is 0.08, which is equivalent to 0.8σ. For individuals with cognitive skills below the average, the gap is 0.7σ. In the case of interpersonal aspirations, the socioeconomic gap is 0.6σ for individuals with high interpersonal skills. The difference increases to 1.5σ for individuals with low interpersonal skills.

The effects of increasing initial aspirations fades out after 20 periods approximately. Figure 6 shows the changes in log-wages, separately by groups. Each line in this plot represents one of the four subgroups created according to their values of $\boldsymbol{\theta_0}$. Low-SES individuals, with high skills but low aspirations in both dimensions, are the most benefited group.

First, there is a contemporaneous effect by means of directly increasing task intensities. Second, there is a dynamic effect through aspirations update and skills accumulation. Our estimates of the parameter $q_{k,3}$ governing the persistence of aspirations is 0.67 and 0.65 for cognitive and interpersonal, respectively, implying that any transitory increase will diminish its effect on outcomes over time. Despite the fade out, the wage effect is sizeable during the initial periods. Table 11 shows the ratio between the cumulative wage levels in the counterfactual and the baseline over the lifecycle, separately by skill groups.[9] As Figure 6 shows, during the initial 15 periods wages increase in the counterfactual and then the effect disipates. The results indicate that for high-skilled individuals the cumulative wages relative to the baseline increase by

[9]We compute the ratio $\sum_{t=1}^{T} w_{it}^{counter} / \sum_{t=1}^{T} w_{it}^{bench}$ for different values of T.

4%, 3%, and 2% after 5, 10, and 15 periods, respectively. We find similar, but slightly smaller values for the remaining groups.

Figures 7 and 8 display the differences between the baseline and counterfactual occupational tasks. In the first period, the increase in the cognitive task rank between 0.06σ-1.2σ and declines rapidly. After five periods, the change is smaller than 0.02σ for all skill groups. For interpersonal tasks, the initial change is substantially smaller.

6 Conclusion

We set out to investigate the role of aspirations on education and labor market outcomes and find that these early characteristics of workers matter considerably. Aspirations affect both education choice as well as wages and occupation choices. Our paper sheds light on how much better high ability workers would fare in the labor market if they had started their post-high school life with higher aspirations, but more work is needed regarding the formation and malleability of aspirations. Our descriptive regressions suggest that aspirations depend on parental occupations among other factors. Combined with our model simulations, we conclude that even conditional on skill, high ability children born to lower socio-economic status parents may have lower aspirations than their high socio-economic status counterparts and underachieve in terms of both education attainment and labor market outcomes. This mechanism can lead to intergenerational effects and could potentially have important implications for explaining racial and gender gaps in the labor market.

7 Tables and Figures

Table 1: Occupational Aspirations at One-Digit Classification

	Observations	Percentage
Professional	1,721	48.5
Managers	310	8.7
Sales	126	3.6
Clerical	176	5.0
Craftsmen	405	11.4
Operatives	398	11.2
Transport	21	0.6
Laborers	41	1.2
Farmers	303	8.5
Service	49	1.4
All men	3,550	100

Each row corresponds to a one-digit occupational category from the Occupational Classification System. Farmers include "Farmers" and "Farm Laborers"; Service includes "Service Workers" and "Private Household Workers".

Table 2: Aspirations and Family Background

	Cognitive	Interpersonal
IQ/10	0.012***	0.009***
	(0.001)	(0.001)
HS Rank/10	0.009***	0.004***
	(0.001)	(0.001)
Father Occ: Cognitive	0.032	-0.032
	(0.029)	(0.032)
Father Occ: Interpersonal	0.054*	0.118***
	(0.030)	(0.033)
Father Education	0.003***	0.003***
	(0.001)	(0.001)
Mother Education	0.002***	0.001*
	(0.001)	(0.001)
Family Income (1957)	0.001***	0.000**
	(0.000)	(0.000)
Observations	2834	2834
R^2	0.22	0.11

Robust standard errors in parenthesis. Tasks and aspirations are normalized to have mean 0.5 and standard deviation 0.1.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: College Attendance

	(1)	(2)	(3)
Occ. Aspiration (1957): Cognitive	2.30***	1.16***	1.02***
	(0.14)	(0.14)	(0.14)
Occ. Aspiration (1957): Interpersonal	-0.09	0.28**	0.22*
	(0.14)	(0.13)	(0.13)
College in city	0.11***	0.10***	0.07***
	(0.02)	(0.02)	(0.02)
IQ/10		0.07***	0.05***
		(0.01)	(0.01)
HS Rank/10		0.04***	0.04***
		(0.00)	(0.00)
Family Background	No	No	Yes
Observations	2834	2834	2834
R^2	0.22	0.35	0.38

Robust standard errors in parenthesis. The dependent variable is an indicator equals to one if the respondent attended college. Aspirations are normalized to have mean 0.5 and standard deviation 0.1. Family background includes father's occupational choice, father's education, mother's education, and family income in 1957.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: OLS Regressions of Tasks and Wage

	x_{it}^C	x_{it}^I	$\ln(w_{it})$
Occ. Aspiration (1957): Cognitive	0.109***	-0.029***	0.379**
	(0.006)	(0.008)	(0.050)
Occ. Aspiration (1957): Interpersonal	-0.013***	0.148***	-0.418***
	(0.005)	(0.007)	(0.046)
College	0.051***	0.053***	0.219***
	(0.001)	(0.001)	(0.007)
IQ/10	0.004***	0.002***	0.020***
	(0.000)	(0.000)	(0.003)
HS Rank/10	0.003***	0.002***	0.012***
	(0.000)	(0.000)	(0.001)
Family Background	Yes	Yes	Yes
Potential Experience	Yes	Yes	Yes
Observations	45604	45604	40427
R^2	0.25	0.16	0.37

Robust standard errors in parentheses. Family background includes father's education, mother's education, and family income in 1957. Potential experience includes a quadratic in age minus years of education.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: IV Regressions of Tasks and Wage

	x_{it}^{C}	x_{it}^{I}	$\ln(w_{it})$
Occ. Aspiration (1957): Cognitive	0.127***	-0.015	0.174**
	(0.012)	(0.015)	(0.081)
Occ. Aspiration (1957): Interpersonal	-0.008	0.152***	-0.556***
	(0.006)	(0.008)	(0.063)
College	0.033***	0.039***	0.495***
	(0.010)	(0.013)	(0.088)
IQ/10	0.005***	0.003***	0.002
	(0.001)	(0.001)	(0.006)
HS Rank/10	0.003***	0.003***	0.001
	(0.000)	(0.001)	(0.004)
Family Background	Yes	Yes	Yes
Potential Experience	Yes	Yes	Yes
Observations	45604	45604	40427
R^2	0.24	0.16	0.35
IV F-Test	302.27	302.27	252.27

College is instrumented with a binary variable equals to one if there is a college or university in the city where the respondent graduated from high school. Family background includes father's education, mother's education, and family income in 1957. Potential experience includes a quadratic in age minus years of education.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: College Attendance (controlling for initial skills)

	(1)	(2)
Asp_{i0}^{C}	2.76^{***}	0.23^{***}
	(0.02)	(0.03)
Asp_{i0}^{I}	0.16^{***}	0.05^{***}
	(0.02)	(0.02)
θ_{i0}^{C}		0.35^{***}
		(0.00)
θ_{i0}^{I}		0.02^{***}
		(0.00)
Background	Yes	Yes
Observations	42180	42180
R^2	0.31	0.60

Each regression employs simulated data using the model estimates and 10 simulations per individual. Asp_{i0}^{C} and Asp_{i0}^{I} correspond to the simulated initial cognitive and interpersonal aspirations, respectively, while θ_{i0}^{C} and θ_{i0}^{I} correspond to simulated skills along the same dimensions. All regressions include controls for proximity to a college or university in the city. Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Tasks (Controlling for initial skills)

	Cognitive (x_{it}^C)		Interpersonal (x_{it}^I)	
	(1)	(2)	(3)	(4)
Asp_{i0}^C	0.064***	0.061***	-0.051***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Asp_{i0}^I	-0.005**	-0.008***	0.048***	0.006***
	(0.000)	(0.000)	(0.001)	(0.001)
College	0.067***	0.065***	0.073***	0.073***
	(0.000)	(0.000)	(0.000)	(0.000)
θ_{i0}^C		0.002***		-0.001***
		(0.000)		(0.000)
θ_{i0}^I		0.001**		0.008***
		(0.000)		(0.000)
Potential Experience	Yes	Yes	Yes	Yes
Observations	1844840	1844840	1844840	1844840
R^2	0.57	0.57	0.25	0.26

Each regression employs simulated data using the model estimates and 10 simulations per individual. Asp_{i0}^C and Asp_{i0}^I correspond to the simulated initial cognitive and interpersonal aspirations, respectively, while θ_{i0}^C and θ_{i0}^I correspond to simulated skills along the same dimensions. Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Wage (controlling for initial skills)

	(1)	(2)	(3)	(4)
College	0.206***	0.154***	0.071***	0.021***
	(0.001)	(0.001)	(0.001)	(0.001)
Asp_{i0}^{C}	0.311***	0.202***	0.278***	0.120***
	(0.004)	(0.005)	(0.004)	(0.005)
Asp_{i0}^{I}	0.041***	-0.014***	-0.007**	-0.015***
	(0.003)	(0.004)	(0.003)	(0.004)
θ_{i0}^{C}		0.043***		0.042***
		(0.001)		(0.001)
θ_{i0}^{I}		0.011***		0.003***
		(0.000)		(0.000)
x_{it}^{C}			0.895***	0.876***
			(0.009)	(0.009)
x_{it}^{I}			1.025***	1.025***
			(0.004)	(0.011)
Potential Experience	Yes	Yes	Yes	Yes
Observations	1844648	1844648	1844648	1844648
R^2	0.49	0.49	0.51	0.52

Each regression employs simulated data using the model estimates and 10 simulations per individual. Asp_{i0}^{C} and Asp_{i0}^{I} correspond to the simulated initial cognitive and interpersonal aspirations, respectively, while θ_{i0}^{C} and θ_{i0}^{I} correspond to simulated skills along the same dimensions. Standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Changes in Variance of Tasks and Wages

	Benchmark (1)	Counterfactual (2)	Ratio (2)/(1)
$Var(x_{it}^C)$	0.003	0.0003	0.11
$Var(x_{it}^I)$	0.008	0.007	0.93
$Var(w_{it})$	0.31	0.19	0.60

Notes:

Table 10: Differences in Aspirations between High-SES and Low-SES Individuals, by Skill Groups

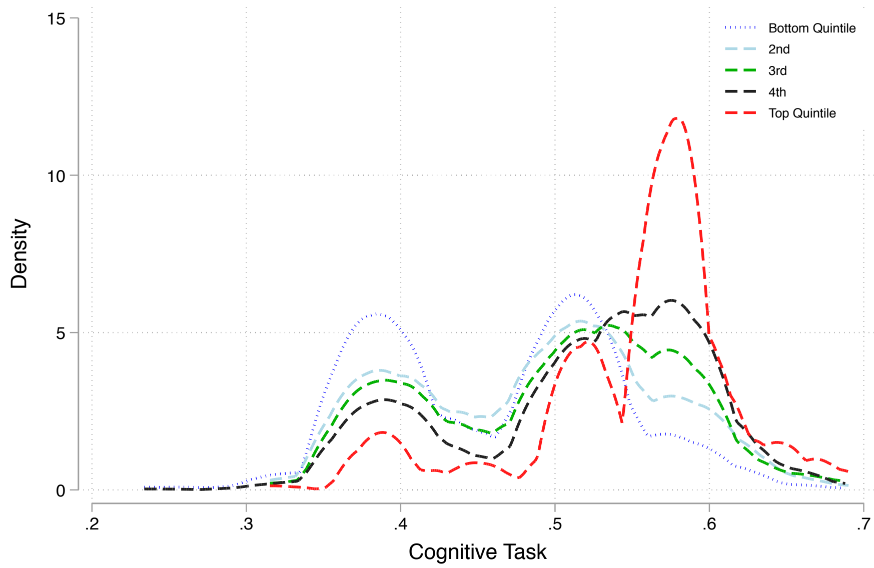
	High Skilled		Low Skilled	
	Top-quartile SES	Bottom-quartile SES	Top-quartile SES	Bottom-quartile SES
Asp_{i0}^C	0.59	0.51	0.49	0.42
Asp_{i0}^I	0.53	0.47	0.58	0.43

Table 11: Relative Increase in Cumulative Wages for Low-SES Individuals, by Skill Groups

	↑ High Cognitive		↑ Low Cognitive	
	↑ High Interpersonal	↑ Low Interpersonal	↑ High Interpersonal	↑ Low Interpersonal
By period 5	1.037	1.019	1.031	1.022
By period 10	1.030	1.016	1.021	1.015
By period 15	1.022	1.012	1.015	1.011
All periods	1.007	1.004	1.005	1.004

Figure 1: Aspirations by IQ Quintile

(a) Cognitive aspirations



(b) Interpersonal aspirations

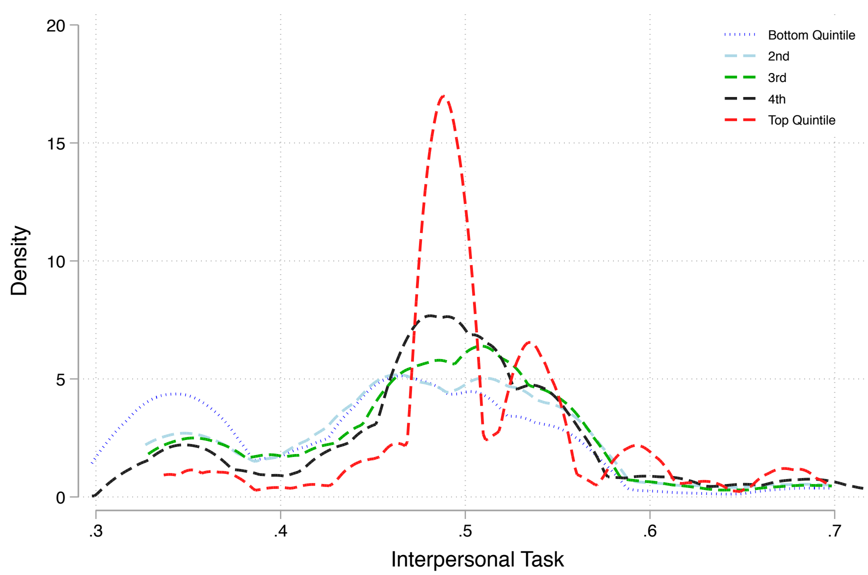


Figure 2: Updating Aspirations

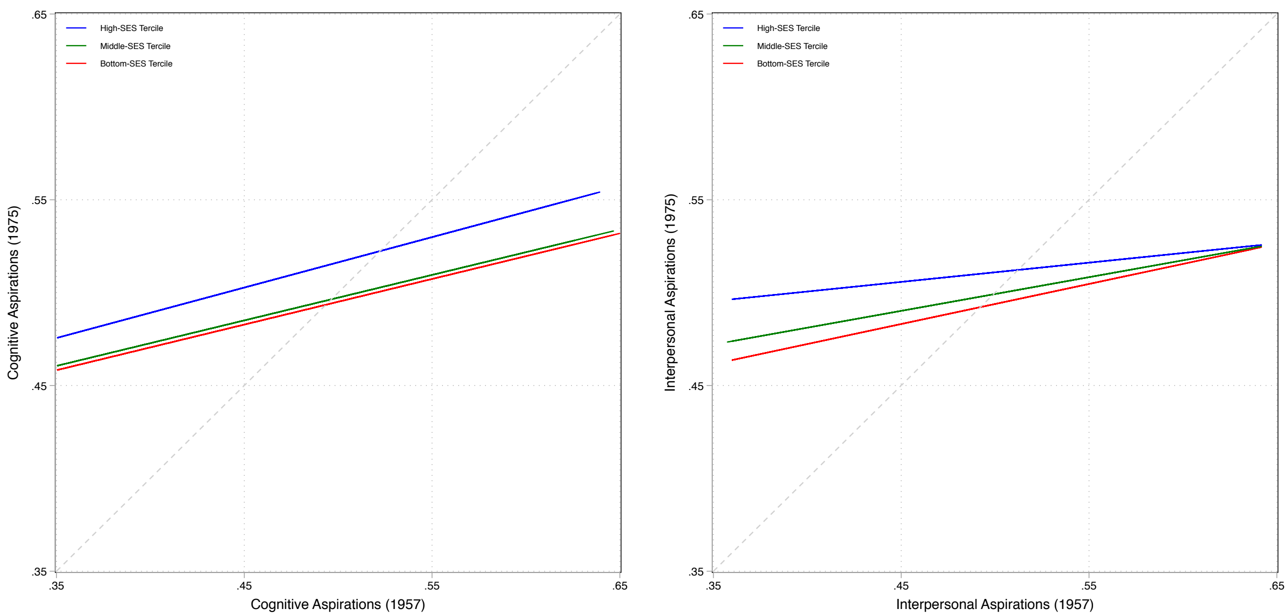


Figure 3: Model Timing

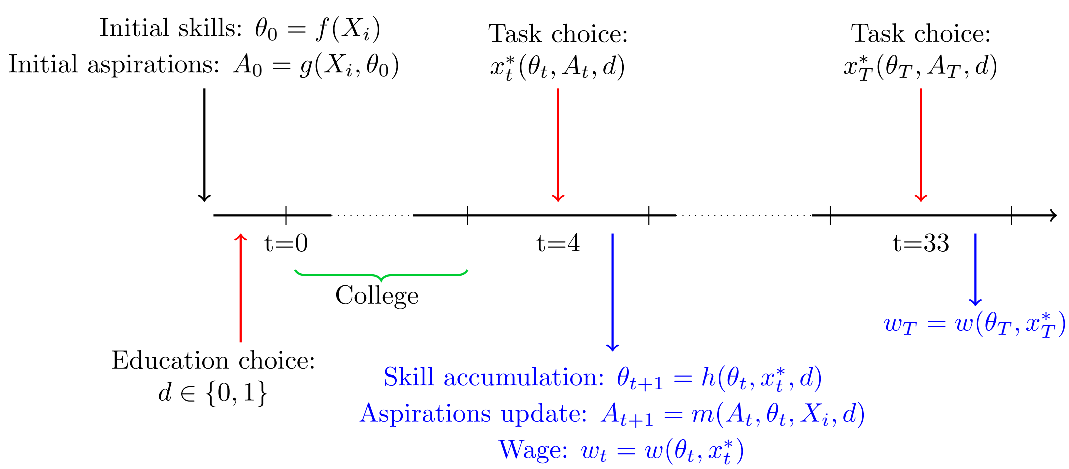


Figure 4: Model Fit

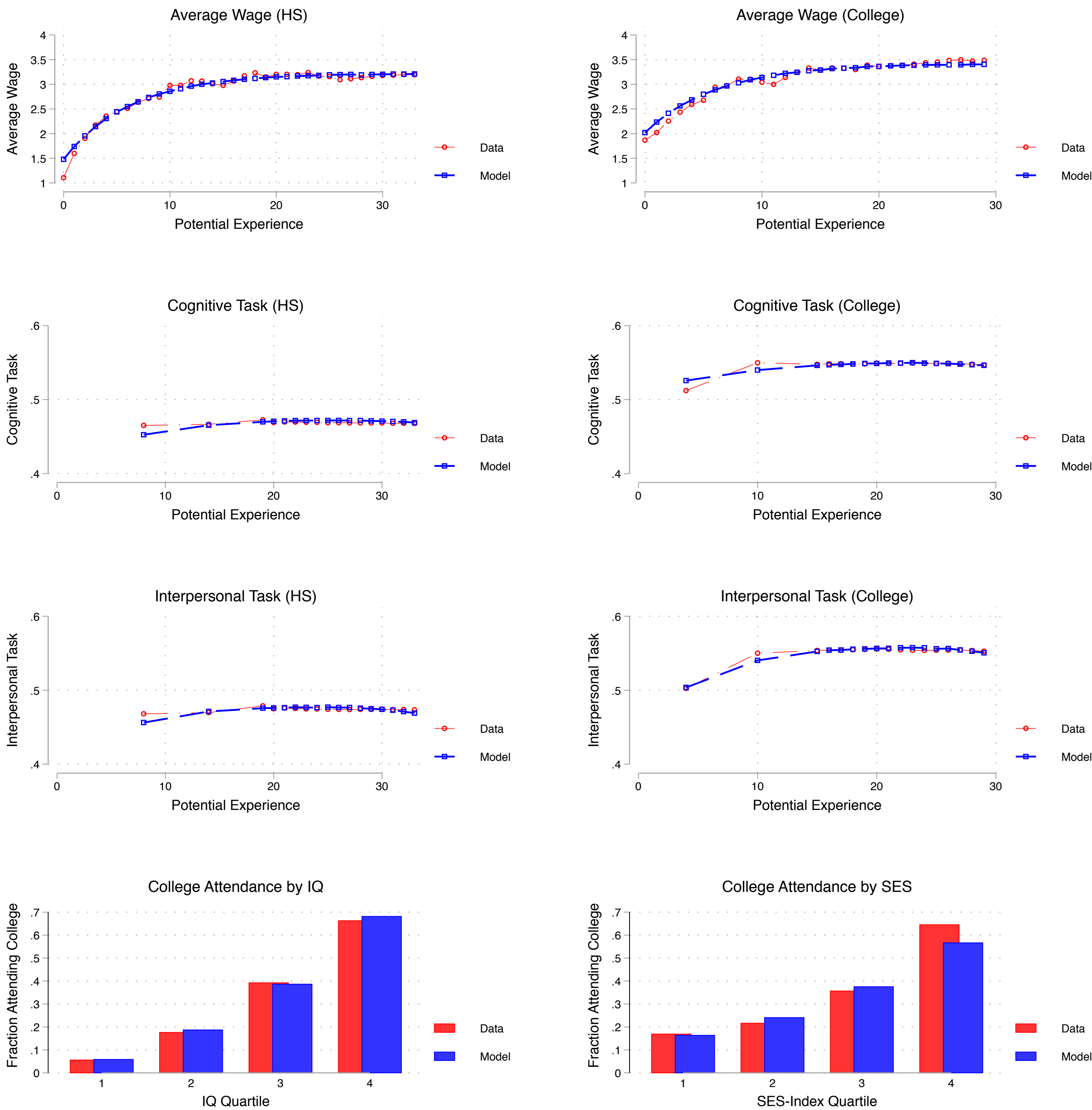


Figure 5: Differences in Education Attainment

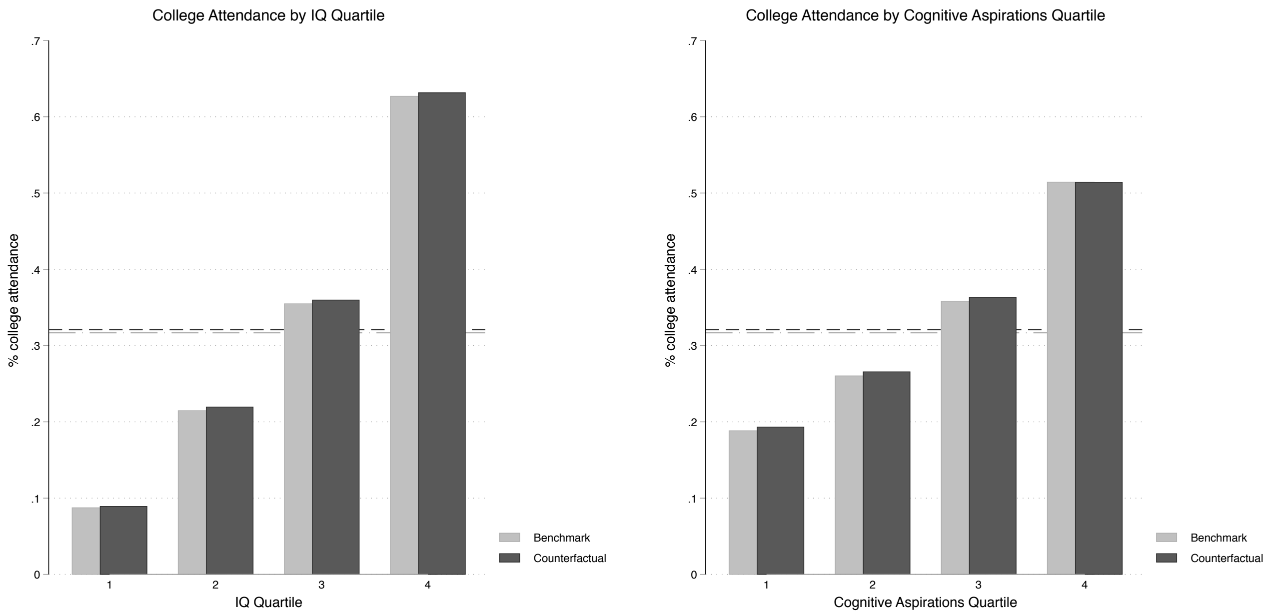


Figure 6: Differences in Wages for Low-SES Individuals, by Skill Groups

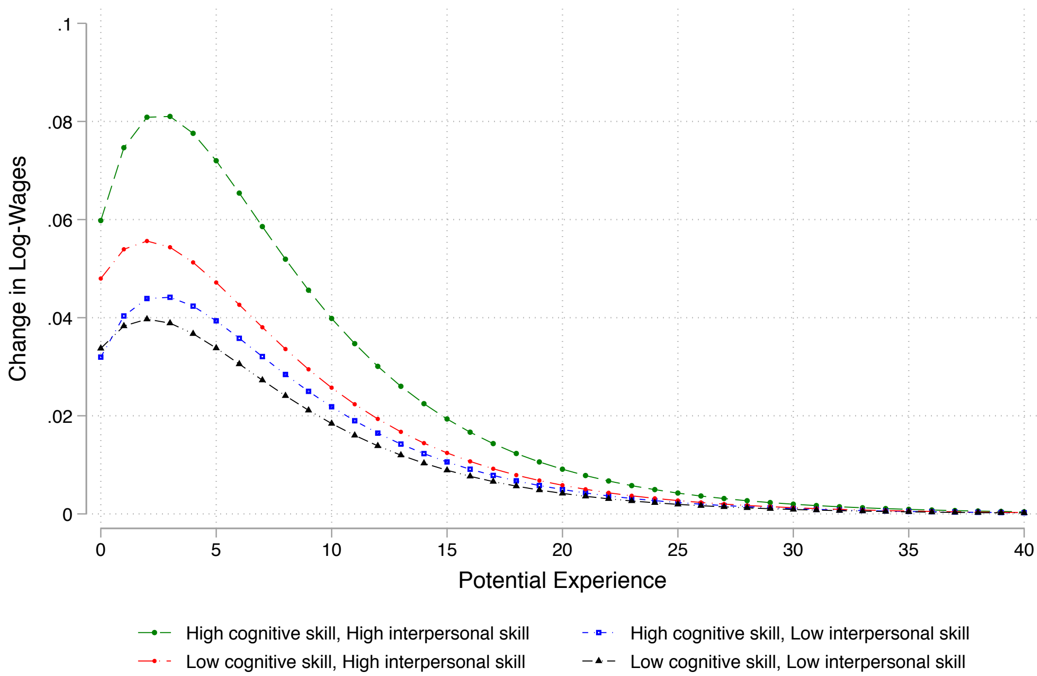


Figure 7: Differences in Cognitive Tasks for Low-SES Individuals, by Skill Group

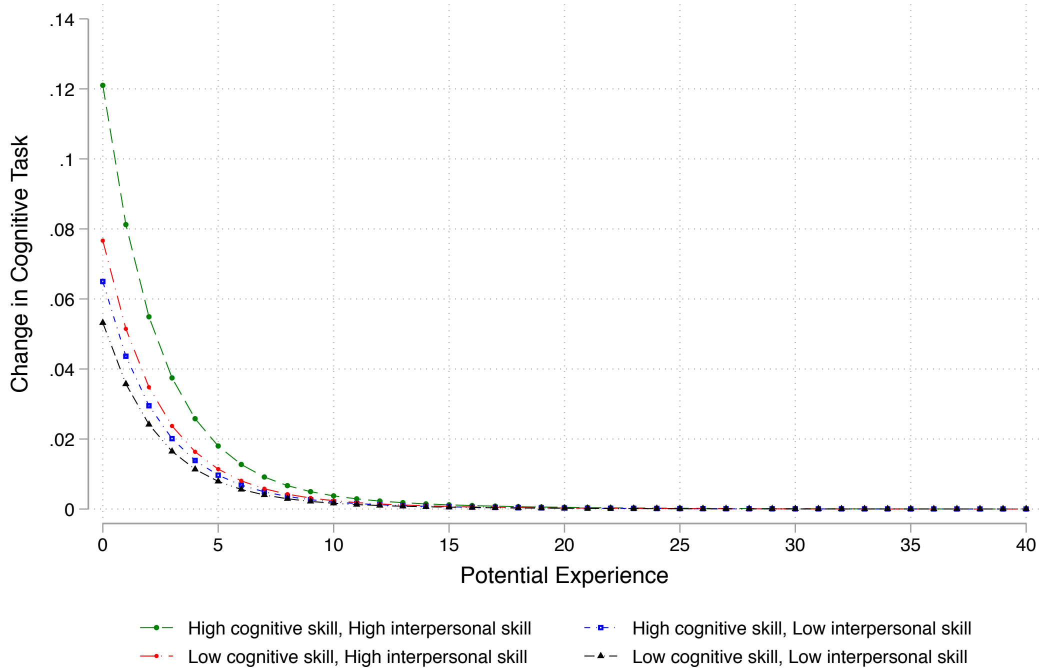
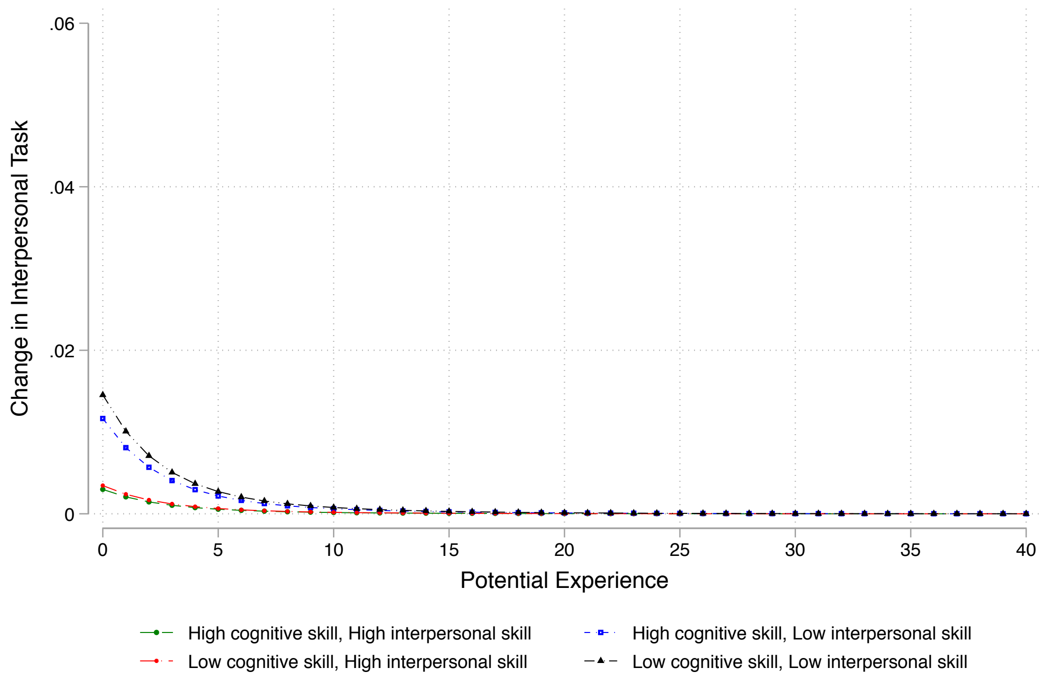


Figure 8: Differences in Interpersonal Tasks for Low-SES Individuals, by Skill Group



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A Appendix

A.1 Model Solution

Following the notation of Yamaguchi (2012), we refer to the state variables by a (9x1) vector $z_t' = \{d, \mathrm{A}_t, \theta_t, \nu_t, \mathrm{SES}, d \times \mathrm{SES}\}$. Notice we include SES and $d \times$ SES as additional state variables to incorporate heterogeneity in the aspirations update function while at the same time keeping the linearity of the optimal task.

State variables evolve as follows:

$$z_{t+1} = l_0 + L_1 z_t + L_2 x_t + \epsilon_{t+1}$$

Where:

$$l_0^T = \begin{bmatrix} 0 & q_{C,0} & q_{I,0} & s_{C,0} & s_{I,0} & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$L_1 = \begin{bmatrix} 1 & 0 & & \dots\dots\dots & & & & 0 & 0 \\ q_{C,1} & q_{C,3} & 0 & q_{C,2} & 0 & 0 & 0 & q_{C,4} & q_{C,5} \\ q_{I,1} & 0 & q_{I,3} & 0 & q_{I,2} & 0 & 0 & q_{I,4} & q_{I,5} \\ s_{C,1} & 0 & 0 & s_{C,3} & 0 & 0 & 0 & 0 & 0 \\ s_{I,1} & 0 & 0 & 0 & s_{I,3} & 0 & 0 & 0 & 0 \\ 0 & 0 & & \dots\dots\dots & & & & 0 & 0 \\ 0 & 0 & & \dots\dots\dots & & & & 0 & 0 \\ 0 & 0 & & \dots\dots\dots & & & & 1 & 0 \\ 0 & 0 & & \dots\dots\dots & & & & 0 & 1 \end{bmatrix}$$

$$L_2 = \begin{bmatrix} 0 & \dots & 0 & s_{C,2} & 0 & \dots & 0 \\ 0 & \dots & 0 & 0 & s_{I,2} & \dots & 0 \end{bmatrix}$$

The value function is period t is given by:

$$\begin{aligned} V_t(z_t) = \max_{x_t} r_0 + r_1' x_t + r_2' z_t + x_t' R_3 x_t + x_t' R_4 z_t + z_t' R_5 z_t \\ + \beta \cdot \Big[q_{0,t+1} + q_{1,t+1}'(l_0 + L_1 z_t + L_2 x_t + \epsilon_{t+1}) \\ + (l_0 + L_1 z_t + L_2 x_t + \epsilon_{t+1})' Q_{2,t+1} (l_0 + L_1 z_t + L_2 x_t + \epsilon_{t+1}) \Big] \end{aligned}$$

Where:

$$r_1 = \begin{bmatrix} p_{C,1} + g_{C,0} \\ p_{I,1} + g_{I,0} \end{bmatrix}$$

$$r_2' = \begin{bmatrix} 0 & \dots & 0 & p_{C,2} & p_{I,2} & 0 & \dots & 0 \end{bmatrix}$$

$$R_3 = \begin{bmatrix} -g_{C,3} - g_{C,4} & 0 \\ 0 & -g_{I,3} - g_{I,4} \end{bmatrix}$$

$$R_4 = \begin{bmatrix} g_{1,C} & 2g_{4,C} & 0 & g_{2,C} + p_{3,C} & 0 & 1 & 0 & 0 & 0 \\ g_{1,I} & 0 & 2g_{4,I} & 0 & g_{2,I} + p_{3,I} & 0 & 1 & 0 & 0 \end{bmatrix}$$

$$R_5 = \begin{bmatrix} 0 & \dots & 0 & 0 \\ 0 & \dots & -g_{4,C} & 0 \\ 0 & \dots & 0 & -g_{4,I} \\ 0 & \dots & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & \dots & 0 & 0 \end{bmatrix}$$

This functional form of the value function leads to a quadratic function of the state variables z_t. The first-order condition with respect to x_t leads to a linear function of z_t. See the Appendix C in Yamaguchi (2012) for details about the derivation.

A.2 List of Moments

Table A.1: Static Moments

Variable	Moment	N
Wage (HS)	mean	34
Cognitive task (HS)	mean	17
Manual task (HS)	mean	17
Wage (College)	mean	30
Cognitive task (College)	mean	17
Manual task (College)	mean	17
Aspirations	mean, variance	4
College enrollment	mean	1
College enrollment by IQ quartile		4
College enrollment by cognitive aspiration quartile		4
Wage	variance	2
Cognitive task	variance	2
Manual task	variance	2
$\text{cov}(wage_t, \text{Asp}_{k,1957})$ (HS)		12
$\text{cov}(wage_t, \text{Asp}_{k,1957})$ (College)		12
$\text{cov}(x_{t,k}, \text{Asp}_{k,1957})$ (HS)		12
$\text{cov}(x_{t,k}, \text{Asp}_{k,1957})$ (College)		12
$\text{cov}(\text{Asp}_{k,1957}, \text{Asp}_{k,1975})$ (HS)		2
$\text{cov}(\text{Asp}_{k,1957}, \text{Asp}_{k,1975})$ (College)		2
Total		**203**

Table A.2: Dynamic Moments

OLS Regressions	N
Initial cognitive aspiration	4
Initial interpersonal aspiration	4
Education Level	7
Education Level (+interactions)	9
Cognitive task (+interactions)	9
Interpersonal task (+interactions)	9
Wage	8
Wage (+interactions)	9
Initial cognitive task	5
Initial interpersonal task	5
IV Regressions	
Cognitive task	8
Interpersonal task	8
Wage	8
FE Regressions	
Cognitive task	1
Interpersonal task	1
Wage	4
Total	**99**

A.3 Model Estimates

Table A.3: Wage Equation

Parameter	Variable	Estimate	Std. Error
p_0	Constant	1.361	0.004
p_{1C}	$x_{t,C}$	0.527	0.012
p_{2C}	$\theta_{t,C}$	0.312	5.1×10^{-4}
p_{3C}	$x_{t,C} \times \theta_{t,C}$	-0.083	0.001
p_{1I}	$x_{t,I}$	0.079	0.008
p_{2I}	$\theta_{t,I}$	0.066	0.003
p_{3I}	$x_{t,I} \times \theta_{t,I}$	-0.012	0.003
σ_η	Shock	0.417	0.029

Table A.4: Effect on Skills of Attending College

Parameter	Variable	Estimate	Std. Error
ρ_C	Cognitive Skill	0.154	0.022
ρ_I	Interpersonal skill	0.292	0.124

Table A.5: Costs of Attending College

Parameter	Variable	Estimate	Std. Error
γ_0	College Proximity	4.649	1.093
γ_1	$\theta_{0,C}$	608	10.2
γ_2	$\theta_{0,I}$	45.2	4.96
σ_ζ	Shock	0.242	0.055

Table A.6: Technology Parameters

Cognitive Skills $\theta_{t+1,C}$

Parameter	Variable	Estimate	Std. Error
$s_{0,C}$	Constant	0.285	0.004
$s_{1,C}$	College	0.007	0.002
$s_{2,C}$	$x_{t,C}$	1.197	0.004
$s_{3,C}$	$\theta_{t,C}$	0.841	5.5×10^{-4}
σ_{ϵ_C}	Shock	0.108	0.024

Interpersonal Skills $\theta_{t+1,I}$

Parameter	Variable	Estimate	Std. Error
$s_{0,I}$	Constant	-0.045	0.004
$s_{1,I}$	College	0.002	0.003
$s_{2,I}$	$x_{t,I}$	0.804	0.003
$s_{3,I}$	$\theta_{t,I}$	0.812	0.001
σ_{ϵ_I}	Shock	0.807	0.050

Table A.7: Initial Skills

Initial Cognitive Skill $\theta_{0,C}$

Parameter	Variable	Estimate	Std. Error
$\alpha_{1,C}$	IQ	0.089	0.006
$\alpha_{2,C}$	SES Index	0.072	0.008
$\alpha_{3,C}$	HS Rank	0.172	0.007
$\sigma_{\eta_{\theta,C}}$	Shock	0.264	0.009

Initial Interpersonal Skill $\theta_{0,I}$

Parameter	Variable	Estimate	Std. Error
$\alpha_{1,I}$	IQ	0.002	0.011
$\alpha_{2,I}$	SES Index	-0.016	0.024
$\alpha_{3,I}$	HS Rank	-0.122	0.026
$\sigma_{\eta_{\theta,I}}$	Shock	0.213	0.018

Table A.8: Initial Aspirations

Initial Cognitive Aspiration $A_{0,C}$

Parameter	Variable	Estimate	Std. Error
$\beta_{0,C}$	Constant	0.494	8.9×10^{-4}
$\beta_{1,C}$	IQ	0.045	0.002
$\beta_{2,C}$	SES Index	0.023	0.003
$\beta_{3,C}$	HS Rank	0.048	0.002
$\sigma_{\eta_{A,C}}$	Shock	0.008	0.007

Initial Interpersonal Aspiration $A_{0,I}$

Parameter	Variable	Estimate	Std. Error
$\beta_{0,I}$	Constant	0.494	0.003
$\beta_{1,I}$	IQ	0.014	0.003
$\beta_{2,I}$	SES Index	0.010	0.003
$\beta_{3,I}$	HS Rank	0.040	0.007
$\sigma_{\eta_{A,I}}$	Shock	0.051	0.008

Table A.9: Aspirations Update

Cognitive Aspirations $A_{t+1,C}$

Parameter	Variable	Estimate	Std. Error
$q_{0,C}$	Constant	0.153	3.0×10^{-4}
$q_{1,C}$	College	0.024	3.1×10^{-4}
$q_{2,C}$	$\theta_{t,C}$	0.003	8.2×10^{-5}
$q_{3,C}$	$A_{t,C}$	0.669	7.7×10^{-4}
$q_{4,C}$	SES	0.004	5.9×10^{-4}
$q_{5,C}$	SES $\times$ College	-0.005	5.0×10^{-4}
σ_{ϵ_C}	Shock	0.033	3.7×10^{-4}

Interpersonal Aspirations $A_{t+1,I}$

Parameter	Variable	Estimate	Std. Error
$q_{0,I}$	Constant	0.158	0.002
$q_{1,I}$	College	0.012	0.002
$q_{2,I}$	$\theta_{t,I}$	0.004	0.001
$q_{3,I}$	$A_{t,I}$	0.654	0.005
$q_{4,I}$	SES	-0.004	0.006
$q_{5,I}$	SES $\times$ College	0.011	0.007
σ_{ϵ_I}	Shock	0.037	0.008

Table A.10: Job Preferences

Cognitive Preferences

Parameter	Variable	Estimate	Std. Error
$\Sigma_{1,C}$	$x_{t,C}$	0.153	0.059
$\Sigma_{2,C}$	$x_{t,C}$ × College	0.491	0.016
$\Sigma_{3,C}$	$x_{t,C} \times \theta_{t,C}$	0.153	0.002
$\Sigma_{4,C}$	$x_{t,C}^2$	-4.022	0.016
$\Sigma_{5,C}$	$(x_{t,C} - A_{t,C})^2$	-13.453	0.754
Σ_C	Shock	0.457	0.023

Interpersonal Preferences

Parameter	Variable	Estimate	Std. Error
$\Sigma_{1,I}$	$x_{t,I}$	1.791	0.011
$\Sigma_{2,I}$	$x_{t,I}$ × College	0.373	0.005
$\Sigma_{3,I}$	$x_{t,I} \times \theta_{t,I}$	0.341	0.002
$\Sigma_{4,I}$	$x_{t,I}^2$	-3.351	0.005
$\Sigma_{5,I}$	$(x_{t,I} - A_{t,I})^2$	-0.284	0.147
Σ_I	Shock	0.249	0.008

A.4 Goodness of Fit

Table A.11: OLS Cognitive Aspirations Update - Below Median

Parameter	Sample		Simulation
	Estimate	S.E.	Estimate
Constant	0.422	0.016	0.466
Education	0.060	0.007	0.076
A_{i0}^{C}	0.129	0.031	0.075
A_{i0}^{I}	-0.016	0.031	0.001

Table A.12: OLS Cognitive Aspirations Update - Above Median

Parameter	Sample		Simulation
	Estimate	S.E.	Estimate
Constant	0.464	0.039	0.490
Education	0.056	0.006	0.071
A_{i0}^{C}	0.076	0.075	0.021
A_{i0}^{I}	-0.014	0.024	0.010

Table A.13: OLS Interpersonal Aspirations Update - Below Median

Parameter	Sample		Simulation
	Estimate	S.E.	Estimate
Constant	0.436	0.021	0.484
Education	0.056	0.007	0.038
A_{i0}^{C}	-0.147	0.068	-0.022
A_{i0}^{I}	0.235	0.095	0.010

Table A.14: OLS Interpersonal Aspirations Update - Above Median

Parameter	Sample		Simulation
	Estimate	S.E.	Estimate
Constant	0.439	0.039	0.454
Education	0.044	0.005	0.046
A_{i0}^C	0.034	0.060	0.019
A_{i0}^I	0.065	0.026	0.028

Table A.15: OLS Wage

Parameter	Sample		Simulation
	Estimate	S.E.	Estimate
Constant	1.77	0.08	0.84
Education	0.20	0.02	0.07
Pot. Exp.	0.79	0.03	1.07
Pot. Exp.^{2}	-0.15	0.005	-0.22
x_{it}^C	1.01	0.19	0.97
x_{it}^I	-0.16	0.11	1.06
A_{i0}^C	0.38	0.20	0.35
A_{i0}^I	-0.38	0.15	-0.01

Table A.16: OLS Education

Parameter	Sample		Simulation
	Estimate	S.E.	Estimate
Constant	-0.16	0.05	-0.08
College Proximity	0.05	0.02	-0.01
IQ	0.06	0.01	0.05
HS Rank	0.16	0.01	0.15
A_{i0}^C	0.79	0.09	0.64
A_{i0}^I	0.14	0.09	0.16
SES Index	0.08	0.01	0.06

Table A.17: IV Cognitive Task

Parameter	Sample		Simulation
	Estimate	S.E.	Estimate
Constant	0.43	0.04	0.25
Education	0.17	0.38	0.04
Pot. Exp.	0.02	0.07	0.04
Pot. Exp.^{2}	-0.01	0.01	-0.01
A_{i0}^C	0.00	0.38	0.40
A_{i0}^I	-0.03	0.08	0.002
IQ	-0.004	0.04	-0.01
HS Rank	-0.01	0.06	-0.01

Table A.18: IV Interactive Task

Parameter	Sample		Simulation
	Estimate	S.E.	Estimate
Constant	0.37	0.03	0.41
Education	0.16	0.34	0.09
Pot. Exp.	0.06	0.06	0.07
Pot. Exp.^{2}	-0.10	0.01	-0.02
A_{i0}^C	-0.11	0.34	-0.08
A_{i0}^I	0.12	0.06	0.06
IQ	-0.01	0.03	0.002
HS Rank	-0.01	0.05	-0.002

Table A.19: IV Wage

Parameter	Sample		Simulation
	Estimate	S.E.	Estimate
Constant	1.77	0.08	0.84
Education	0.20	0.02	0.07
Pot. Exp.	0.79	0.03	1.07
Pot. Exp.^{2}	-0.15	0.005	-0.22
A_{i0}^C	1.01	0.19	0.97
A_{i0}^I	-0.16	0.11	1.06
IQ	0.38	0.20	0.35
HS Rank	-0.38	0.15	-0.01

Table A.20: FE Cognitive Task

Parameter	Sample		Simulation
	Estimate	S.E.	Estimate
$x_{it-1}^C - \bar{x}_i^C$	0.65	0.01	0.59

Table A.21: FE Interactive Task

Parameter	Sample		Simulation
	Estimate	S.E.	Estimate
$x_{it-1}^I - \bar{x}_i^I$	0.64	0.01	0.63

Table A.22: FE Wage

Parameter	Sample		Simulation
	Estimate	S.E.	Estimate
$x_{it-1}^C - \bar{x}_i^C$	0.38	0.20	0.77
$x_{it-1}^I - \bar{x}_i^I$	-0.06	0.12	1.00
Pot. Exp.	0.76	0.02	1.09
Pot. Exp.^{2}	-0.15	0.01	-0.23