Did the apple fall far from the tree?
Uncertainty and learning about ability with family-informed priors

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Abstract

This paper examines the effect of uncertainty and learning about ability on intergenerational correlations in education and labor market outcomes, when children and their parents utilize family signals while forming initial beliefs about ability. I examine this question by using a cohort study and rich administrative data to estimate a dynamic discrete choice structural model of education and occupational decisions, incorporating multidimensional skills and ability endowments, as well as uncertainty and learning about ability, starting from a family-driven prior.

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1.1. Introduction

There is increasing recognition of the role that uncertainty and learning about ability plays in the choices and economic fortunes of individuals. Since Johnson (1978) and Jovanovic (1979), this line of inquiry has had a long history in the study of employment and the labor market. More recent work has emphasized that learning about ability is an important determinant of choices and outcomes in education as well. In analyses of both education and employment, structural analyses in particular have played a central part in estimating the importance of ability uncertainty and learning for economic inequality.

Since Becker and Tomes (1986), a nearly distinct literature has examined how innate ability affects education and labor market outcomes with a primary emphasis on the role of the family. A key insight from this intergenerational literature has been that families play a crucial role in the extent of human capital investments for new generations, both in terms of the resources families provide (that tend to be endogenous to ability), but also because of the genetic factors that bestow a correlation in ability from one generation to the next.

This analysis seeks to bridge these two literatures by analyzing the extent of uncertainty about ability, and the effects of belief updating on human capital decisions in education and the labor market when families provide useful initial signals of ability. This research question has important insights for both literatures, as it suggests that while family priors may be helpful in forming priors about childrens' ability when faced with uncertainty, it may impede intergenerational mobility by causing families to underestimate the extent to which their children's ability differs from their own.

To examine this question, I integrate family-informed prior beliefs into a model of post-secondary educational and occupational choice similar to Arcidiacono et. al. (2016), estimated using rich administrative data from Sweden. Using this model, I estimate the extent of learning about ability during early adulthood, the degree of correlation between initial family-informed ability beliefs and posterior beliefs, and finally the responsiveness of human capital choices to self-perceived ability.

From this analysis, I find there is a substantial but also very heterogeneous reduction in uncertainty about ability during early adulthood, with average declines through age 26 that ranged from a high of 61.7% (for Blue Collar occupational ability) to less than 10% (for some types of higher educational ability). But because of the dynamic nature of human capital choices, and the high level of sensitivity of human capital choices to perceived ability, individuals are expected to make human capital choices in a manner that reinforces intergenerational persistence in human capital. Decisions made before age 21 tend to rely on beliefs that are estimated to have a correlation upwards of $\rho = 0.5$ with parental SES signals, while after age 26 this correlation is generally closer to $\rho = 0.2$. The importance of prior investment and the presence of large switching costs imply a persistent effect of initial parental SES signals of ability, despite an eventual correction of beliefs away from these signals.

In addition, this correction in beliefs is itself only partial and ability uncertainty remains substantial throughout this period. In essence, because most young adults tend to have limited or no experience in several of the possible human capital choices, they gain information about their potential in these paths only through a weaker form of correlated learning, and thus may never fully become aware of the potential in a given choice of education or career. To the extent that this uncertainty persists, parental SES will continue to help shape beliefs childrens' perceptions of ability.

1.2. Related Literature

> Human capital is by far the most important form of capital in modern economies. The economic successes of individuals, and also of whole economies, depends on how extensively and effectively people invest in themselves.
>
> Gary Becker
> *The Age of Human Capital*

Nobel Laureate Gary Becker championed the perspective that human capital investments stand at the heart of economics' central aims and interests — a primary basis for understanding not only poverty and inequality, but also economic efficiency and growth. As a result, Becker was quite naturally preoccupied with the question of why human capital investments differ so dramatically.

The critical role of parents in both the choice and financing of educational decisions of their children led Becker to consider intergenerational models of human capital investment and earnings mobility. "Human Capital and the Rise and Fall of Families", Becker's 1986 joint work with Nigel Tomes, not only formed the core of his contribution to the study of intergenerational dynamics of human capital accumulation and earnings mobility, but also stands as the basic framework from which nearly all intergenerational modeling derives.

The key insight from that framework is that parents transmit their fortunes in two key ways: first, through the biological inheritance of traits related to achievement (i.e. inherited ability), and second, by supplying the environments and investments that support children's achievement. The second channel, canonically stylized as financial investments, is notably affected by the first in that higher ability parents will tend to make more money and thus have greater financial resources with which to invest. The result of Becker-Tomes is that families make conditionally optimal human capital decisions, but because of the role of endogenous finances, higher and lower SES children of equal potential receive different human capital investments – and so, different labor market outcomes.

Following Becker and Tomes (1986), a large amount of research has sought to test the model and quantify its implications. A central aim within this literature has been to understand broadly how much of intergenerational persistence is due to biological factors ("nature") and how much of it arises due to environmental factors ("nurture"). Empirical studies from both economics and behavioral genetics, traditionally using variation from twins and adoptees, have yielded a standard view that genetic factors generally account for between 40-60% of variation in cognitive ability, with broadly similar findings about educational attainment and earnings in most contexts (e.g. Björklund, Lindahl, and Plug (2006), Grönqvist, Öckert, and Vlachos (2017), Polderman, Benyamin, de Leeuw, Sullivan, van Bochoven, Visscher, and Posthuma (2015), Sacerdote (2011), Smith-Woolley, Ayorech, Dale, von Stumm, and Plomin (2018)).

Recent advances have offered salient critiques to this literature (for instance, highlighting epigenetics and the lack of clear distinction between genetics and environment), as well as offering new ways of exploring genetic predictors of success (most notably, genome-wide association studies and polygenic score analysis). Yet the principal conclusions about the importance of genetic explanators have so far remained essentially intact (Harden, 2021).[1]

In addition to exploration of the nature versus nurture decomposition implied by Becker and Tomes, a great deal of analysis has also pursued refinements to the model. Some of the most important extensions to emerge from this literature have focused on the multi-stage nature of human capital investment decisions, often emphasizing the importance of early human capital investments as emphasized most prominently by James Heckman (e.g. Caucutt and Lochner (2019), Cunha and Heckman (2007), Lee and Seshadri (2018), Restuccia and Urrutia (2004)).[2]

The intergenerational modeling literature has so far not reckoned with the question of learning about ability, which has been a prominent (and growing) emphasis especially within the study of life cycle labor market inequality. This question has historically been most associated with the study of labor search and matching, following the seminal theory contributions of Johnson (1978) and Jovanovic (1979, 1984).

Dynamic discrete choice structural methods have been the primary method of quantifying the importance of learning about ability on the labor market, including the work of James (2012), Miller (1984), Nagypál (2007), Pastorino (2015, 2019), and Sullivan (2010).

[1]In addition, popular perception about the heritability of traits and outcomes appears similar to the scientific consensus. (Willoughby et al., 2019).

[2]Other notable contributions have also considered multiple type of ability, as well as considering borrowing constraints and endogenous preferences.

A notable example of reduced form analysis of employee learning on the labor market is Fredriksson, Hensvik, and Skans (2018).

Recent evidence also suggests that learning about ability is an important part of educational decisions as well. Learning about ability has recently been implicated in schooling effort (2010, Bandiera, Larcinese, and Rasul (2015), Goulas and Megalokonomou (2021)), course selection (Gonzalez, 2017) and educational track choice (Bobba and Frisancho, 2016), college application strategies Bond et al., 2020, college major choice (Arcidiacono, 2004; Li, 2018; Rury and Carrell, 2021), and college dropout decisions (Arcidiacono, Aucejo, et al., 2016; Stinebrickner and Stinebrickner, 2012).

Estimated impacts of learning about ability are quite large, both in education and employment. Stinebrickner & Stinebrickner for example find that as much as 40% of the college dropout decisions in the setting they examine were due to learning about ability. Similarly, the value of learning about multidimensional ability across employment has been estimated at about one year (James, 2012) and 32 months (Gorry et al., 2019).

To the extent that uncertainty and learning about multidimensional ability is sufficiently important, this poses a couple of significant concerns for the traditional model of human capital investment in intergenerational settings. First, it may imply that the use of educational attainment to summarize the human capital investment behaviors of individuals mischaracterizes important parts of this dynamic. Whether or not one goes to college may not be an indicator of whether the returns to college are sufficiently high relative to employment, but rather an indicator of whether the perceived returns to college are greater than the returns to acquiring more information about occupational fits. Broadly, individuals maximize their human capital by making the decisions that they believe to be optimal both in the acquisition of new skills (via learning in school or on the job), but also in terms of learning about what skills they already possess.

Furthermore, the extent to which individuals are forced to make a long sequence of human capital decisions under uncertainty, and the critical dependence of contemporaneous choices on past decisions (characterized by greater ability uncertainty), may dramatically impede the type of efficient human capital investment typically assumed in models of intergenerational mobility.

Utilization of familial signals in the formation of initial beliefs about ability — although instrumental in improving beliefs over fully naive expectations, nevertheless is likely to exacerbate the extent to which ability uncertainty hampers intergenerational mobility. Although family-informed signals of ability may be unbiased in the limited information context in which true ability is unobserved, it is necessarily biased towards parental outcomes when considering the full-information context hitherto assumed in intergenerational models.

In contrast to the standard Becker-Tomes model, wherein investments are conditionally optimal responses to endowments of income and ability, uncertainty about ability and family-influenced priors suggest that households may mis-invest in a manner that reflects the bias of assumed ability persistence. Because of the dynamic structure of human capital investments and the higher relative return to earlier human capital investments (popularly known as the "Heckman Curve"), mis-investment that occurs during early life periods of substantial ability uncertainty can not easily be corrected in later periods.[3]

1.3. Data and Estimation Sample

Data used in estimation are primarily from Swedish administrative register sources collected by Statistics Sweden (*Statistiska centralbyrån*). Educational data for youth comes from the Educational Register. The Educational Register includes data on higher education enrollment, course completion, degree completion, and financial aid.

Data on income and occupation comes from a combination of register sources. The primary occupational and wage data source is the *Structural Wage Statistics*, an employment survey covering all public sector employees and a sample of firms in the private sector that accounts for about half of private sector employees each year. I further observe employment earnings by firm and workplace through the Register-based Labor Market Statistics (RAMS) administrative register. Finally, I observe summary measures of total earnings from employment each year from the Longitudinal database on education, income and employment (LOUISE).

LOUISE is also the primary basis for data on the demographic characteristics of individuals. This includes an individual's age, sex, and country of birth. To facilitate identification of family linkages, I further draw on the Multigenerational Register, which identifies the parents of all individuals in the population since 1961.

Finally, to empirically validate the ability beliefs model and conduct follow-up analysis, I link the administrative data to a rich cohort study of youth: the Evaluation through Follow-Up (ETF) Survey, conducted by the Department of Education at the University of Gothenburg. The ETF Survey elicits (among other things) students' perception of ability, attitudes towards education, and future plans at multiple points during compulsory and upper secondary education. The population of the ETF Survey is a stratified random sample of students that consists of about 10,000 students, or about 10% of all Swedish students, in each cohort.

In order to take draw insights from both the ETF Survey and administrative data, I estimate the structural model for a sample of the Swedish population born in the same year that coincides with an ETF cohort. Specifically, I estimate the model for male students born in 1992, coincident with the 1992 ETF birth cohort. I further limit the sample to individuals who have completed three-year upper secondary schooling by 2011. The final estimation sample consists of 17,234 individuals, 1,346 of which are observed in the ETF.

[3]Further, the self-productivity of human capital investments may imply that later life ability beliefs do not converge to potential at birth, but instead reflect the consequences of early childhood investments.

Individuals are observed for the period 2011-2018, corresponding to 137,523 person-year observations.

1.4. Model

1.4.1. Model Overview and Choice Structure

In the model, forward looking individuals make a series of decisions about education and employment to maximize the discounted present value of their lifetime utilities. Individuals start off having completed a three year upper secondary schooling degree, conferring eligibility to pursue higher education. They begin making choices about education and employment.

In education, individuals choose whether or not to pursue a STEM undergraduate degree, a non-STEM undergraduate degree, a four-year professional degree, or not pursue further education. If the students are already enrolled in education, they can choose whether to drop out or change programs. If a student has completed an undergraduate or professional degree, they can also choose whether or not to pursue graduate education (Masters/Doctoral degree). When choosing to participate in education, they can enroll either part-time or full-time.

In employment, individuals can choose whether or not to pursue a white collar or blue collar job. Designation of a job as either a white collar or blue collar occupation is based on the International Standard Classification of Occupations (ISCO) classification schema, ISCO-88. White collar jobs are those defined by ISCO-88 as having a skill level of at least 3 (out of 4), corresponding to skills "usually obtained as the result of study at a higher educational institution." The following Occupational Groups satisfy this skill level requirement: (1) Legislators, Senior Officials, and Managers, (2) Professionals, and (3) Technicians and Associate Professionals. Blue collar jobs are defined as all other jobs.

In addition to the choice of occupational sector, when pursuing employment an individual also chooses how much labor to supply, either working part-time or full-time. Finally, an individual also has the option to pursue neither education nor employment, a choice that I refer to as home production.

When making education and occupational decisions, the individual maximizes the expected discounted present value of their intended careers. Forming these expectations requires the agent to make assumptions about the way in which the economy functions: most notably, how educational achievement and earnings are "produced" as functions of one's investment decisions and other characteristics. I assume that the individual has complete information about the production functions of the economy, utilizing the same estimates as those produced by the econometric estimation of the model. In the following sections, I specify the assumed production functions of education and employment outcomes in the economy.[4]

1.4.2. Production of educational achievement

I assume that achievement in a given period is a linear function of its determinants. In education, I treat the credit completion rate, G_{imt}, as the relevant achievement outcome. Credit completion rate is defined as the number of credits the individual successfully completes (conditional on course registration pace) in higher education degree type m.[5]

The assumed determinants of achievement are the child's background characteristics X_{it} (consisting of age and parental national origin), labor market participation (full or part-time), L_{it}, ability A_{im}, and idiosyncratic productivity shocks $_{it} \sim N(0, \sigma_t^2)$.

The production function of educational achievement can thus be expressed as follows:

$$G_{imt} = \gamma_1 X_{it} + \gamma_2 L_{it} + A_{im} + {}_{imt} \tag{1.1}$$

1.4.3. Production of income in employment

Employment is characterized by both occupation (blue-collar or white-collar) and employment intensity (full or part-time). The relevant outcome variable for employment in occupation l is log wages, w_{ilt}, which depends on the following features: Observable worker characteristics, X_{ilt}, occupation-specific ability, A_{il}, Sector-specific time dummies, δ_{lt}, and idiosyncratic productivity shocks, $e_{ilt} \sim N(0, \sigma_l^2)$.

[4]Future work will extend the model considerably from the basic education and occupational choice structure outlined here, in two key ways: First, educational decisions will consider not only post-secondary schooling choices, but decisions from *mellanstadiet* (i.e. "middle school"), including time investment during compulsory schooling (captured by the ETF) and choice of upper secondary schooling track. Second, occupational choice will extend beyond the basic blue collar / white collar occupational choice outlined here, to instead include several occupations and multidimensional occupational ability. Similar to Sullivan (2010), future revisions will incorporate 6 occupational sectors, defined across 4 different ISCO skill levels. Occupational sector (1) is elementary labor, defined at ISCO Skill Level 1. At ISCO Skill Level 2, there are occupational sectors (2) Clerical, services, and sales workers, and (3) Craft, trade, and skilled agricultural workers. At ISCO Skill Level 3, there are occupational sectors (4) Non-STEM Technicians and Associate Professionals and (5) STEM Technicians and Associate Professionals. Finally, at ISCO Skill Level 5, there is occupational sector (6) Professional or managerial workers. Extending the model to this longer horizon and more multi-dimensional characterization of human capital offers great advantage in being able to capture the full life-cycle effect of ability uncertainty and highlights that this uncertainty entails an exploration-exploitation trade-off in human capital investment, which may heterogeneous effects across family background.

[5]In future revisions, I will have access to college grades, via the national study result system *Ladok*, managed by the consortium of the major higher education providers in Sweden. In the meantime, credit completion rate would appear to provide a good proxy for grade performance. In particular, in the Swedish setting an individual in principle has the ability to retake courses until they achieve their desired result. Consequently, pace of completion varies widely and correlates closely with grade performance.

Observable work characteristics are considered to include demographics (age and parental origin), educational characteristics (level of educational attainment and type of degree), and finally occupational characteristics (years of experience and full or part-time status). The assumed income production function is thus as follows:

$$w_{ilt} = \delta_{lt} + \gamma_1 X_{ilt} + A_{il} + {}_{ilt} \tag{1.2}$$

1.4.4. Ability Beliefs

In both education and work, a prominent component of the assumed production functions is ability. Yet, as I have motivated, ability is not a fully observable characteristic to either the individual or the econometrician. In the presence of ability uncertainty, I assume that individuals use their experiences and knowledge about the structure of the economy to form Bayesian beliefs about ability.

More specifically, a person's latent ability, A_i, is a multi-dimensional vector consisting of ability specific to each educational type and employment sector. Ability is assumed to be distributed multivariate normal, with unconstrained covariance matrix, Δ. Individuals are assumed to not know their own ability (*...how far away did the apple fall?*), but are assumed to understand the distribution of outcomes for people that are observational similar to themselves and use this to form rational expectations about their ability.[6] As they observe further signals of their ability, individuals update their beliefs about ability according to Bayes' Rule for the multivariate normal distribution. Notably, this design allows for correlated learning about ability across types.

To demonstrate how ability and beliefs about ability are incorporated into the model, I highlight here the example of someone in the 2^{nd} year of a STEM bachelors degree. Restating the assumed production function of academic achievement (and denoting STEM undergraduate education as $\{B, S\}$):

$$G_{it}^{B,S} = \gamma_1^{B,S} X_{it} + \gamma_2^{B,S} L_{it} + A_i^{B,S} + {}_{it}^{B,S}$$

Note from this process that there are two components which are not directly observable, ability $A_i^{B,S}$ and productivity shocks ${}_{it}^{B,S}$. Re-expressing ability as a function of observed grades, observable determinants (X_{it} and L_{it}), and finally unobserved productivity shocks, we have:

$$A_i^{B,S} = G_{it}^{B,S} - \gamma_1^{B,S} X_{it} - \gamma_2^{B,S} L_{it} - {}_{it}^{B,S}$$

If a student thus knew how much of their grade performance was due to the productivity shock, ${}_{it}^{B,S}$, then he could infer his precise ability as the difference between observed

[6]Further analyses will consider minimal deviations from rationality

grades and predicted grades, inclusive of the productivity shock. Yet since neither choice-specific ability nor productivity shocks are directly observable, inference about ability is not so straightforward. Performance over time still contains meaningful information about ability however. Note in particular that productivity shocks are assumed random and mean zero. In this case,

$$\mathbb{E}\left[A_i^{B,S}\right] = \mathbb{E}\left[G_{it}^{B,S} - \gamma_1^{B,S} X_{it} - \gamma_2^{B,S} L_{it} - {}_{it}^{B,S}\right]$$

$$\mathbb{E}\left[A_i^{B,S}\right] = G_{it}^{B,S} - \gamma_1^{B,S} X_{it} - \gamma_2^{B,S} L_{it} \equiv \underbrace{s_{it}^{B,S}}_{\text{ability signal}}$$

This is to say that if a person understands how grades are produced, and can observe all the determinants of grade performance except for latent ability and some noise (productivity shocks), then the person knows that on average, ability will equal the difference between the grades they obtained and what would be expected given their observable characteristics. Grades therefore provide *signals* of ability, which students can use to update ability beliefs (through Bayesian updating).

Although the previous example illustrates how individuals can update their beliefs about ability using their experiences, it cannot tell us how individuals should form their ability beliefs before they've had the chance to learn from experience. Without knowing anything more than the production function of achievement and their observable characteristics that go into achievement, it is clear that their ex-ante expected ability would be zero (i.e. the average of ability in the overall population). And indeed, this is precisely how initial beliefs are specified in the canonical ability learning model of Arcidiacono et. al. (2016).

However, suppose that individuals know about some attributes they have, z_{it}, that are predictive of ability but don't otherwise have a direct affect on achievement. In this case, they can use that information about predictors of ability to form beliefs. In particular, note that for the "residual" determinants of grades, without conditioning on the information z_{it} then $\mathbb{E}\left[A_i^{STEM} + {}_{it}^{STEM}\right] = 0$. However, with z_{it} in the information set, we instead have $\mathbb{E}\left[A_i^{STEM} + {}_{it}^{STEM} \mid z_{it}\right] = \mathbb{E}\left[A_i^{STEM} \mid z_{it}\right]$. Put simply, if students know about personal attributes that are predictors of their ability, then they can use their knowledge of the economy to form initial beliefs based on individuals with similar predictive attributes tend to perform, rather than relying on "naive" initial beliefs that convey no precision.

In the structural model that I estimate, I assume that households use the following parental signals of ability: each parents' educational level and subject (STEM or non-STEM), occupation (blue or white collar), and the logged average of the primary parental earners' disposable income over the five previous years.

1.4.5. Utility

Having demonstrated how individuals are assumed to produce educational achievement and incomes, I now turn to their objective function in making decisions.

Individuals are assumed to be forward looking and choose the sequence of education (j) and labor market (k) decisions (d_{it}) that maximizes the present value of expected lifetime utility:[7]

$$V_t \equiv \max \mathbb{E} \left[\sum_{t=1}^{T} \beta^{t-1} \sum_{j} \sum_{k} (u_{jk}(Z_{it})) + {}_{ijkt}) 1\{d_{it} = (j, k)\} \right] \tag{1.3}$$

where $Z_{it} = (Z_{1it}, Z_{2it})$ denotes the variables that affect the utility of schooling and work respectively, β is the discount rate, and ${}_{ijkt}$ is a choice-specific idiosyncratic shock, assumed distributed Type 1 Generalized Extreme Value (GEV).

Components of the utility term, u_{jk} include several features. During both schooling and work, utility includes controls for both demographics, ability measures, and controls for the previous choice (thereby incorporating switching costs). Unique aspects for educational choices include the expected ability in schooling option j. Unique aspects of the utility term for employment includes the expected log wages in occupational sector k. The home sector is set as the reference sector, hence utility of this option is normalized to 0.[8]

1.5. Estimation

To solve the dynamic programming problem of individuals (and their families), I use the conditional choice probability (CCP) estimation methods introduced by Hotz and Miller (1993), simplifying estimation by avoiding the need for full solutions methods.

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[7] For presentational purposes, I abstract here from the probabilities that an individual is able to choose a given schooling or an employment option (i.e., there probability of admission into a degree program, as well as the probability of a job offer in an occupation). Formally, however, I allow the choice set of an individual i at time t to $D_{i,t}$ to depend on their accumulated skills until that time. Schooling choice probabilities are directly estimated using admissions data from the education register, while job offer arrival rates are treated as a latent variable, which is allowed to depend on both observable predictors of performance as well as expected ability.

[8] In future revisions, utility weights will be allowed to vary by latent class of the individual, thereby incorporating permanent type-specific unobserved heterogeneity. Future revisions will also incorporate education-specific financial transfers, both student aid and expected parental transfers. Expected parental transfers are drawn from two large surveys, the Survey of Household Finances and the Level of Living Survey.

1.5.1. Details of CCP Estimation

First, note the value function (eq 3) can be re-expressed as a Bellman equation:

$$V_t \equiv \max \mathbb{E}\left[\sum_{t=1}^{T} \beta^{t-1} \sum_j \sum_k (u_{jk}(Z_{it})) + {}_{ijkt}) 1\{d_{it} = (j,k)\}\right] \tag{1.4}$$

$$V_t = \underbrace{u_{jk}(Z_{it}) + {}_{ijkt}}_{\text{flow utility}} + \underbrace{\beta \mathbb{E}\left[V_{t+1}(Z_{i,t+1} \mid Z_{it}, d_{it} = (j,k))\right]}_{\text{continuation value}} \tag{1.5}$$

Define the ex ante value function, $\bar{V}_t$ as the expected value of the value function at the beginning of time t, before ${}_{ijkt}$ is revealed: $\bar{V}_t(Z_{i,t}) = \int V_t f()d_t$.

The *conditional value function*, which is the expected discount present value of utility of a given choice at time, t, conditional on the history until t, can be expressed as:

$$v_{jkt}(Z_{it}) = u_{jk}(Z_{it}) + \beta \mathbb{E}\left[\bar{V}_{t+1}\left(Z_{i,t+1} \mid Z_{it}, d_{it} = (j,k)\right)\right] \tag{1.6}$$

The assumption of Type 1 GEV errors implies the choice structure follows the dynamic logit model. The ex ante value function, $\bar{V}_t$ is then:

$$\bar{V}_t(Z_{i,t}) = \ln\left(\sum_{d_{t+1} \in D} \exp\left(v_t(Z_t, d_{i,t+1})\right)\right) + \underbrace{\gamma}_{\text{Euler's constant}} \tag{1.7}$$

For a given arbitrary reference choice, $d^*_{i,t}$, we can then multiply and divide by conditional value function of the choice inside the log:

$$\bar{V}_t(Z_{i,t}) = \ln\left(\exp v_t(Z_t, d^*_{i,t+1}) \frac{\sum_{d_{t+1} \in D} \exp v_t(Z_t, d_{i,t+1})}{\exp v_t(Z_{it}, d^*_{i,t+1})}\right) + \gamma \tag{1.8}$$

Notice again that by the logit structure of the choice that:

$$\frac{\sum_{d_{t+1} \in D} \exp\left(v_t(Z_t, d_{i,t+1})\right)}{\exp v_t(Z_t, d^*_{i,t+1})} = p(d^*_{i,t+1} \mid Z_{i,t})^{-1} \tag{1.9}$$

Hence:

$$\bar{V}_t(Z_{i,t}) = \ln\left(\exp(v_t(Z_t, d^*_{i,t+1}))p(d^*_{it} \mid Z_{i,t})^{-1}\right) + \gamma = v_t(Z_t, d^*_{i,t+1}) - \ln p(d^*_{it}) + \gamma \tag{1.10}$$

Using this result for the ex ante value function, the conditional value function becomes:

$$v_{jkt}(Z_{it}) = u_{jk}(Z_{it}) + \beta \int \left(v_t(Z_t, d^*_{i,t+1}) - \ln p(d^*_{i,t+1} \mid Z_{i,t})\right) dZ_{i,t+1} + \beta\gamma \tag{1.11}$$

$$v_{jkt}(Z_{it}) = u_{jk}(Z_{it}) + \beta \int \left(v_t(Z_t, d^*_{i,t+1}) - \ln p(d^*_{i,t+1} \mid Z_{i,t+1}) f(Z_{i,t+1} \mid Z_{i,t}, d_{it}) \right) dZ_{i,t+1} + \beta\gamma \tag{1.12}$$

From this result, the state transitions and conditional choice probabilities can be directly estimated – the only component of the future value term that needs further simplification is the remaining conditional value term, $v_t(Z_t, d^*_{i,t+1})$.

The approach to handling this term is to work instead with *differences* in conditional value terms, by any given choice $d_{i,t} = (j, k)$ and home production, $d_{i,t} = (0, 0)$. The difference in values between these these two paths show finite dependence – that is, after a finite number of periods, the future values of both paths are the same. For example, consider two possible sequences starting from a period, t, in which an individual might choose to either work in a blue collar occupation or choose home production. Assuming the person chose to initially work in blue collar employment, the person might then choose home production. Meanwhile, for the sequence that began with home production, the person might then choose to work in blue collar employment in $t+1$. Each sequence would result in the person having the same amount of experience as blue collar employment, but the future values would not yet line up due to switching costs from the current occupation in $t+1$. Choosing the same occupation in $t+2$, however, would result in the future value terms being equivalent between the two paths.

This finite dependence is used to achieve a cancellation of future value after two periods, hence by working with the difference in conditional value functions, $v_{jkt} - v_{00t}$, it is necessary only to work with the conditional choice probabilities along the finite dependence path.

The conditional choice probability therefore results in a procedure where the differenced value functions can be estimated by a two-stage estimation process: first estimating the conditional choice probabilities, $p(d^*_{i,t+1} \mid Z_{i,t+1})$, then estimating flow utilities by re-expressing the conditional value functions as a function of flow utilities and the conditional choice probabilities along the finite dependence path.[9]

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[9]The two-stage estimation process relies on separability between the choices and flow utility. Following Arcidiacono, Aucejo, et al., 2016, however, I will in future revisions account for permanent unobserved heterogeneity in preferences and ability incorporated by allowing for latent types which affect both utility parameters and education/wage production. With unobserved types, sequential estimation of production and utility parameters fails because the likelihood function is no longer additively separable between the two. With unobserved heterogeneity, estimation of the structural model instead relies on iterative application of the Expectation-Maximization algorithm to restore additive separability, following Arcidiacono and Jones, 2003 and Arcidiacono and Miller, 2011. A latent variable approach will also be used to account for heterogeneous job offer arrival rates across occupations and skill types. Specifically, I will allow the job offer probability for person i and occupation j, λ_{ij} to be a latent value which depends on the both observable determinants of worker productivity as well an unobserved ability.

1.6. Results

1.6.1. Descriptive evidence of parentally informed beliefs

Before turning to the estimates from the structural model, I first use data from the ETF Survey to demonstrate empirical support for the fundamental model assumption that youth utilize family-informed priors. Tables 1.1 and 1.2 document descriptive evidence that parental education and labor market outcomes shape ability beliefs even after controlling for observed ability.

Table 1.1 reports estimates of ability beliefs for grade 6 (*Mellanstadiet*: middle-stage lower secondary education), while Table 1.2 reports estimates for grade 9 (*Högstadiet*: upper-stage lower secondary education).[10] Although the ETF Study elicits ability beliefs in several subjects in some grades, I focus here only on math and language (Swedish).

For each subject, the ETF asks students about how capable they consider themselves in each of several concrete tasks.[11] Responses are elicited on a one to five Likert scale, with 1 being the lowest level of self-assessed ability, and 5 being the highest. Overall ability beliefs are constructed as the sum of the task-specific ability ratings. Rating scores are then normalized before performing regression analysis.[12]

Linear regression is used to estimate ability beliefs as a function of test performance, gender, parental origin, and parental predictors of ability, which include education and the income of the primary parental earner.

Assessed performance in grade 6 is based on psychometric tests of ability administered to students. For Swedish, the relevant assessments are two tests of vocabulary: a synonyms test and an antonyms test. For math, the relevant aptitude tests are a number series test and a paper folding test that measures spatial reasoning.[13]

Assessed performance in grade 9 is based on results from the national standardized tests in Swedish and math. The Swedish exam is divided into three parts, with each part producing a mark of either Fail, Pass, Pass with Distinction, or Pass with High Distinction. The math exam, meanwhile, is graded based on the number of answers to problems that

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[10] Performance and ability beliefs data are also elicited for grade 12, corresponding to upper secondary education, but are not presently available to the author. Delivery of grade 12 data for the ETF is expected in January 2023, with future revisions incorporating this data.

[11] Swedish ability sub-tasks include the ability to (1) read and understand a text, (2) read aloud for the whole class, (3) read the subtitles to a film, (4) write a story, (5) participate in a discussion, (6) give an oral presentation, and (7) be good at spelling. Ability sub-tasks are (1) mental arithmetic, (2) calculate sums and multiplication, (3) calculate percentages, (4) calculate area and circumference, (5) solve equations, (6) solve math problems, (7) explain math problems, and (8) work on large math assignments or projects.

[12] Results are also estimated by ordered logit regression on the raw composite scores, yielding very similar results.

[13] Results are similar if all measures of ability are included in each regression.

Table 1.1. Linear regression of Grade 6 ability beliefs on aptitude tests and parental predictors

	Swedish	Math
Constant	-1.131 (0.312)	-0.351 (0.296)
Synonyms test score	0.028 (0.013)	–
Synonyms test score^2	-0.000 (0.000)	–
Antonyms test score	0.030 (0.014)	
Antonyms test score^2	-0.000 (0.000)	
Number series test score	–	0.003 (0.008)
Number series test score^2	–	0.001 (0.000)
Paper folding test score	–	-0.001 (0.009)
Paper folding test score^2	–	0.000 (0.000)
Highest education, primary parental earner:		
... Less than 3 year Upp Sec	-0.020 (0.041)	-0.063 (0.040)
... Upper secondary: Non-STEM	0.178 (0.050)	–
... Upper secondary: STEM	–	-0.009 (0.051)
... Bachelors: Non-STEM	0.062 (0.059)	0.109 (0.058)
... Bachelors: STEM	-0.157 (0.116)	0.013 (0.120)
... Graduate/Professional: Non-STEM	0.031 (0.066)	0.063 (0.066)
... Graduate/Professional: STEM	0.076 (0.068)	0.038 (0.067)
Highest education, secondary parental earner:		
... Less than 3 year Upp Sec	0.042 (0.061)	-0.058 (0.036)
... Upper secondary: Non-STEM	0.090 (0.066)	–
... Upper secondary: STEM	–	-0.011 (0.071)
... Bachelors: Non-STEM	0.154 (0.070)	0.058 (0.049)
... Bachelors: STEM	0.197 (0.167)	-0.030 (0.167)
... Graduate/Professional: Non-STEM	0.115 (0.078)	-0.021 (0.063)
... Graduate/Professional: STEM	0.093 (0.107)	0.217 (0.092)
Log Disposable income, primary parental earner	0.032 (0.033)	0.017 (0.031)
Female	0.157 (0.025)	-0.081 (0.025)
Parent born in:		
... Europe (except former USSR)	-0.311 (0.091)	-0.383 (0.097)
... Former USSR (except Visegrád group[b])	0.227 (0.186)	0.109 (0.240)
... Latin America	0.079 (0.111)	-0.017 (0.122)
... Africa	0.244 (0.116)	-0.032 (0.142)
... Middle East	0.326 (0.092)	0.083 (0.099)
... Asia	0.013 (0.108)	-0.011 (0.103)
Joint Significance: Parental Education	$p < 0.001$	$p < 0.001$
Joint Significance: Parental Education and Income	$p < 0.001$	$p < 0.001$
Observations	6015	5467

Exponentiated coefficients; Standard errors in parentheses

[a] The educational reference category is a STEM 3 year upper secondary degree for Swedish ability, and a non-STEM 3 year upper secondary degree for Math.

[b] Countries in the Visegrád group comprise the Czech Republic, Hungary, Poland and Slovakia, which are included in "Europe (except former USSR)".

[c] Parents born in North America (United States and Canada) and Oceania (primarily Australia and New Zealand) are also included within the Europe category. This is due to the small number of parents observed with these national origins and the high degree of cultural, social, and economic similarity between these countries and their European colonizers (popularly expressed in economics via the moniker "Neo-Europes," following Acemoglu et al., 2001).

Table 1.2. Linear regression of Grade 9 ability beliefs on standardized tests scores, grade 6 assessments, and parental predictors

	Swedish	Math
Constant	-1.190 (0.260)	-1.187 (0.255)
Grade 9 Standardized Test Result		
... Swedish Part A: Fail	-0.214 (0.063)	–
... Swedish Part A: Pass with Distinction	0.130 (0.034)	–
... Swedish Part A: Pass with High Distinction	0.263 (0.044)	–
... Swedish Part B: Fail	-0.295 (0.123)	–
... Swedish Part B: Pass with Distinction	0.351 (0.031)	–
... Swedish Part A: Pass with High Distinction	0.565 (0.040)	–
... Swedish Part C: Fail	-0.172 (0.057)	–
... Swedish Part C: Pass with Distinction	0.169 (0.030)	–
... Swedish Part A: Pass with High Distinction	0.258 (0.043)	–
... Math: Points with grade Pass	–	0.016 (0.003)
... Math: Points with grade Pass with Distinction	–	0.046 (0.002)
Grade 6 Aptitude Test Result	–	
... Synonyms test score	0.012 (0.003)	–
... Antonyms test score	0.012 (0.004)	–
... Number Series test score	–	0.010 (0.002)
... Paper folding test score	–	0.001 (0.002)
Highest education, primary parental earner:		
... Less than 3 year Upp Sec	-0.018 (0.041)	0.027 (0.035)
... Upper secondary: Non-STEM	0.074 (0.049)	–
... Upper secondary: STEM	–	0.093 (0.047)
... Bachelors: Non-STEM	0.027 (0.052)	-0.007 (0.048)
... Bachelors: STEM	-0.131 (0.107)	0.039 (0.096)
... Graduate/Professional: Non-STEM	0.056 (0.056)	-0.018 (0.052)
... Graduate/Professional: STEM	-0.047 (0.060)	-0.044 (0.054)
Highest education, secondary parental earner:		
... Less than 3 year Upp Sec	0.025 (0.059)	-0.032 (0.034)
... Upper secondary: Non-STEM	0.071 (0.064)	–
... Upper secondary: STEM	–	0.024 (0.061)
... Bachelors: Non-STEM	0.092 (0.065)	0.012 (0.043)
... Bachelors: STEM	-0.062 (0.134)	-0.140 (0.127)
... Graduate/Professional: Non-STEM	0.077 (0.073)	-0.088 (0.054)
... Graduate/Professional: STEM	0.007 (0.091)	0.225 (0.073)
Log Disposable income, primary parental earner	0.063 (0.029)	0.037 (0.028)
Female	0.032 (0.025)	-0.097 (0.022)
Joint Significance: Parental Education	$p = 0.124$	$p = 0.011$
Joint Significance: Parental Education and Income	$p = 0.019$	$p = 0.009$
Observations	5568	5230

Robust t statistics in parentheses

[a] The educational reference category is a STEM 3 year upper secondary degree for Swedish ability, and a non-STEM 3 year upper secondary degree for Math.
[b] Estimates for parental birthplace omitted.

earned the mark of Pass, as well as the number of answers that received the mark of Pass with distinction. Prior performance from aptitude tests in Grade 6 are also included in the grade 9 ability beliefs regressions.

Parental education is defined separately for each parent based on whether they are the primary or secondary earner (effectively allowing parents' choice of education, and thereby the signaling value of parental education, to depend on whether the parent expected to be the primary earner). The income measure is the log of disposable income (defined over the previous 5 years), for the primary earner.[14]

Results in both grade 6 and grade 9 are consistent with a large effect of parental predictors of ability (education and income) on students' perceptions of their own ability. Parental predictors of ability are jointly significant for both Swedish and math in both grade 6 and 9, although education predictors alone are no longer significant at confidence standard levels for Swedish in grade 9 ($p = 0.124$).

The direction and magnitude of the estimated effects of parental education are consistent with the notion that human capital is not only vertically differentiated, but also multidimensional in nature. Parental educational attainment where the degree subject corresponds to the elicited ability belief (STEM degrees for math, non-STEM degree for Swedish) is generally estimated to have a much more positive effect on ability beliefs than higher parental educational levels in a contrasting degree field.[15]

The overall impact of parental education is quite large: In grade 6, if both parents possessed graduate degrees matching the elicited subject, ability beliefs are predicted to be 0.15 and 0.25 standard deviations higher for Swedish and math, respectively, than if parents only had upper secondary degrees not corresponding to the elicited ability subject. In grade 9, these estimates fall slightly, but are still quite sizeable at 0.13 and 0.18 standard deviations, respectively. The decline in the estimated impact of parental predictors of ability on beliefs in grade 9 relative to grade 6 is consistent with learning, with prior performance estimated to have a large, significant effect on contemporaneous ability beliefs.

1.6.2. Production parameters

Having demonstrated strong empirical support for the notion that youth utilize family driven priors in forming beliefs about their own ability, I turn now to the results of the structural model. I first discuss estimates of the human capital production functions. Educational and earnings productions parameters are reported in Tables 1.3 and 1.4.

[14] Model selection for both education and income was based on the penalized Bayesian information criterion. Alternatives included parental attainments measures by sex (i.e. father, mother), the maximum attainment between parents, and attainment for each parent sorted by income.

[15] An exception, however, is in grade 6, where having a parent with a non-STEM bachelors degree is estimated to have a more positive impact on math ability beliefs than if that parent had a STEM bachelors degree.

Educational achievement (modelled as standardized scores of the credit completion rate) is strongly increasing in parental predictors of ability, in addition to GPA percentile in upper secondary education, and having completed a university preparatory (rather than vocational) upper secondary degree.

The effects of family predictors of ability are estimated via auxiliary regression as a basis for family-informed initial beliefs about ability, but crucially enter production only through the initial prior ability beliefs. A one standard deviation increase in the family ability signal is estimated to increase educational performance by 0.06-0.10 standard deviations conditional on other determinants of performance.

Besides education and ability predictors, student employment is also estimated to have a significant (albeit largely negative) effect on performance. Full-time employment reduces credit completion rates by 0.11 standard deviations in non-STEM degrees, while it is estimated to have a near zero effect on STEM bachelor and graduate degree completion rates, and positive effects on STEM professional degrees.

For earnings (Table 1.4), higher levels of education are associated with large increases in predicted log earnings. Similarly STEM degrees have large but heterogeneous (by degree level) effects on earnings. The main effect of a STEM degree is a 13-14% increase in earnings. Family ability signals once again predict large effects on achievement, with a 1 standard deviation increase in the ability signal estimated to increase earnings by 3.1-5.6%. Estimates are consistent with positive returns to experience, although results suggests that earnings are concave in occupational experience over the time horizon of the panel.

1.6.3. Utility parameters

Flow utility parameters for education are reported in Table 1.5. For both education and employment, the utility of home production (not working, not enrolled in school) is normalized to zero.

Educational flow utility parameters

A primary consideration for the interpretation of the structural model is how ability beliefs affects utility. Recall that the model structure implies that ability beliefs may affect utility (and therefore choices) in two keys ways. First, ability affects the affected future stream of payoffs to a decision – e.g. if I think I am good at STEM, then I think I am more apt to complete a STEM degree and get a job that pays well in the future. But in addition to this future value of a choice, ability beliefs are allowed to also affect the utility derived by a choice in the current period (the flow utility). In the context of employment this is quite natural – it amounts to supposing that I care about the money I make right now. But in education, flow utility is also important. A large body of research has found that students' enjoyment of education is a key determinant of their choice behavior (e.g. Gong, Lochner, Stinebrickner, and Stinebrickner (2019), Jacob, McCall, and Stange (2018), and

Table 1.3. Educational Performance (standardized credit completion rate) production parameters:

	(1) Bachelors Non-STEM	(2) Bachelors STEM	(3) Prof. (4+ yr) Non-STEM	(4) Prof. (4+ yr) STEM	(5) Graduate
Family Ability Signal (Standardized)	0.059 (0.010)	0.075 (0.012)	0.095 (0.014)	0.055 (0.011)	0.068 (0.021)
Upper Secondary degree: Univ Prep	0.063 (0.065)	0.198 (0.075)	0.239 (0.113)	0.582 (0.154)	0.450 (0.303)
Upper Secondary GPA Percentile	0.559 (0.082)	1.047 (0.080)	0.846 (0.132)	1.685 (0.148)	1.070 (0.290)
Univ Prep degree × Upper Sec GPA Percentile	0.097 (0.091)	-0.187 (0.114)	-0.089 (0.149)	-0.434 (0.174)	-0.388 (0.341)
Part-time employment	-0.050 (0.024)	-0.036 (0.026)	-0.064 (0.030)	0.040 (0.032)	-0.016 (0.049)
Full-time employment	-0.113 (0.048)	0.000 (0.052)	-0.113 (0.055)	0.319 (0.059)	0.078 (0.074)
Full-time enrollment rate	-0.077 (0.023)	-0.065 (0.024)	-0.125 (0.028)	0.031 (0.025)	-0.009 (0.046)
Parent born in:					
... Europe (except former USSR)	0.317 (0.117)	-0.570 (0.186)	0.428 (0.129)	-0.108 (0.117)	0.240 (0.207)
... Former USSR (except Visegrád group)	0.231 (0.122)	-0.574 (0.194)	0.409 (0.151)	-0.138 (0.095)	0.181 (0.212)
... Latin America	-0.036 (0.083)	0.029 (0.115)	-0.034 (0.126)	-0.190 (0.099)	-0.282 (0.270)
... Africa	-0.116 (0.102)	-0.343 (0.118)	-0.127 (0.149)	-0.184 (0.155)	-0.017 (0.191)
... Middle East	-0.213 (0.047)	-0.080 (0.052)	0.013 (0.054)	-0.160 (0.050)	0.013 (0.079)
... Asia	-0.036 (0.065)	0.025 (0.069)	0.024 (0.086)	0.026 (0.066)	-0.035 (0.110)
Constant	-0.893 (0.072)	-1.174 (0.078)	-1.424 (0.128)	-1.630 (0.142)	-0.995 (0.526)
Observations	8526	6443	5943	6737	2152

Estimates of the educational production parameters from the structural model (as discussed in Section 1.4.2).
Bootstrapped Standard errors in parentheses

Table 1.4. Log Earnings Production Parameters

	(1) Blue Collar	(2) White Collar
Highest degree completed		
... Vocational Upper Secondary: non-STEM	0.116 (0.003)	0.086 (0.007)
... Vocational Upper Secondary: non-STEM	-0.019 (0.004)	0.057 (0.007)
... Univ Prep Upper Secondary: non-STEM	0.138 (0.016)	0.089 (0.024)
... Univ Prep Upper Secondary: STEM	0.113 (0.015)	0.080 (0.011)
... Bachelors degree: non-STEM	0.253 (0.020)	0.169 (0.012)
... Bachelors degree: STEM	0.282 (0.032)	0.169 (0.015)
... Professional degree: non-STEM	0.179 (0.024)	0.185 (0.011)
Full-time employment	0.249 (0.003)	0.251 (0.005)
Occupational experience	0.249 (0.006)	0.170 (0.006)
Occupational experience^2	-0.017 (0.001)	-0.015 (0.001)
Educational experience		
... Bachelors deg., 1 year	-0.290 (0.010)	–
... Bachelors deg., 2 years	-0.417 (0.013)	–
... Bachelors deg., 3 years	-0.337 (0.016)	–
... Bachelors deg., 4+ years	-0.130 (0.012)	–
... Graduate deg., 1 year	–	-0.382 (0.031)
... Graduate deg., 2 years	–	-0.290 (0.024)
... Graduate deg., 3 years	–	-0.095 (0.025)
... Graduate deg., 4+ years	–	0.015 (0.058)
... Professional deg., 1 year	–	-0.180 (0.018)
... Professional deg., 2 years	–	-0.341 (0.025)
... Professional deg., 3 years	–	-0.371 (0.019)
... Professional deg., 4+ years	–	-0.218 (0.013)
Constant	10.454 (0.031)	9.727 (0.041)
Observations	65029	24106

Bootstrapped Standard errors in parentheses

Estimates of the earnings production parameters from the structural model (as discussed in Section 1.4.3).

Lazear (1977)). And specifically, it is quite natural to suppose that I will enjoy school (or particular subjects) more if I'm good at it.

The estimation of the utility parameters in the structural model allows me to to directly test whether ability beliefs affect educational choices above and beyond their future returns, and indeed I largely find that this is the case. In the flow utility estimates, ability beliefs are reflected in the estimated effects of predicted performance on the utility of a given choice, with the relevant measure of performance in education the predicted completion rate.

Except for non-STEM professional degrees and graduate degrees, the results of Table 1.5 suggest that utility of a given educational choice is substantively and significantly increasing in ability across all degree types except for Graduate and Non-STEM professional degrees. The very high average completion rates (90%) for graduate students, reported in Appendix 1.11 might suggest the reason why flow utility is not currently estimated to be responsive to ability beliefs for graduate education: there is very little variation in expected performance for individuals who choose graduate education currently.[16]

In addition to the flow utility estimates associated with ability, several other features of the flow utility parameter estimates are notable. First among these, indicators for previous educational choices indicate that there are very large switching costs across all educational choices (that is, utility is strongly increasing in pursuing the same degree as in the previous period). This is again quite consequential to the model, as it implies that early decisions have substantial momentum, even if ability beliefs or other circumstances change. These early decisions of course are made using ability beliefs that may be characterized by greater uncertainty and greater reliance on parental SES ability signals.

Finally, employment during education is also estimated to have consistently negative, significant effects across all degrees, although having previously worked part-time in a white collar occupation is estimated to increase the utility of higher education. The potential burden of working and studying at the same time renders this an unsurprising result, but it is also a meaningful result for the model, as it implies that simultaneous exploration of different human capital paths is quite costly.

Occupational flow utility parameters

Table 1.6 reports flow utility estimates for occupational choices. The immediate focus of this table is the estimated effect of predicted earnings. Recall from Section 1.4.3 that earnings are assumed to be a function of ability, education, and occupational experience, with ability having a one-to-one effect on predicted earnings. Thus the large estimated effect sizes for predicted earnings equates across occupations again directly translate to a large estimated effect size of perceived ability (as with the interpretation of expected

[16]As a part of upcoming revisions with supplementary data, I will be however be able to incorporate higher education applications and associated admission hazards, wherein these results might be recoverable.

Table 1.5. Flow utility estimates: educational choices

	Bachelors Non-STEM	Bachelors STEM	Professional Non-STEM	Professional STEM	Graduate
Constant	−5.14 (0.13)***	−4.38 (0.13)***	−6.37 (0.17)***	−6.62 (0.19)***	−1.10 (0.26)***
Predicted completion rate	0.30 (0.04)***	0.29 (0.04)***	0.11 (0.06)	0.41 (0.05)***	0.10 (0.07)
Parent born in:					
... Europe, except former USSR	−0.23 (0.12)*	−0.31 (0.12)*	−0.37 (0.14)*	−0.33 (0.16)*	0.20 (0.24)
... Former USSR	−0.41 (0.23)	−0.29 (0.24)	−0.49 (0.31)	0.29 (0.26)	0.51 (0.41)
... Latin America	0.16 (0.15)	−0.29 (0.20)	−0.24 (0.20)	0.10 (0.23)	−0.62 (0.30)*
... Africa	0.03 (0.18)	0.33 (0.19)	−0.43 (0.24)	−0.14 (0.28)	0.21 (0.38)
... Middle East	−0.03 (0.12)	0.15 (0.12)	0.06 (0.14)	−0.10 (0.15)	0.25 (0.23)
... Asia	−0.04 (0.14)	0.11 (0.15)	−0.40 (0.19)*	0.19 (0.17)	0.14 (0.25)
High school GPA Percentile	1.84 (0.06)***	1.91 (0.07)***	3.38 (0.11)***	4.54 (0.13)***	–
Previous Enrollment:					
... Upper Secondary Type: Univ Prep	1.22 (0.04)***	0.63 (0.04)***	1.81 (0.05)***	1.37 (0.06)***	–
... Upper Secondary: Vocational	−0.62 (0.10)***	−0.39 (0.09)***	−1.18 (0.19)***	−0.00 (0.10)	–
... Upper Secondary: Univ Prep	−0.47 (0.07)***	−0.46 (0.09)***	−0.71 (0.10)***	0.02 (0.07)	–
... Bachelors: non-STEM	4.83 (0.04)***	0.03 (0.20)	0.84 (0.15)***	−1.12 (0.38)***	1.01 (0.13)***
... Bachelors: STEM	0.02 (0.17)	5.25 (0.05)***	−0.51 (0.32)	1.12 (0.15)***	0.78 (0.13)***
... Professional degree: non-STEM	0.50 (0.17)***	−0.74 (0.41)	5.91 (0.07)***	−0.52 (0.36)	0.17 (0.24)
... Professional degree: STEM	−1.17 (0.34)***	0.87 (0.17)***	0.50 (0.21)*	5.72 (0.07)***	2.38 (0.13)***
... Graduate degree	–	–	–	–	3.21 (0.12)***
Previous employment:					
... Blue collar PT	0.19 (0.05)***	−0.15 (0.06)*	−0.01 (0.07)	−0.07 (0.08)	−0.77 (0.12)***
... Blue collar FT	0.22 (0.08)*	−0.19 (0.10)	0.08 (0.12)	−0.67 (0.15)***	−1.65 (0.29)***
... White collar PT	0.52 (0.06)***	0.45 (0.07)***	0.49 (0.08)***	0.58 (0.09)***	−0.92 (0.10)***
... White collar FT	−0.58 (0.20)***	−1.23 (0.23)***	−0.74 (0.33)*	−1.60 (0.31)***	−2.36 (0.17)***
Work PT	−0.90 (0.04)***	−1.21 (0.05)***	−0.96 (0.06)***	−1.55 (0.06)***	−0.90 (0.10)***
Work FT	−2.30 (0.07)***	−2.46 (0.08)***	−2.57 (0.11)***	−2.48 (0.10)***	−2.38 (0.11)***

Estimates of the structural model flow utility parameters for educational choices.
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.
Robust Standard errors in parentheses.

performance in education). In the wage results, this estimated effect on flow utility is of course quite natural – it simply corresponds to the assumption that individuals care about how much they'll be paid and believe that how good they are at an occupational will be reflected in its pay.

Similar to education, care should be taken in the interpretation of several of the flow utility parameters. As with education, the structural model does not currently incorporate a demand-side model for employment opportunities (another planned extension). As such, estimated parameters on educational attainment (e.g. high school GPA percentile, upper secondary schooling type, higher educational enrollment and completion) are likely to reflect, in part, differences in the availability of employment in a given occupational sector.

Table 1.6. Flow utility estimates: occupational choices

	Blue collar PT	Blue Collar FT	White collar PT	White collar FT
Constant	-53.10^{***}	-61.08^{***}	-53.86^{***}	-68.53^{***}
	(0.07)	(0.06)	(0.24)	(0.09)
Predicted earnings	4.54^{***}	4.93^{***}	4.34^{***}	5.13^{***}
	(0.01)	(0.00)	(0.02)	(0.01)
High school GPA Percentile	-0.57^{***}	-0.81^{***}	0.89^{***}	0.58^{***}
	(0.03)	(0.04)	(0.05)	(0.06)
Parent born in:				
... Former USSR	-0.48^{***}	-0.59^{***}	-0.33^{*}	-0.15
	(0.11)	(0.16)	(0.14)	(0.18)
... Latin America	-0.02	-0.28^{*}	-0.31^{*}	-0.19
	(0.08)	(0.12)	(0.12)	(0.14)
... Africa	-0.16	-0.26^{*}	-0.13	-0.27
	(0.09)	(0.13)	(0.12)	(0.17)
... Middle East	-0.46^{***}	-0.45^{***}	-0.18^{***}	-0.30^{***}
	(0.04)	(0.06)	(0.05)	(0.07)
... Asia	-0.21^{***}	-0.18^{*}	-0.48^{***}	-0.19
	(0.06)	(0.09)	(0.08)	(0.11)
Upper Secondary Type: Univ Prep	0.34^{***}	0.07^{*}	0.53^{***}	0.49^{***}
	(0.02)	(0.03)	(0.03)	(0.04)
Previous Enrollment:				
... Upper Secondary: Vocational	1.85^{***}	1.81^{***}	1.37^{***}	-0.14
	(0.03)	(0.05)	(0.05)	(0.17)
... Upper Secondary: Univ Prep	1.53^{***}	1.63^{***}	1.38^{***}	-0.03
	(0.04)	(0.07)	(0.05)	(0.18)
... Bachelors: non-STEM	0.56^{***}	0.29^{***}	0.31^{***}	0.73^{***}
	(0.04)	(0.07)	(0.04)	(0.06)
... Bachelors: STEM	0.12^{*}	0.07	0.11^{*}	0.53^{***}
	(0.05)	(0.09)	(0.05)	(0.06)
... Professional degree: non-STEM	-0.32^{***}	-0.83^{***}	0.75^{***}	1.70^{***}
	(0.05)	(0.11)	(0.06)	(0.07)
... Professional degree: STEM	-0.89^{***}	-1.05^{***}	0.33^{***}	0.95^{***}
	(0.05)	(0.12)	(0.05)	(0.07)
Previous employment:				
... Blue collar PT	2.17^{***}	1.86^{***}	-0.30^{***}	0.37^{***}
	(0.03)	(0.04)	(0.06)	(0.06)
... Blue collar FT	1.77^{***}	3.54^{***}	0.79^{***}	1.82^{***}
	(0.05)	(0.05)	(0.09)	(0.08)
... White collar PT	-0.62^{***}	-0.37^{*}	2.92^{***}	2.11^{***}
	(0.07)	(0.14)	(0.04)	(0.05)
... White collar FT	0.15	2.00^{***}	3.15^{***}	4.79^{***}
	(0.17)	(0.15)	(0.10)	(0.10)
Graduated bachelors	-0.86^{***}	-0.58^{***}	0.08	1.25^{***}
	(0.07)	(0.09)	(0.06)	(0.07)
Graduated professional degree	-0.05	0.18	-0.31^{***}	1.23^{***}
	(0.09)	(0.11)	(0.08)	(0.08)

Estimates of the structural model flow utility parameters for occupational choices.
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.
Robust Standard errors in parentheses.

The model estimates for educational attainment parameters are largely consistent with this consideration. Relative to a vocational upper secondary schooling, university preparatory upper secondary schooling is estimated to increase the utility of white collar work and blue collar part-time work, but has a near zero effect for full-time blue collar employment. This finding regarding full-time employment may likewise be an artefact of lacking a demand-side. Alternatively, it may be a genuine reflection of students who choose a university-preparatory education (more closely aligned to white-collar work) having a greater preference for the non-pecuniary aspects of white collar occupations.

Similar results and logic applies to other educational attainment parameter estimates. Having been enrolled in school in the previous period has an estimated positive effect regardless of schooling option. Estimated effects for blue collar occupations and part-time white collar employment are highest for lower levels of schooling, with very large effects for previous vocational upper secondary enrollment in blue collar employment. For full-time white collar employment, however, utility estimates are highest for having been previously enrolled in a professional degree. Having completed a professional degree is similarly estimated to have a large positive effect on the utility of employment in white collar occupations, while having a bachelors degree has a positive effect (relative to upper secondary level education) for all occupations except for part-time white collar employment.

Finally, another important group of parameter estimates are those concerning employment in previous period (largely an indication of switching costs). As with education flow utility results, the large positive estimates for previous employment matched to the current occupational choice (relative to previous employment in another sector/intensity) suggest a cost in in deviating from the occupational choice in the previous period. The only exception among these results is part-time white collar employment, where the estimates indicate that individuals would usually prefer full-time white collar employment if possible.

1.6.4. Ability beliefs

The sensitivity of choices to perceived ability and the large costs of deviating from previous behavior found in the previous section (for both education and employment) suggests a key role for earlier decisions made under less accurate ability beliefs. In order to understand the extent to which this costly re-adjustment of human capital paths leads to ex-post sub-optimal human capital attainment and intergenerational persistence, it is thus essential to understand the pace at which youth are able to correct beliefs and how closely initial family-informed priors correspond to posterior ability beliefs. I examine this central question in the following section.

Ability correlation and correlated learning

To begin this examination of ability and ability belief, I first document the estimated population variances and correlational structure of ability from the structural model in Table 1.7.

Table 1.7. Correlation Matrix of Unobserved Abilities

	Bachelors, Non-STEM	Bachelors, STEM	Professional, Non-STEM	Professional, STEM	Blue Collar	White Collar
Bachelor, Non-STEM	1.000					
Bachelor, STEM	0.184	1.000				
Professional, Non-STEM	0.322	0.309	1.000			
Professional, STEM	0.233	0.420	0.138	1.000		
Blue Collar	0.036	0.055	0.060	0.154	1.000	
White Collar	0.061	0.083	0.038	0.102	0.241	1.000
Standard Deviation	0.955	0.942	0.951	0.931	0.365	0.382

Structural estimates of the population-level variance and correlation in unobserved abilities.

Recall that ability is defined such that it has a unit coefficient in the production of educational and occupational performance, hence it is expressed in the unit of the relevant outcome variables. For education, this is the standardized educational performance measure (here the credit completion rate), while for occupational performance, the relevant outcome is log earnings.

With this interpretation in mind, the first major finding is that heterogeneity in ability is quite important in terms of relevant human capital outcomes. A one standard deviation change in ability amounts to almost a one-standard deviation change in education performance ($0.931 - 0.955\sigma$) across educational options. In employment, a one standard deviation change in ability would be expected to change log earnings by about 44% in blue collar employment and 47% in white-collar employment.

The next major question concerns the correlation in abilities across different human capital choices. In education, ability beliefs exhibit modest correlation within educational level, with a correlation of $\rho = 0.184$ between STEM and non-STEM bachelors degrees and $\rho = 0.138$ between professional degrees. Beliefs are more strongly correlated within degree subject across levels, however. The belief correlation between non-STEM degrees at the bachelors and professional level is estimated at $\rho = 0.233$, while the correlation between STEM degrees at each level is $\rho = 0.420$.

Ability beliefs for employment are weakly correlated with educational ability beliefs across degree level and subject. In both Blue Collar and White Collar employment, posterior ability beliefs are most closely correlated with performance in professional STEM degrees ($\rho = 0.154$ and $\rho = 0.102$ respectively). Performance is more highly correlated across occupational types, however, at $\rho = 0.241$.

When interpreting both the standard deviations and correlations of abilities, it is important to recall that the analysis procedure estimates the residual component of ability from the structural production models. Since these models take into account important measures of prior human capital attainment (e.g. upper secondary schooling program type and GPA), what is being captured is essentially the variation in ability not explained by overall measures of attainment at age 18. The key insight here is that this residual variation in ability is not only substantial (as seen in the estimated standard errors), but that it is also tends to be fairly idiosyncratic across potential human capital paths.

Belief updating and persistent uncertainty

An important implication of the generally modest levels of ability correlation between different human capital-based tasks is that learning about one's aptitude for a given task through direct experience of that task does not generalize well to better accuracy about beliefs in other tasks.

The learning model assumes that individuals update their beliefs about ability not only through direct experience, but also through correlated learning, i.e. when they update beliefs about one ability type through direct experience, they also use their knowledge of the population-level correlation in abilities to update their beliefs about their ability in other domains as well. But when this correlation is low (as it often appears in these results), the efficacy of learning without direct experience is also low. This implication manifests itself quite clearly in the results of Table 1.8 and 1.9.

Table 1.8 presents estimates of the reduction in the uncertainty surrounding ability beliefs, expressed by the posterior variance of individual's ability beliefs. By examining the mean percent change in these variances, we see that the rate of learning about ability is very heterogeneous across human capital types.

Table 1.8. Mean change in variance of beliefs relative to age 19

Age	Bach Non-STEM	Bach STEM	Prof Non-STEM	Prof STEM	Grad	Blue Collar	White Collar
20	-2.5%	-2.5%	-1.8%	-2.9%	-0.3%	-15.1%	-4.8%
21	-5.0%	-4.9%	-3.5%	-5.3%	-0.6%	-25.6%	-8.3%
22	-7.3%	-6.9%	-5.1%	-7.2%	-1.2%	-33.9%	-11.8%
23	-9.2%	-8.4%	-6.3%	-8.5%	-2.2%	-41.1%	-15.5%
24	-10.6%	-9.5%	-7.4%	-9.5%	-3.3%	-46.9%	-20.2%
25	-11.8%	-10.3%	-8.1%	-10.1%	-4.1%	-51.1%	-25.0%
26	-13.6%	-11.6%	-9.7%	-11.5%	-5.1%	-61.7%	-35.9%

Structural estimates of the change in posterior ability belief variances by age. Estimates correspond to the average of the percent change in posterior ability belief variances relative to age 19.

There is substantial and consistent reduction in beliefs about Blue Collar employment, for example, with posterior ability belief variances at age 26 that are on average 61.7% smaller than at age 19. The pace and total extent of learning about ability for White Collar employment is on average less than in Blue Collar employment, but nonetheless quite substantial, with a 35.9% average reduction in ability belief variances.

The pace of learning is much less substantial for abilities across higher education types. For non-graduate degrees, learning about ability is greatest for non-STEM bachelor degrees (13.6% reduction in posterior ability beliefs variances between 19 and 26 on average), and lowest for non-STEM professional degrees (9.7%). Beliefs about ability for graduate education shows the least change in uncertainty on average, with only a 5.1% reduction on average.

To gain a complete picture of why these reductions are so heterogeneous, it is instructive to look at descriptive statistics about how much direct experience of educational or occupational paths young adults have. These results are presented in Table 1.9.

It is immediately evident that young adults tend to have much more experience in occupational paths, both in terms of the share of individuals with some experience and in terms of the average years of experience. This finding is most striking for Blue Collar employment, where 67% of the sample has at least some experience. Among those who have Blue Collar experience, this experience moreover tends to be quite substantial – with 95% of them having at least two years of experience, and 81% having at least four years of experience. Experience in white collar employment is considerably less, but still substantial. 35% of the sample has some experience in white collar employment, among which 89% have at least two years of experience.

In comparison, exposure to higher education human capital choices is very limited. For university-level education, most people have no experience of a given degree type by age 26, with the share ranging from 84% for non-STEM bachelors degrees to 91% for STEM professional degrees. Only 5% of the sample had at least one year of experience of a graduate degree.

These large differences in levels of direct experience to a given education or work choice closely corresponds to the differences in ability uncertainty reduction documented in Table 1.8. Blue Collar employment is the category for which there is, by a considerable margin, both the largest amount of experience among young adults and the largest reduction in ability uncertainty. White Collar employment comes a different second in both respects, but equally enjoys a much larger level of experience and much larger reduction in ability uncertainty than any educational path. Among educational degrees, the most amount of learning ability occurs for bachelors education (especially non-STEM bachelors), which are once again the degrees with the highest share of young adults having at least some experience. Finally, the least learning about ability overall occurs for graduate education, which also is the human capital choice for which young adults have the least amount of experience.

Table 1.9. Human capital experience by age

	Bach Non-STEM	Bach STEM	Prof Non-STEM	Prof STEM	Grad	Blue Collar	White Collar
Age 19							
Average years	0.02	0.02	0.01	0.03	0	0.33	0.07
Share no experience	0.98	0.98	0.99	0.97	1	0.66	0.93
Share 1 year	0.02	0.02	0.01	0.03	0	0.19	0.07
Age 20							
Average years	0.08	0.07	0.05	0.09	0	0.80	0.19
Share no experience	0.94	0.95	0.96	0.94	1	0.51	0.87
Share 1 year	0.04	0.03	0.03	0.03	0	0.19	0.07
Share 2 years	0.02	0.02	0.01	0.03	0	0.30	0.06
Age 21							
Average years	0.16	0.14	0.10	0.16	< 0.01	1.26	0.31
Share no experience	0.91	0.92	0.95	0.92	> 0.99	0.44	0.84
Share 1 year	0.04	0.03	0.02	0.02	< 0.01	0.12	0.06
Share 2+ years	0.05	0.05	0.03	0.06	0	0.44	0.10
Age 22							
Average years	0.25	0.21	0.15	0.23	0.01	1.73	0.44
Share no experience	0.89	0.91	0.94	0.92	0.99	0.40	0.80
Share 1 year	0.03	0.03	0.02	0.01	0.01	0.09	0.07
Share 2+ years	0.08	0.07	0.05	0.07	<0.01	0.51	0.13
Age 23							
Average years	0.33	0.27	0.21	0.28	0.04	2.22	0.60
Share no experience	0.87	0.90	0.93	0.91	0.97	0.37	0.77
Share 1 year	0.03	0.02	0.01	0.01	0.01	0.07	0.07
Share 2+ years	0.10	0.08	0.06	0.08	0.01	0.56	0.16
Age 24							
Average years	0.40	0.32	0.27	0.33	0.07	2.73	0.81
Share no experience	0.86	0.89	0.92	0.91	0.96	0.35	0.72
Share 1 year	0.03	0.02	0.01	0.01	0.02	0.05	0.07
Share 2+ years	0.12	0.09	0.06	0.08	0.02	0.60	0.21
Age 25							
Average years	0.46	0.35	0.31	0.37	0.10	3.26	1.08
Share no experience	0.84	0.88	0.92	0.91	0.95	0.34	0.68
Share 1 year	0.02	0.02	0.01	0.01	0.01	0.04	0.06
Share 2+ years	0.14	0.11	0.07	0.08	0.05	0.74	0.32
Age 26							
Average years	0.50	0.38	0.35	0.39	0.13	3.77	1.40
Share no experience	0.84	0.88	0.91	0.91	0.95	0.33	0.65
Share 1 year	0.02	0.02	0.01	0.01	0.01	0.03	0.04
Share 2+ years	0.14	0.11	0.07	0.08	0.05	0.64	0.32

Average years of experience and share of population with a given years of experience in a given education or occupation type, by age for the structural estimation sample. Occupational experience before age 18 is excluded.

An interesting insight into the interplay between the rate of learning and the amount of experience with a given choice is found in the comparison of results for STEM bachelors and professional degrees. The pace of learning about ability for STEM professional degrees tends to closely track with the STEM bachelors degree, although the average reduction in uncertainty relative to age 19 is initially larger for the professional degree, but in later years (age 25 and 26) is instead larger for the STEM bachelors degree.

A likely reason for this phenomenon is differences in exposure patterns. The STEM professional degree initially attracts slightly more students than the corresponding bachelors degree from age 19-20, and the average years of experience also ends up being slightly higher for the professional degree (at 0.37 years compared to 0.35 for the general STEM bachelors). Yet after age 20, the STEM bachelors continues to attract new first-time enrollees at a higher rate than the professional degree (explaining it's higher overall share of students with some exposure at 26), while students in the professional degree tend to stay enrolled for larger (in part because these degrees are often four years instead of three).

Because the reduction in uncertainty is largest in initial periods of exposure to a choice, the larger fraction of the population with at least some experience in the STEM bachelors (12% relative to 9%) has a slightly larger impact than the difference in average years of experience. Finally, ability in STEM bachelors and professional degrees displays the highest rate of correlation amongst all ability types ($\rho = 0.42$), therefore correlated learning will tend to reduce the impact of these differences in the amount of direct experience.

In sum, the structural model estimates about the extent of learning alongside descriptive statistics concerning experience suggest a view that direct experience is a key driver of learning about ability, and without that experience, substantial uncertainty persists. This is a result that was largely anticipated based on the foregoing estimates of correlation in ability types. Yet the large differences in experience levels between human capital choices shown here, and the consequent large differences in persistent uncertainty about ability is noteworthy and perhaps less obvious ex ante.

Diminishing role of parental ability signals

In the discussion of the utility parameter estimates, I have noted that the results from the structural model indicate that ability beliefs – and especially early ability beliefs – are an important determinant of human capital outcomes, both because of the responsivity of choice utility to expected ability in that domain, but also because of the large switching costs associated with changing human capital paths. In the discussion so far about ability beliefs, I have also noted that for the most part, learning about ability is neither rapid nor complete, but instead largely depends on direct experience in a given human capital path so that one obtains direct feedback about ability. Because correlated learning about ability is estimated to be quite limited, learning about one's aptitude in choices that are not directly pursued likewise tends to be quite limited.

In this context then, there appears to be a degree of path dependence. Early ability beliefs shape early human capital choices, which are not only costly to reverse, but also determine what dimensions of ability young adults learn about – with relatively little learning about ability outside of the path that is chosen.

A critical question then is how much family SES signals affect ability beliefs, especially early beliefs that are the most important. Recall that although family SES signals were were shown to meaningful predictors of ability in Section 1.6.2, their effects sizes are small relative to the overall variance in ability shown in 1.7.[17] Yet without further learning, ability beliefs will tend to primarily rely on these family ability signals in a manner that is disproportionate to their overall correlation with ability.[18] I therefore present the estimated correlation of posterior ability beliefs with family-informed priors, by age, in Table 1.10.

Table 1.10. Correlation of posterior ability beliefs to family-informed priors, by age

Age	Bach Non-STEM	Bach STEM	Prof Non-STEM	Prof STEM	Grad	Blue Collar	White Collar
19	0.651	0.701	0.774	0.278	0.525	0.928	0.756
20	0.493	0.553	0.698	0.170	0.509	0.514	0.508
21	0.352	0.418	0.586	0.121	0.481	0.353	0.360
22	0.230	0.354	0.524	0.105	0.461	0.290	0.302
23	0.244	0.317	0.483	0.102	0.430	0.267	0.267
24	0.220	0.295	0.450	0.095	0.388	0.252	0.243
25	0.210	0.285	0.433	0.097	0.350	0.247	0.225
26	0.197	0.276	0.410	0.092	0.305	0.242	0.202

Structural estimates of the correlation between Bayesian posterior ability beliefs by age to initial ability beliefs based on family SES signals.

[17] It is important to once again note, however, that the ability analyzed here is an *ability residual* after accounting for observable human capital attainment at age 18. To the extent familial determinants of ability shape these outcomes, the underlying unconditional correlation might be expected to be much higher. A central finding of this analysis however, is that there is a substantial amount of ability that is not captured by human capital at age 18, for which parental SES signals are still estimated to provide a valuable and influential signal. Using that signals, however, means basing ability beliefs and consequent human capital decisions on SES, when ultimately this is a poor indicator of true ability.

[18] Recall that initial family-informed priors are based on the expected distribution of ability conditional on SES signals (directly estimated in the model via auxiliary regression). The operative question is not then whether family-informed signals reduces the accuracy of beliefs, or is a biased signal in the initial limited information context. Rather, the question in essence is how much are ability beliefs biased towards parental SES in a complete information context, because these signals are immediately observable and learning about ability is rather slow.

The relatively small correlation of family-informed priors to age 26 posterior beliefs suggests that although learning about ability may not be rapid, it is enough to see a substantial reduction in the role of family-informed priors by age 26 *on average*. Several important caveats remain, however. First, because these correlations are a function of the updating documented in Section 1.6.4, the level of persistence for an individual will depend on which educational and occupational experiences they've pursued. Second, with the exception of STEM professional degrees, the posterior correlations after age 26 tend to be higher than the true correlations implied by the effect sizes documented in Section 1.6.2, with less commonly chosen choices (e.g. non-STEM professional degrees and Graduate degrees) still showing quite substantial posterior correlation ($\rho = 0.410$ and $\rho = 0.305$, respectively) even after age 26.

Finally, although the correlation of ability beliefs with family is declining over time, this correlation remains substantial in the most critical early periods, with the exception of beliefs about ability in a STEM professional degree. After age 20, the estimated posterior ability belief correlation is in the region of $\rho = 0.5$ for most ability types (with the exception of professional degrees, where the correlation is $\rho = 0.170$ for a STEM degree and $\rho = 0.698$ for a non-STEM degree). After age 21, the correlation is around $\rho = 0.35$ for non-STEM bachelors and both occupation types, and substantial higher (ρ betwen 0.418 and 0.586) for other educational abilities with the exception of the STEM professional degree, where the correlation is already low $\rho = 0.121$. These trends continue in a similar fashion: the correlations continue to decline but in the interim exhibit an effect that is disproportionate to their predictive value.

These results suggest that although parentally SES signals are typically not a strong predictor of latent multi-dimensional abilities, they nevertheless exert a meaningful influence on beliefs for some time, especially during earlier periods that have the most influence on overall human capital attainment.

1.7. Conclusion

This study has taken up the question of how Bayesian uncertainty about ability interacts with family background in the determination of human capital attainment. Specifically, this study began with the recognition that nearly all intergenerational human capital models and empirical studies of intergenerational persistence assign a substantial fraction of persistence to biological determinants about ability.

In light of these results, and similar lay perception of ability persistence epitomized by the expression "the apple doesn't fall far from the tree," I argue that it is rational for households (i.e. parents or youth themselves) to use family signals of ability to inform beliefs about childrens' ability. I highlight, however, that without being able to directly observe the ability of family members either, the most natural family ability signals might be markers of socio-economic status (i.e. education and labor market outcomes) that are in part functions of ability in the classic Becker-Tomes model and much of the ensuing literature. But if SES informs ability beliefs, this may hinder the assumed optimality of human capital investments conditional on income and ability in traditional human capital models. And in so doing, this interaction between ability uncertainty and SES may serve as an important source of intergenerational persistence largely unaddressed in the current literature.

To begin the exploration of this issue, I first verified empirical support for the notion that parental SES signals inform ability beliefs, using the Evaluation through Follow-Up Study of Swedish youth. Using the 1992 ETF Cohort, I estimated that parental SES measures (income and educational attainment) are indeed statistically significant and economically meaningfully predictors of elicited ability beliefs even after controlling for actual performance in standardized tests. These results are consistent across beliefs about ability in both language (Swedish) and math, as well at assessments that occurred at two different points of education: grade 6 (Mellanstadiet) and grade 9 (Högstadiet).

As a part of these findings, regression results further suggest that parental SES signals have a larger effect on child ability beliefs at grade 6 than in grade 9, and that parental education affects beliefs not only through the level of parental attainment, but also through the field of their degree. Children of parents with STEM degrees tend to have more positive beliefs about their ability in math, while children of parents with non-STEM degrees tend to have more positive beliefs about their ability in Swedish. These results are consistent with the assumption of Bayesian belief updating about ability that is multi-dimensional in nature.

The overall results suggests that moving from parental education at the upper secondary level and un-matched (i.e. non-STEM for math, and STEM for Swedish), to education at the graduate level and matched, would increase child beliefs about ability in Swedish by 0.15 standard deviations in grade 6 and 0.13 standard deviations in grade 9. For ability beliefs in math, this difference in parental education is predicted to increase child beliefs about ability by 0.25 standard deviations in grade 6, and 0.18 standard deviations in grade 9.

With empirical support for the notion that parental SES signals of ability affect beliefs about the ability of children (as would be expected by a rational expectations Bayesian framework), I then turned to an exploration of the consequences of learning about ability with family-informed priors, through estimation of a dynamic discrete choice structural model of human capital decisions for young adults. The estimation sample consisted of all Swedish males born in 1992 that had completed upper secondary schooling by 2011 (corresponding generally to age 19). Swedish administrative data sources then allowed me to follow the education and employment decisions of these young men through adulthood, spanning ages 19 to 26.

The structural model consists of estimating the human capital (education and occupation) choices that maximize an individual's discounted present value of utility. As a part of this estimation procedure, the structural model also estimates the relevant production functions that are assumed to govern educational and occupational attainment (and therefore inform agents expectations of future returns). In addition, the structural estimation procedure directly models Bayesian beliefs about ability (or more specifically, ability residuals after accounting for human capital attainment before age 19). As motivated by the descriptive ETF analysis, these beliefs are assumed to utilize parental SES characteristics as initial ability signals, and ability beliefs are updated after each period based on the feedback gained from observed educational and occupational performance (i.e. performance in higher education and earnings in employment). Indirect (correlated) learning is also permitted in the model, which is premised on individuals updating their belief about a given ability type even without direct feedback, by using their knowledge of the estimated correlation in unobserved abilities in conjunction with the signals they did receive.

Using this framework, I once again found that parental SES signals are a relevant predictor of ability, with a 1 standard deviation increase in parental SES signals increasing educational performance by about 0.06 to 0.10 standard deviations, and earnings in employment by about 3.1 to 5.6%, conditional on other characteristics and human capital attainment by age 19. I then showed that human capital choices are estimated to be highly responsive to perceived ability. Ability beliefs are estimated to steer human capital choices in a couple of ways. First, ability affects the current ("flow") utility of a choice, through its substantial estimated effects on earnings for occupational choices and enjoyment (or lack thereof) of schooling for educational choices. Second, it affects the expected future stream of payoffs in a similar manner.

The utility model results also imply that re-orientation of human capital paths in response to learning is quite costly. Utility parameters associated with choices in the previous period indicate that there are substantial switching costs in not continuing to make the same education or occupational choice that was made in previous periods, regardless of what that previous choice was. These estimates costs are in addition to the foregone returns to the previous decision (e.g. experience in a given occupation, quicker paths to educational completion in earnings for staying in the same educational degree). As such, the model estimates imply that it is not only ability beliefs that are important, but especially the beliefs a person has at younger ages.

These results lead to the central question of how do beliefs evolve, and what is the role that family signals are expected to play. I examined these questions through analysis of estimated rational expectations Bayesian beliefs from the structural model. These results suggest that the scope of unobserved ability at age 19 tends to be quite substantial as a fraction of overall performance in a given educational or occupational choice. Learning about these abilities moreover appears very heterogeneous, with a reduction in average ability uncertainty as high as 61.7% (for Blue Collar Employment), and as low as 9.7% for non-STEM professional degrees and 5.1% for graduate degrees. These differences are driven in large part by differences in the amount of direct exposure to a given choice that a young person has – with most young men having experience with blue collar employment, but less so with white collar employment, and a small fraction having experience in any given higher education path.

Results suggest that ability correlations in this context tend to be rather low, outside of the correlation in ability between STEM bachelor and professional degrees and, to a lesser extent, blue collar and white collar occupations. With little direct exposure to most choices, this mild rate of correlated learning leads to estimates that suggest most people tend to have persistent uncertainty about their ability in various domains outside of blue collar employment.

Given that beliefs are not estimated to converge quickly to the true beliefs, this raises the possibility that family-informed priors may have a persistent influence on ability beliefs, despite being a comparatively small determinant of residual productivity at age 19. Table 1.10 showed that although the correlation of ability beliefs by age 26 tends to be low, it is nevertheless larger than expected based on the auxiliary regression of performance residuals on family SES signals. And perhaps more crucially, parental SES signals are estimated to have quite large impacts on beliefs at earlier ages that tend to be the most consequential for overall human capital attainment.

In summary, this study has provided preliminary evidence that uncertainty about ability is an important factor in human capital attainment, and that in the context of this uncertainty, parental SES signals are likely to distort ability beliefs (and consequent human capital decisions) in a manner that contributes to intergenerational persistence in outcomes, despite being ex ante unbiased.

Given the importance of this question, and the preliminary nature of these findings, further analysis of this question appears warranted. In follow up work, I will aim to gain better insights into the questions through several revisions and extensions. First, I will use the model to conduct counterfactual analysis of human capital outcomes and intergenerational correlations in outcomes if students had instead started their decisions at age 19 with the posterior ability beliefs estimated after age 26. Given the crucial insight that ability beliefs are most important – and likely most distorted – early on, I will also extend the model to consider decisions from grade 6. In addition, I will allow for greater heterogeneity in human capital, and especially allow for occupational skills that are not only vertically differentiated (as with blue collar and white collar employment) but also horizontally differentiated (i.e. several occupation types, with multiple choices at a given level of skill). Finally, more work will be done to improve technical features of estimation, including data quality improvements (e.g. direct use of grades for educational performance, instead of credit completion rates) and greater sophistication of the structural model (for example, techniques that account for permanent econometrician-unobserved heterogeneity of individuals). These improvements should not only add important new insights to this analysis, but also make it more robust.

1.A Appendix

Table 1.11. Characteristics of Students Enrolled in Higher Education, by Type

	(1) Bachelors Non-STEM	(2) Bachelors STEM	(3) Prof. (4+ yr) Non-STEM	(4) Prof. (4+ yr) STEM	(5) Graduate
Credit Completion Rate	0.75	0.75	0.79	0.83	0.90
	(0.216)	(0.203)	(0.205)	(0.161)	(0.138)
Father Born Sweden (Share)	0.79	0.79	0.81	0.83	0.80
	(0.407)	(0.409)	(0.390)	(0.377)	(0.402)
Mother Born in Sweden (Share)	0.81	0.79	0.82	0.82	0.80
	(0.396)	(0.409)	(0.383)	(0.383)	(0.402)
Vocational Upper Secondary, 3 years (Share)	0.33	0.53	0.19	0.30	0.27
	(0.470)	(0.499)	(0.390)	(0.458)	(0.447)
Univ. Prep. Upper Secondary, 3 years (Share)	0.67	0.47	0.81	0.70	0.73
	(0.470)	(0.499)	(0.390)	(0.458)	(0.447)
Upper Secondary GPA (Percentile)	0.58	0.60	0.70	0.78	0.76
	(0.254)	(0.252)	(0.251)	(0.197)	(0.204)
Employed Part-Time (Share)	0.39	0.29	0.33	0.19	0.33
	(0.488)	(0.455)	(0.472)	(0.396)	(0.470)
Employed Full-Time (Share)	0.06	0.06	0.08	0.06	0.16
	(0.245)	(0.235)	(0.264)	(0.233)	(0.369)
Part-Time Studies (Share)	0.49	0.55	0.37	0.50	0.56
	(0.500)	(0.498)	(0.483)	(0.500)	(0.497)
Full-Time Studies (Share)	0.51	0.45	0.63	0.50	0.44
	(0.500)	(0.498)	(0.483)	(0.500)	(0.497)
Observations	8632	6483	5991	6766	2182

Table 1.12. Parental Characteristics of Students: Father and Family Income

	(1) Bachelors Non-STEM	(2) Bachelors STEM	(3) Prof. (4+ yr) Non-STEM	(4) Prof. (4+ yr) STEM	(5) Graduate
Disposable Income per parent	12.61	12.56	12.68	12.71	12.71
	(0.384)	(0.445)	(0.429)	(0.446)	(0.451)
Father's Educ.: Primary or less (Share)	0.10	0.08	0.11	0.11	0.12
	(0.302)	(0.279)	(0.311)	(0.313)	(0.320)
Father's Educ.: Compulsory (Share)	0.01	0.02	0.01	0.01	0.01
	(0.113)	(0.152)	(0.113)	(0.099)	(0.093)
Father's Educ.: Upper sec., 2 years or less (Share)	0.07	0.06	0.05	0.03	0.05
	(0.263)	(0.237)	(0.219)	(0.178)	(0.212)
Father's Educ.: Upper sec., 3 years (Share)	0.25	0.28	0.20	0.17	0.18
	(0.435)	(0.449)	(0.403)	(0.378)	(0.384)
Father's Educ.: Bachelors (Share)	0.09	0.08	0.09	0.07	0.07
	(0.284)	(0.275)	(0.280)	(0.253)	(0.263)
Father's Educ.: Professional (Share)	0.10	0.08	0.11	0.10	0.10
	(0.304)	(0.271)	(0.318)	(0.295)	(0.300)
Father's Educ.: Some higher ed (Share)	0.09	0.09	0.17	0.19	0.16
	(0.292)	(0.283)	(0.373)	(0.388)	(0.365)
Father's Education Subject: STEM (Share)	0.40	0.52	0.40	0.56	0.50
	(0.490)	(0.499)	(0.491)	(0.496)	(0.500)
Father's Occupation: White Collar (Share)	0.65	0.62	0.72	0.76	0.72
	(0.477)	(0.486)	(0.451)	(0.429)	(0.448)
Observations	8632	6483	5991	6766	2182

Table 1.13. Parental Characteristics of Students: Mother

	(1) Bachelors Non-STEM	(2) Bachelors STEM	(3) Prof. (4+ yr) Non-STEM	(4) Prof. (4+ yr) STEM	(5) Graduate
Mother's Educ.: Primary or less (Share)	0.06	0.05	0.05	0.05	0.06
	(0.237)	(0.228)	(0.226)	(0.222)	(0.237)
Mother's Educ.: Compulsory (Share)	0.01	0.02	0.01	0.01	0.01
	(0.111)	(0.141)	(0.098)	(0.091)	(0.106)
Mother's Educ.: Upper sec., 2 years or less (Share)	0.04	0.04	0.02	0.02	0.02
	(0.195)	(0.191)	(0.135)	(0.133)	(0.139)
Mother's Educ.: Upper sec., 3 years (Share)	0.21	0.20	0.17	0.16	0.18
	(0.409)	(0.398)	(0.372)	(0.365)	(0.383)
Mother's Educ.: Bachelors (Share)	0.13	0.14	0.15	0.15	0.16
	(0.340)	(0.347)	(0.357)	(0.355)	(0.362)
Mother's Educ.: Professional (Share)	0.18	0.17	0.20	0.19	0.20
	(0.381)	(0.378)	(0.402)	(0.391)	(0.400)
Mother's Educ.: Some higher ed (Share)	0.10	0.09	0.14	0.15	0.13
	(0.298)	(0.289)	(0.345)	(0.362)	(0.336)
Mother's Education Subject: STEM (Share)	0.06	0.07	0.07	0.12	0.10
	(0.234)	(0.263)	(0.255)	(0.326)	(0.296)
Mother's Occupation: White Collar (Share)	0.60	0.60	0.69	0.70	0.66
	(0.491)	(0.489)	(0.465)	(0.456)	(0.473)
Observations	8632	6483	5991	6766	2182

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