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Rémi Piatek • Pia Pinger

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German Socio-Economic Panel Study (SOEP)
DIW Berlin
Mohrenstrasse 58
10117 Berlin, Germany

Contact: Uta Rahmann | urahmann@diw.de

Maintaining (Locus of) Control?*

Assessing the impact of locus of control on education decisions and wages

Rémi Piatek
University of Chicago
piatek@uchicago.edu

Pia Pinger
University of Mannheim
ZEW, IZA
ppinger@rumms.uni-mannheim.de

Abstract

This paper establishes that individuals with an internal locus of control, i.e., who believe that reinforcement in life comes from their own actions instead of being determined by luck or destiny, earn higher wages. However, this positive effect only translates into labor income via the channel of education. Factor structure models are implemented on an augmented data set coming from two different samples. By so doing, we are able to correct for potential biases that arise due to reverse causality and spurious correlation, and to investigate the impact of premarket locus of control on later outcomes.

JEL Classification: C31, J24, J31.
PsycINFO Classification: 2223, 3120.
Keywords: locus of control, wages, latent factor model, data set combination.

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1 Introduction

Does it make a difference if you think *you* can make a difference? Will it affect your decision making, or even your productivity? In response to such kinds of questions, the economic literature has recently come to acknowledge the considerable importance of *personality traits* in explaining education choices, as well as a large variety of labor market outcomes. The present paper focuses on *locus of control*, one dimension of personality that measures the extent to which individuals believe that what happens to them in life is related to their own actions and decisions, or on the contrary to fate and luck. We contribute to the existing literature on personality traits by investigating the impact of locus of control on wages, while making a distinction between the direct—or *productive*—impact of locus of control, and the indirect—or *behavioral*—impact that works through education decisions.

We find that locus of control is an important predictor of the decision to obtain higher education. Furthermore, we find that *premarket* locus of control, defined as locus of control measured at the time of schooling—before the individual enters the labor market—does not significantly affect later wages after controlling for education decisions. In light of the existing literature, which finds mostly positive effects of contemporaneous locus of control measures on wages, this indicates that it is important to distinguish between *premarket* skills and those that are already influenced by labor market experience and age. Last, simulation of our model shows that moving individuals from the first to the last decile of the locus of control distribution significantly shifts the distribution of schooling choices, thus indirectly affecting later wages.

From a methodological point of view, there are two major econometric problems at stake in the economic literature on personality traits: measurement error and endogeneity (Bowles and Gintis, 2002; Borghans et al., 2008). First, measurement error arises because certain traits or characteristics are measured by questions or tests that are imperfect proxies of the true latent ability. Yet, in general, most psychological measures are designed to capture a particular latent trait or skill, such that factor analytical approaches can be used to distinguish true latent abilities from measurement error (Borghans et al., 2008; Heckman et al., 2006b; Hansen et al., 2004). Second, endogeneity arises in the study of the impact of locus of control on labor market outcomes for two reasons. On the one hand, the results may be flawed by reverse causality, as (anticipated) labor market outcomes may affect locus of control (e.g., see Trzcinski and Holst, 2010; Gottschalk, 2005). For this reason, locus of control measures may reflect, rather than cause, the outcomes they are supposed to predict (Borghans et al., 2008). In this case, the coefficient on locus of control is biased, because of nonzero covariance between the measures and the error term. On the other hand, both outcomes and measures may be affected by past labor market experiences, which are usually not accounted for. The consequence is, again, an overestimation of the locus of control coefficient due to spurious correlation.

In the literature, four main strategies have been adopted to address this endogeneity issue. First, Duncan and Morgan (1981) and Duncan and Dunifon (1998) using the PSID, extract measures of personality traits as measured 15-25 years prior to earnings. A similar strategy has been adopted by Heckman et al. (2006b), who use locus of control measurements in the NLSY taken at age 14-22 to explain later outcomes. Second, Bowles et al. (2001), using the National Longitudinal Survey of Young Women (NLSYW), employ contemporary measurements of locus of control, which they purge of past wage influences. Third, Osborne (2000) uses past skills to instrument for contemporaneous skill measures. Last, Cunha and Heckman (2008) explicitly model development and accumulation of skills as a technology of skill formation, in which investments in one period affect the productivity of investments in subsequent periods. However, their focus is mainly on early childhood development of skills, and not on the impact of labor market experiences and various life-time shocks on skill development and income.

Using data from the German Socioeconomic Panel (SOEP), we address the problem of measurement error by extracting a latent factor reflecting locus of control. In addition, we account for the problem of reverse causality and truncated life-cycle data in that we combine information on both young individuals, who have not yet entered the labor market, and on older, working-age individuals. Our estimation approach follows the work by Heckman et al. (2006b), Hansen et al. (2004), Carneiro et al. (2003) in that we use Markov chain Monte Carlo (MCMC) methods to simulate the parameters of the model. Specifically, we use a Gibbs sampler with flat priors that sequentially draws the parameters of interest from their respective conditional distributions. Furthermore, we build on a strategy developed in Cunha et al. (2005), which allows us to retrieve the distribution of locus of control from a sample of young individuals, and to estimate its impact on outcomes in a sample of older individuals.

The contribution of this paper is twofold. First, we apply novel econometric methods and show that Bayesian factor structure models can be a solution to endogeneity problems if researchers are confronted with truncated life cycle data, as is very often the case in the fields of personality and economics. Second, embedding our empirical results in a simple theoretical framework, we establish that locus of control only affects the psychic cost of education but is not directly rewarded on the labor market of young professionals.

The paper proceeds as follows. Section 2 provides an overview of the existing literature on locus of control. In Section 3, a simple framework is introduced to help understand the potential impact of locus of control on education decisions and labor market outcomes. Section 4 describes our estimation strategy relying on data set combination to identify the full likelihood. The Bayesian approach used to sample the parameters of interest is outlined, and an overview of the data is provided. Section 5 presents the results of our analysis. Section 6 concludes.

2 Locus of Control

Since the seminal works of Mincer (1958) and Becker (1964), human capital is defined as the stock of knowledge and personal abilities an individual possesses, and is perceived as a factor of production that can be improved through education, training and experience. The focus usually lies on estimating returns to education, training, experience or cognitive skills (Psacharopoulos, 1981; Card, 1999; Heckman et al., 2006a).[1] However, this concept mainly refers to the cognitive abilities of an individual, while more recently other facets of human capital have come to the forefront. Bowles and Gintis (1976) were among the first to point out what seems intuitively obvious: economic success is only partly determined by cognitive abilities and knowledge acquired in schools. Personality, incentive-enhancing preferences and socialization are other important components of human capital (Heckman et al., 2006b; Heineck and Anger, 2010).[2] Furthermore, a vast literature in experimental economics is currently emerging, which analyzes the economic impact of risk aversion, reciprocity, self-confidence and time preference (Dohmen et al., 2010; Falk et al., 2006; Frey and Meier, 2004).

We decide to focus on locus of control, one of the measures of personality traits that is prominent also in the economic literature (Heckman et al., 2006b; Judge and Bono, 2001; Andrisani, 1977; 1981; Osborne, 2000). Originally, locus of control is a psychological concept, generally attributed to Rotter (1966), that measures the attitude regarding the nature of the causal relationship between one's own behavior and its consequences. In this concept, which is related to self-efficacy, people who believe that they can control reinforcements in their lives are called *internalizers*. People who believe that fate, luck, or other people control reinforcements, are termed *externalizers*. Generally, externalizers (in this taxonomy, the low-

[1]See Gebel and Pfeiffer (2010), Pischke and Von Wachter (2008), Lauer and Steiner (2000), Flossmann and Pohlmeier (2006) for estimates of returns to education or skills in the German context.

[2]For an overview of the interrelationships between different psychological and economic concepts, see Borghans et al. (2008).

ability types) do not have much confidence in their ability to influence their environment, and do not see themselves as responsible for their lives. Therefore, these individuals are generally less likely to trust their own abilities or to push themselves through difficult situations. Conversely, internalizers (the high-ability types) perceive themselves as more capable of altering their economic situation.

Mostly on empirical grounds, many studies agree that locus of control affects a variety of economic choices individuals make (behavioral impact). This is particularly true for education decisions, which most researchers find to be highly influenced by locus of control.[3] For instance, Coleman and DeLeire (2003) present a model of locus of control and education decisions, where locus of control is viewed as a behavioral trait that affects education decisions, because it has an impact on personal beliefs about the effect of education on expected earnings. Using the National Education Longitudinal Study (NELS), the authors find locus of control to have a high and significant impact on schooling decisions, as well as on ex-ante expected earnings conditional on schooling. Similarly, recent evidence by Caliendo et al. (2010) on German unemployment data shows that locus of control is a behavioral trait that affects the subjective probability of finding a job, which in turn leads to an increased search effort and higher reservations wages. Contrary to this, using the National Longitudinal Survey of Youth (NLSY), Cebi (2007) concludes that locus of control has a productive impact on labor market outcomes and no effect on education choices.

Evidence on the effect of locus of control on labor market returns is mixed (productive impact). For example, Andrisani (1977), using the National Longitudinal Study (NLS), finds a positive effect of locus of control on several measures of earnings and occupational attainment of young and middle-aged men. Yet, Duncan and Morgan (1981) find mostly non-significant effects of locus of control on the change in hourly earnings of individuals in

[3] Already 40 years ago, the famous Coleman report (Coleman, 1968) reported that locus of control was not only an important predictor of academic performance, but even a more important determinant of educational achievement than any other factor in a student's background (Coleman and DeLeire, 2003).

the Panel Study of Income Dynamics (PSID). To our knowledge, an analysis of the impact of locus of control on wages using German data has only been conducted by Heineck and Anger (2010), as well as by Flossmann et al. (2007), with both studies finding positive effects.[4] We add to this literature by using factor structure models to account for measurement error and endogeneity issues caused by the use of contemporaneous measurements.

3 Empirical Model

Consider a simple model where each individual chooses between obtaining higher education or not. Premarket locus of control, as imperfectly measured by a set of response variables, is captured by a latent factor θ, which influences both schooling decisions and labor market outcomes. The concept of locus of control and its potential impact on education decisions and labor market outcomes is explained in Section 3.1, while the empirical setup of the model is detailed in Section 3.2.

3.1 How locus of control impacts education and labor market outcomes

In this section, we present a theoretical framework for how *premarket* locus of control may affect labor market returns. We assume that the role of locus of control for wages is potentially twofold. First, it may indirectly affect wages through its effect on education decisions, and secondly, it may have a direct influence on labor market returns after the education decision is controlled for.

In our study, locus of control is a latent variable, denoted by θ, that is continuously distributed in the range $(-\infty, +\infty)$, where smaller values represent a more external locus and larger values a more internal locus of control. We assume that an individual's psychic costs of education and wage are both functions of θ. Hence, individuals with $\theta \rightarrow -\infty$ are

[4] Furthermore, Gallo et al. (2003) and Uhlendorff (2004) use German data to investigate the impact of locus of control on transitions from unemployment to employment.

likely to have higher psychic costs of education and earn lower wages, while individuals with $\theta \to +\infty$ incur lower costs of obtaining a degree and earn more.

In a typical model of human capital investment, individuals decide on the level of education based on the expected returns to the respective choice, net of the costs associated with this choice. In this framework, locus of control may affect the perceived psychic costs of education, e.g., because individuals with a more external locus of control believe ex ante that they would need to work harder than internalizers to feel well-prepared for the exams (behavioral impact). Furthermore, locus of control may be viewed as a skill with a direct impact on wages, for example because employers value having employees who exhibit a higher locus of control (productive impact).

Assume that there are two education levels, denoted by $S = 0, 1$, and that agents maximize the latent utility associated with education to make their decision. Let U^* denote this latent utility. The arguments of this function will be specified later. Hence, individuals attend higher education, $S = 1$, if:

$$U^* \geq 0,$$

and $S = 0$ otherwise. The latent utility from obtaining higher education is a function of discounted future earnings and of education costs. If wages w_t^s in period t conditional on schooling s, as well as the costs of education C, can all be modeled in an additively separable manner, we can specify:

$$\begin{aligned} w_t^0 &= X_{wt}\beta_0 + \theta\alpha_0 + \varepsilon_{0t}, \\ w_t^1 &= X_{wt}\beta_1 + \theta\alpha_1 + \varepsilon_{1t}, \\ C &= X_C\beta_C + \theta\alpha_C + \varepsilon_C, \end{aligned}$$

with $\mathrm{E}[\varepsilon_1|X_{wt},\theta] = \mathrm{E}[\varepsilon_0|X_{wt},\theta] = \mathrm{E}[\varepsilon_C|X_C,\theta] = 0$. Here α_s, β_s (with $s \in \{0,1\}$) and α_C, β_C measure the impact of premarket locus of control θ and observable characteristics (X_{wt}, X_C) on wages and education costs, respectively. Since locus of control is determined before the individual enters the labor market, it does not depend on time t in our model. Moreover, ε_{st} and ε_C are random and independent idiosyncratic shocks. The total utility from education, accounting for the discounted flow of ex post earnings, is then:

$$\begin{aligned} U^*(X_w, X_C, \theta, \delta, t_1) = &\sum_{t=t_1}^{T} \delta^t \left(X_{wt}\beta_1 + \theta\alpha_1 + \varepsilon_{1t} \right) \\ &- \sum_{t=0}^{T} \delta^t \left(X_{wt}\beta_0 + \theta\alpha_0 + \varepsilon_{0t} \right) \\ &- \left(X_C\beta_C + \theta\alpha_C + \varepsilon_C \right), \end{aligned} \tag{3.1}$$

where $X_w = (X_{w1}, \ldots, X_{wT})$, t_1 represents the time required to achieve higher education, T is the life horizon, and δ denotes the discount rate, which for simplicity is assumed to be constant over time.

By differentiating Equation (3.1) with respect to θ, it appears that a ceteris paribus change in locus of control affects education decisions as follows:

$$\frac{\partial U^*(X_w, X_C, \theta, t_1)}{\partial \theta} = \alpha_1 \sum_{t=t_1}^{T} \delta^t - \alpha_0 \sum_{t=0}^{T} \delta^t - \alpha_C.$$

Given that α_1 and α_0 are independent of t, and making use of revealed education choices, our goal is to identify α_1, α_0 and α_C. More precisely, we are investigating whether locus of control enters the education decision and outcomes both directly as a skill, in which case we would have $\alpha_1 > 0$ and $\alpha_0 > 0$, or only indirectly via the costs of education, in which case $\alpha_C < 0$. We cannot identify α_C directly, because we do not observe education costs. However, we can make inference on the overall impact of locus of control on education choices, and given the identification of α_1 and α_0, we can retrieve α_C. More specifically, if we find that $\alpha_1 = \alpha_0 = 0$, we know that any impact of locus of control on education choices must work through α_C.

The empirical model we specify in the next section is an approximation to this very simple theoretical framework. By combining different subsamples and using revealed schooling decisions, we are able to identify the impact of premarket locus of control on wages, and thus to make inferences about its productive or behavioral impact, respectively.

3.2 Specification of the model

To investigate the impact of premarket locus of control on schooling decisions and later outcomes, we use a factor structure model in the spirit of Heckman et al. (2006b), where a single latent factor is assumed to capture the latent trait of interest. The overall simultaneous equation model consists of different sets of equations using continuous, dichotomous and ordered response variables. The latent factor is common across all equations, and therefore represents the only source of dependence between the outcomes, conditional on the observed covariates.

3.2.1 Education decision

Each agent is assumed to choose the level of schooling that maximizes her utility. The utility derived from higher education $S^\star$, where higher education is defined as staying in school beyond compulsory education, is supposed to linearly depend on a vector of personal characteristics X_S and on the latent factor θ:

$$\begin{aligned} S &= \mathbb{1}[S^\star > 0], \\ S^\star &= X_S\beta_S + \theta\alpha_S + \varepsilon_S, \qquad\qquad \varepsilon_S \sim \mathcal{N}(0;\, 1)\,, \end{aligned} \tag{3.2}$$

where β_S denotes the vector of parameters related to personal characteristics, α_S represents the factor loading associated with θ, and ε_S is an idiosyncratic error term assumed to be independent of the covariates and of the latent factor. The indicator function $\mathbb{1}[\cdot]$ is equal to 1 if the corresponding condition is verified, and to 0 otherwise. Conditional on θ, this model is a standard probit when the distribution of the error term is assumed to be standard normal.

3.2.2 Labor market outcomes

Individuals with different levels of schooling become active on different segments of the labor market, where their personal characteristics, as well as their level of locus of control, may be valued differently. Labor market outcomes are modeled as a two-stage process: people first select into the labor market, and then a wage equation is estimated for those actually working. Observed characteristics and locus of control are allowed to play a role in both stages. Estimating the two equations simultaneously makes it possible to correct for potential sample selection bias that might affect the parameters if only the wage equation for working people were estimated (Heckman, 1979).

The labor market participation decision is assumed to be a threshold-crossing model for each level of education $s \in \{0, 1\}$, where the latent utility of working ($E_s^\star$) linearly depends on a set of covariates X_E through a vector of parameters $\beta_{E,s}$, and on the latent factor θ with its associated factor loading $\alpha_{E,s}$:

$$\begin{aligned} &E_s = \mathbb{1}[E_s^\star > 0], \\ &E_s^\star = X_E\beta_{E,s} + \theta\alpha_{E,s} + \varepsilon_{E,s}, \qquad \varepsilon_{E,s} \sim \mathcal{N}(0;\,1)\,, \end{aligned} \tag{3.3}$$

The idiosyncratic error term $\varepsilon_{E,s}$ is assumed to be standard normal and independent of X_E and θ for identification purposes. Nevertheless, this equation should not be regarded as a usual employment equation, but rather considered in a broader sense. People participating in the labor market ($E = 1$) are those who are actually active and declare a positive wage, while the group of non-participating people encompasses unemployed people, but also adult individuals who are not on the market. Therefore, this equation should be interpreted with care,[5] and serves more as a technical means to tackle the selection problem into the sample of people declaring a positive wage.

For wages, a log-linear specification with education group specific parameters is assumed:

$$Y_s = X_Y \beta_{Y,s} + \theta \alpha_{Y,s} + \varepsilon_{Y,s} \qquad \text{for } s = 0, 1, \tag{3.4}$$

where Y_s represents the log hourly wage ($\ln w_s$), X_Y is a set of observed covariates with the associated vector of returns $\beta_{Y,s}$, $\alpha_{Y,s}$ denotes the return to locus of control, and $\varepsilon_{Y,s}$ is an idiosyncratic error term such that $\varepsilon_{Y,s} \perp\!\!\!\perp (\theta, X_Y)$. For the specification of the error term, we relax the usual normality assumption by specifying a mixture of h normal distributions with zero mean:

$$\varepsilon_{Y,s} \sim \sum_{j=1}^{h} \pi_{s,j} \, \mathcal{N}\left(\mu_{s,j};\, \omega_{s,j}^2\right), \qquad \mathrm{E}[\varepsilon_{Y,s}] = \sum_{j=1}^{h} \pi_{s,j} \, \mu_{s,j} = 0, \tag{3.5}$$

for $s = 0, 1$, where $\pi_{s,j}$, $\mu_{s,j}$ and $\omega_{s,j}^2$ denote, respectively, the weight, mean and variance of mixture component j. Mixtures of normals are widely used as a flexible semiparametric approach for density estimation (Ferguson, 1983; Escobar and West, 1995). In our empirical application, we find that a three-component mixture ($h = 3$) for the error term of the wage equation is crucial to achieve a good fit to our data. It allows us to capture unobserved heterogeneity that arises because individuals work in different areas or sectors of modern complex labor markets.[6]

Within this specification, premarket locus of control can affect labor market outcomes both directly and indirectly. The direct effect is measured by the factor loadings $\alpha_{E,s}$ and

[5]Especially for the people who achieve higher education, since in this subsample some individuals who do not participate in the labor market are still enrolled in the education system.

[6]In a frequentist approach, Dagsvik et al. (2010) also find that Gaussian mixtures improve the fit of heavy-tailed log earnings distributions compared to normal distributions.

$\alpha_{Y,s}$, for $s = 0, 1$, while the indirect effect operates through the schooling decision. Two different models are considered. First, we estimate the employment and wage equations without conditioning on education, to capture the total effect of locus of control on wages. To achieve this, individuals from both schooling groups are pooled, and the subscript s is therefore dropped from Equations (3.3) to (3.5). In a second stage, both direct and indirect effects are separately accounted for by specifying the model as stated above. Comparing the results from these two approaches turns out to be instructive to understand through which channels premarket locus of control affects labor market outcomes.

3.2.3 A measurement system for locus of control

In our data, as in most empirical applications, variables measuring latent locus of control come from a psychometric test using Likert scales with a small number of categories. Although techniques to deal with ordinal variables in a multivariate context have a long history in statistics and are now well-documented (see Jöreskog and Moustaki, 2001, for a survey of different approaches), a widespread approach in empirical research consists of ignoring ordinality and treating the manifest items as continuous. This can however distort the results in several ways, especially when the number of categories is limited, and/or the distributions of the answers show high kurtosis.

In this paper, the ordinal nature of the K measurements is explicitly accounted for by specifying that each individual has a latent level of agreement $M_k^\star$ with the corresponding statement k of the corresponding test, for $k = 1, ..., K$. This latent level of agreement is assumed to linearly depend on some covariates X_M and on the factor θ, and is discretized by a set of cut-points $\{\gamma_k\}$ to produce the observed measurement, with C different alternative ordered answers as follows:

$$M_k = c \quad \text{if } \gamma_{k,c-1} \leq M_k^\star < \gamma_{k,c}, \qquad\qquad c = 1, ..., C,$$

$$M_k^{\star} = X_M \beta_{M,k} + \theta \alpha_{M,k} + \varepsilon_{M,k}, \qquad \text{for } k = 1, ..., K, \tag{3.6}$$

where $\beta_{M,k}$ denotes the vector of parameters associated with X_M, $\alpha_{M,k}$ represents the factor loading, and the idiosyncratic error term $\varepsilon_{M,k}$ is assumed to be standard normal and independent of θ and X_M. Assuming standard normality for the error term is the usual solution adopted to guarantee invariance of the latent response variable to scale transformation. As for the cut-points, they are such that $\gamma_{k,0} = -\infty < \gamma_{k,1} = 0 < ... < \gamma_{k,C-1} < +\infty = \gamma_{k,C}$.

3.2.4 Latent factor for locus of control

To complete the specification of the model, one last distributional assumption is required for the latent factor θ. In a similar framework, Carneiro et al. (2003), Hansen et al. (2004) achieve nonparametric identification of the latent factors thanks to some independence and support assumptions. When the measurement system consists of a combination of discrete and continuous outcomes, they first nonparametrically identify the joint distribution of the observed and latent measurements, before turning to the identification of the latent factors and error terms using a theorem proposed by Kotlarski (1967). In our case, this identification strategy cannot be applied, insofar as the measurements are all discrete. Nonparametric identification of the latent factor distribution, as well as of the error term distributions, would only be possible if we first managed to nonparametrically identify the joint distribution of the latent measurements. However, the lack of variability and of exclusion restrictions for each measurement make nonparametric identification and the use of more flexible distributional assumptions such as mixtures impossible. For these reasons, and for the sake of simplicity, we specify a normal distribution and make the following independence assumption:

$$\theta \sim \mathcal{N}\big(0;\, \sigma_\theta^2\big)\,, \qquad \theta \perp\!\!\!\perp (X, \varepsilon),$$

where $X = (X_S, X_E, X_Y, X_M)$ and $\varepsilon = (\varepsilon_S, \{\varepsilon_{E,s}\}, \{\varepsilon_{Y,s}\}, \{\varepsilon_{M,k}\})$.

Since the variance of the latent factor is not constrained, we need to impose one restriction to set the scale of θ. For this purpose of identification, we fix one of the factor loadings to a given value in the measurement system.

4 Estimation strategy

In this section, we present the identification strategy that relies on data set combination in Section 4.1, as well as our estimation method and data in Section 4.2. The parameters of interest are simulated through the implementation of Bayesian Markov chain Monte Carlo techniques.

4.1 Combining data sets to identify the model likelihood

Ideally, we would have access to a data set where individuals are observed at different periods of their life cycle. The likelihood of the model for such an hypothetical sample can be expressed as

$$\begin{aligned} L(\psi|S, E, Y, M, X) = \int_{\Theta} \prod_{s=0}^{1} \big[\Pr(S = s|X_S, \theta, \psi)\, f(E_s|X_E, \theta, \psi) f(Y_s|X_Y, \theta, \psi)\big]^{\mathbf{1}[S=s]} \\ \times \prod_{k=1}^{K} f(M_k|X_M, \theta, \psi)\ \mathrm{d}F_{\theta}(\theta), \end{aligned} \tag{4.1}$$

where ψ represents the vector containing all model parameters, $f(\cdot)$ invariantly denotes a density function, and $F_{\theta}(\cdot)$ is the cumulative distribution function (cdf) of the latent factor θ on the support Θ. In our case, this would require information on people's labor market outcomes and personal background, as well as on their premarket locus of control. Estimation based on the likelihood (4.1) would be straightforward.

Unfortunately, the structure of the SOEP only offers this opportunity for a subsample of the population, which turns out to be too small to conduct any relevant analysis. Although the SOEP is a longitudinal study, youth are surveyed since 2000 only, and many of them still have not entered the labor market in 2008. We therefore have to face a major dilemma: on the one hand, we have a large data set of working-age people (adult sample), but without any information on their locus of control at the time of schooling. On the other hand, a sample of 17-year-olds is available (youth sample), including premarket locus of control measurements, but labor market outcomes only for a very small group of mostly low-educated individuals. The adult and the youth samples can nevertheless be combined to overcome this problem. We rely on an idea implemented in Cunha et al. (2005), which consists of identifying one part of the likelihood in each subsample, getting rid of the unobserved response variables by integrating them out of the likelihood.

To understand the mechanisms of the data set combination, consider the following sketch of proof. First, derive the contribution to the likelihood of a person with higher education. Since her future labor market participation and wage cannot be observed, they are integrated out to provide

$$\begin{aligned}
&\int_\Theta \Pr(S=1|X_S,\theta,\psi)\left\{\iint f(E_1|X_E,\theta,\psi) f(Y_1|X_Y,\theta,\psi)\,\mathrm{d}F_{E_1}(E_1)\,\mathrm{d}F_{Y_1}(Y_1)\right\}\\
&\qquad\qquad \times \prod_{k=1}^{K} f(M_k|X_M,\theta,\psi)\,\mathrm{d}F_\theta(\theta)\\
&= \int_\Theta \Pr(S=1|X_S,\theta,\psi)\prod_{k=1}^{K} f(M_k|X_M,\theta,\psi)\ \mathrm{d}F_\theta(\theta),
\end{aligned}$$

where $F_W(\cdot)$ represents the cdf of the corresponding random variable W. As a consequence, the parameters of the measurement system and of the schooling equation can be identified from the youth sample. However, due to the small sample size of youth who already earn a wage on the labor market, identification and estimation of the parameters of the labor market participation and wage equations from this sample is impossible.

In a similar fashion, consider a person without higher education from the adult sample, whose measurements for premarket locus of control are not observed. Her contribution to the likelihood is

$$\begin{aligned}
&\int_{\Theta} \Pr(S = 0|X_S, \theta, \psi)\, f(E_0|X_E, \theta, \psi) f(Y_0|X_Y, \theta, \psi) \\
&\qquad\qquad \times \left\{ \prod_{k=1}^{K} \int f(M_k|X_M, \theta, \psi)\, \mathrm{d}F_{M_k}(M_k) \right\} \mathrm{d}F_\theta(\theta) \\
&= \int_{\Theta} \Pr(S = 0|X_S, \theta, \psi)\, f(E_0|X_E, \theta, \psi) f(Y_0|X_Y, \theta, \psi)\ \mathrm{d}F_\theta(\theta),
\end{aligned}$$

and is obtained by integrating out the locus of control measures. Full identification of the model is clearly infeasible in this subsample, since no observations on premarket locus of control are available for the adults. However, since we are combining the two data sets and estimating the overall model simultaneously, the distribution of the latent factor is already identified from the youth sample.

Full identification of the model rests on the education equation, which is the only source of common information for most of the sample, and therefore the bridge between the two samples. Although our model can in theory be identified from two non-overlapping samples of youth and adults, in practice we found it helpful to use all available information—i.e., measurement, schooling and labor market information—for the small sample of individuals for whom both labor market outcomes and locus of control measurements are available.

4.2 Estimation

A fully Bayesian approach is used for the estimation of our model. Since the equations are independent once θ is conditioned on, the estimation can be divided into several pieces, and MCMC methods are particularly suited for this kind of problem. In the wake of Cunha et al. (2005), Carneiro et al. (2003), Hansen et al. (2004), we use a Gibbs sampler that sequentially draws the parameters of interest from their respective conditional distributions, using flat priors to remain as general as possible.[7]

Data augmentation procedures (Tanner and Wong, 1987) make it possible to simulate the latent outcomes of the measurement system, of the schooling and labor market participation equations, as well as the latent factor θ.[8] Besides the practical convenience of the approach, augmenting the observed data with the latent variables has another major advantage in our case: the simulated latent factors and outcomes can be saved during the sampling process, and used for post-processing analyses, such as simulations.[9] In Section 5.2 for instance, these simulated variables are used to assess the fit of the model, and to conduct some formal tests.

Bayesian inference for ordinal variable models can be challenging. Slow convergence and high autocorrelation of the parameter chains are typical symptoms of the algorithm failing to cover the entire posterior distribution of the parameters. As noted by Cowles (1996), the high correlation between the cut-points and the latent response variable results in a poor mixing of the Markov chain for the parameters of Equation (3.6). In the end, this can lead to overinflated standard errors of the parameters, or even worse, to wrong estimates (in terms of bias) if the chain is not long enough to provide a representative sample of the conditional distribution. To remedy this problem, several technical improvements have been proposed.[10] We opt for the group transformation approach introduced by Liu and Sabatti (2000), which speeds up convergence and enhances the mixing of the chain, while being less computationally burdensome than other methods. We run a chain of 1,010,000 iterations for each gender. After a burn-in period of 10,000 iterations, 10,000 iterations are saved every 100$^{\text{th}}$ sweep of the Gibbs sampler for post-processing inference. We observe a fast

[7]For technical details on the Gibbs sampler in this framework, see Piatek (2010) where all posterior distributions are derived.

[8]Data augmentation procedures are increasingly used in applied labor market and education research (for recent examples see Horny et al., 2009; Koop and Tobias, 2004; Li, 2006).

[9]See van Dyk and Meng (2001) for a review of data augmentation.

[10]Cowles (1996) introduces a Hastings-within-Gibbs step in the algorithm to draw the cut-points and the latent response variable simultaneously, while Nandram and Chen (1996) propose a simple reparameterization that proves to be particularly effective, especially in the three-category case.

convergence to the stationary distribution, and a good mixing of the chain thanks to the implementation of the group transformation.

4.2.1 Sample construction

We draw a combined sample of 1,534 youth (age 17-24) and 1,192 ‘young adults’ (age 26-35) from recent waves of the SOEP.[11] The special feature of the youth sample is that for these youth, premarket measures of locus of control were administered when they were 17 years of age. In the German education system, individuals decide at around the age of 17 whether to finish their studies with a vocational high school certificate, or to continue their schooling with academic high school credentials. Only the latter entitles agents to attend higher education. Hence, our binary education variable reflects this choice of obtaining a vocational or an academic high school degree. Summary statistics of the education variable in the two samples are presented in Table B.1. For a small part of our youth sample (about 280 individuals), also wage and employment information is available. However, because these individuals can be at most 24 years of age, most of them did not achieve higher education. Furthermore, separate estimations by gender and schooling considerably reduce the available sample size. Hence, as explained in the previous section, we augment the youth sample with a second sample of young adults, whose education and labor market outcomes can be assumed to be generated by the same data generating process. Summary statistics on wages and employment participation of the combined sample can be found in Table B.2. The table displays that males earn higher wages than females, and that the observed wage gap between high and low educated individuals is higher for males than for females. The low levels of labor market participation arise because many individuals still participate in education or training. To fully account for gender differences in the impact of locus of control

[11] See Wagner et al. (2007, 2008) for a detailed description of the dataset.

on education decisions and outcomes, all estimates are obtained separately for males and females.

In order to be able to identify different parts of the likelihood from different samples, we make the assumption that both samples are generated by the same underlying data generating process (DGP). Specifically, we assume that if premarket locus of control and labor market outcomes were available for both youths and adults, we would expect to obtain the same estimated coefficients. This assumption is restrictive in the sense that Table B.1 shows that among the youth sample, there is a slightly higher fraction of highly educated individuals. In order to deal with this problem, we include age and cohort dummies as covariates in the education, employment and wage equations, so as to capture possible time trends or cohort effects.

4.2.2 Locus of control measurements

Table 1: Locus of control, youth sample

		Males		**Females**	
	Variables	**Mean**	**SD**	**Mean**	**SD**
Q1	My life's course depends on me	3.55	0.63	3.51	0.59
Q2	I have not achieved what I deserve	2.05	0.85	1.92	0.79
Q3	Success is a matter of fate or luck	2.22	0.81	2.29	0.77
Q4	Others decide about my life	2.18	0.83	2.12	0.83
Q5	Success is a matter of hard work	3.48	0.62	3.51	0.57
Q6	In case of difficulties, doubt about own abilities	2.08	0.81	2.31	0.85
Q7	Possibilities in life depend on social conditions	2.69	0.78	2.72	0.75
Q8	Abilities are more important than effort	3.02	0.71	3.05	0.69
Q9	Little control over what happens to me	1.92	0.75	1.95	0.76
Q10	Social involvement can help influence social conditions	2.48	0.87	2.51	0.77
	# Observations	760		774	

In the SOEP youth questionnaire, locus of control is measured by a 10-item questionnaire. Each question is answered on a Likert scale ranging from 1 ("disagree completely") to 4 ("agree completely"). Table 1 gives an overview of the questions and items we use.

We check whether, given these measurements, locus of control can indeed be represented by a single factor. Conducting a principal component analysis, and calculating the eigenvalues of the correlation matrix, we find two eigenvalues larger than 1. Hence, the Kaiser criterion (eigenvalue$<$1) is violated. However, the scree plot analysis displayed in Figure B.1 reveals an early flattening of the curve, suggesting no more than one or two underlying factors. Furthermore, locus of control is usually conceptualized as referring to a unidimensional continuum, ranging from external to internal. Hence, we think that we are making a reasonable decision by extracting a single factor. A scatter plot of the respective factor loadings (Figure B.2), with the first two principal factors on the axis, shows that some items load very highly on the extracted locus of control factor (factor 1), while some other items have a loading close to zero (Q1, Q5, Q8 and Q10). Furthermore, the items with a close to zero loading are items that capture an internal attitude, while the other items mostly capture the external dimension of locus of control. Consequently, we can draw two conclusions from this exploratory factor analysis. First, researchers who use an index, constructed for example as the standardized mean of the items, instead of a latent factor, force each of the measurement items to enter the index with an equal weight. Doing this yields a locus of control measure that is flawed by measurement error, and the coefficients are likely to be biased downward due to attenuation bias. Second, in our paper we mostly capture the external attitude dimension of locus of control. For ease of interpretation, in our empirical application we normalize the model such that lower scores of the latent factor are associated with an external locus of control, and higher scores with an internal locus of control. To ensure that our results are not distorted by the inclusion of those items that have a low loading on the locus of control factor, we have conducted robustness checks using only those items loading highly on the first factor. We find that the use of the externalizing items only does not have a major impact on the results.[12]

[12]Results of the robustness check using only the externalizing items can be obtained from the authors upon request.

4.2.3 Covariates

Table 2 summarizes the covariates used for our analysis, and also shows how the two samples are linked by the schooling equation. To account for family background, socioeconomic status and labor market conditions, we control for a large range of background variables, as well as for local unemployment rates at the time of education decisions and labor market outcomes, respectively. In addition, Germany has an education system where tracking already takes place after the fourth grade. Hence, to proxy cognitive skills, and to account for the fact that these cognitive skills might affect the items revealing premarket locus of control, we include the primary school teacher track recommendation as a control variable in the measurement system. Because locus of control is estimated from the residual variance net of covariates in the measurement system, covariates included in the measurement equation are a means to purge locus of control of their influence. However, the inclusion of track recommendation only proxies cognitive skills and the resulting track type. It cannot account for other conflicting effects such as school quality. Hence, locus of control, as identified in this paper, only captures *premarket* locus of control, and not necessarily *pre-compulsory-school* locus of control. Thus we control for track recommendation, parental education and a large set of other background variables to capture school quality, home investment and cognitive ability. Summary statistics of control variables in the measurement and outcome equations can be found in Tables B.3 and B.4.[13]

5 Empirical results

The results are presented and discussed in two stages. We first provide a description of the main findings in Section 5.1, with an emphasis on the statistical significance of the impact of locus of control on the different outcomes, and on the fit of our model. Then, we gain

[13] A detailed description of the coding of all variables can be found in Appendix A.

Table 2: Samples and included covariates for the measurement system, education, employment and wage equations

	Type[a]	Meas.	Educ.	Empl.	Wage
Samples					
Youth sample		✓	✓	(✓)[b]	(✓)[b]
Adult sample		—	✓	✓	✓
Covariates					
Number of siblings	D	✓	—	—	—
% of time in broken family	C	✓	✓	—	—
Father dropout	B	✓	✓	✓	✓
Father grammar school	B	✓	✓	✓	✓
Mother dropout	B	✓	✓	—	—
Mother grammar school	B	✓	✓	—	—
Region: North[c]	B	✓	✓	✓	✓
Region: South[c]	B	✓	✓	✓	✓
Childhood in large city[d]	B	✓	✓	✓	✓
Childhood in medium city[d]	B	✓	✓	✓	✓
Childhood in small city[d]	B	✓	✓	✓	✓
Track recommendation (highest)[e]	B	✓	—	—	—
Track recommendation (lowest)[e]	B	✓	—	—	—
Local unemployment rate	C	—	—	✓	✓
Local unemployment rate (edu)[f]	C	—	✓	—	—
Age of individual	C	—	—	✓	✓
Cohort 26/30	B	—	✓	—	✓
Cohort 31/35	B	—	✓	—	✓
Married	B	—	—	✓	✓
Number of Children	C	—	—	✓	✓

[a]B = Binary, C = Continuous, D = Discrete.
[b]Only a small subsample available for these equations.
[c]Base category is *West Germany*.
[d]Base category is *Childhood in countryside*.
[e]Base category is *Recommendation for middle track*.
[f]When the education decision is made.

more insights in Section 5.2 by conducting some simulations that make it possible to better grasp the magnitude of the impact of locus of control.

5.1 MCMC results

Factor loadings. The factor loadings express how the different measurements and outcomes are affected by the latent factor. The larger the magnitude of the loadings, the higher the contribution of the corresponding measurements to the distribution of the latent factor. In the education, employment and wage equations, the loadings measure the impact of the factor on the respective outcomes. Cross-model comparisons should however be carefully done: the factor loadings of the different models cannot be directly compared, as their magnitude and their sign depend on the normalization retained to set the scale of the factor. We normalize the factor loading of the fourth indicator to -1 in all models, which is a way of anchoring the factor distribution in a real measurement (Cunha and Heckman, 2008).[14] However, contrary to Cunha and Heckman (2008), who anchor the factor in earnings, we cannot give an interpretable metric to the latent factor, because of the ordinal nature of the measurement. Moreover, the respective item of the questionnaire used for the normalization might be perceived differently by males and females, and gender comparisons are therefore not straightforward.

Table 3 summarizes the estimation results for the factor loadings of the different models. The results of the measurement system are in line with our expectations. Typical questions associated with an external locus of control such as 'Success is a matter of fate or luck' (Q3) or 'I have not achieved what I deserve' (Q2) have negative factor loadings, whereas statements reflecting an internal locus of control, such as 'My life's course depends on me' (Q1), have a positive factor loading. Also, the heterogeneity of these factor loadings is worth noting, as well as the fact that some of them are not significantly different from zero.

[14] The fourth indicator is a typical externalizers' statement, hence the normalization to a negative integer.

Table 3: Factor loadings of the model estimated by conditioning labor market outcomes on education [(2) and (4)] and without conditioning on education [(1) and (3)]

	Males				**Females**			
	(1)		(2)		(3)		(4)	
Measurement system: Locus of control items								
Q1	0.354***	(0.087)	0.364***	(0.086)	0.423***	(0.095)	0.440***	(0.101)
Q2	-0.735***	(0.119)	-0.729***	(0.116)	-0.895***	(0.132)	-0.938***	(0.143)
Q3	-0.741***	(0.118)	-0.743***	(0.116)	-0.619***	(0.107)	-0.650***	(0.113)
Q4	-1.000	—	-1.000	—	-1.000	—	-1.000	—
Q5	0.013	(0.074)	0.024	(0.075)	0.026	(0.085)	0.025	(0.089)
Q6	-0.640***	(0.108)	-0.605***	(0.102)	-0.890***	(0.134)	-0.916***	(0.139)
Q7	-0.559***	(0.099)	-0.565***	(0.099)	-0.581***	(0.105)	-0.617***	(0.112)
Q8	-0.195***	(0.072)	-0.197***	(0.072)	-0.107*	(0.078)	-0.112*	(0.082)
Q9	-1.045***	(0.175)	-1.035***	(0.175)	-1.781***	(0.309)	-1.858***	(0.332)
Q10	-0.122**	(0.067)	-0.140**	(0.068)	0.143**	(0.078)	0.146**	(0.080)
Education choice								
S	0.634***	(0.134)	0.404***	(0.118)	0.444***	(0.123)	0.364***	(0.127)
Labor market participation								
E	0.055	(0.136)			-0.021	(0.131)		
E_0			0.757***	(0.287)			0.357**	(0.222)
E_1			-0.126	(0.331)			-0.268	(0.286)
log Wages								
Y	0.181***	(0.041)			0.121***	(0.048)		
Y_0			0.007	(0.060)			0.058	(0.064)
Y_1			-0.072	(0.086)			0.020	(0.087)
Variance of the latent factor								
σ^2_θ	0.635***	(0.138)	0.622***	(0.135)	0.446***	(0.092)	0.411***	(0.088)

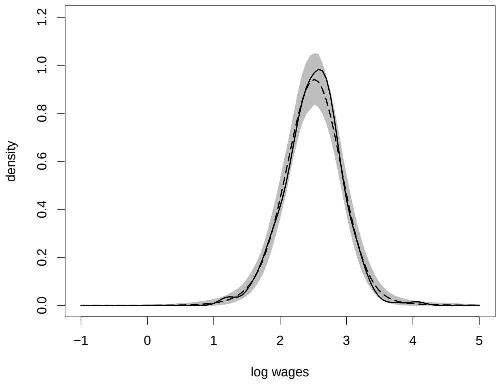
Notes: Factor loading of item 4 (statement reflecting an external locus of control) fixed to -1 to set the scale of the latent factor. Standard errors in brackets. Significance check: */**/*** if zero lies outside the 90%/95%/99% confidence interval of the posterior distribution of the corresponding parameter.

In the outcome system of equations, the factor loading of the education equation is always significant and positive, indicating an actual impact of locus of control. When we do not control for education [columns (1) and (3)], wages appear to be affected by locus of control, whereas this impact vanishes when education is controlled for [columns (2) and (4)]. Hence, with respect to the theoretical framework laid out in Section 3.1, we can conclude that the impact of premarket locus of control on w_t^0 and w_t^1, denoted by α_0 and α_1 respectively, is zero. However, we find that locus of control does have an impact on education decisions ($P(S = 1)$), and thus on wages in the end. Hence, reverting to Equation (3.1), we can conclude that locus of control does not affect education decisions via higher expected wages (α_0,α_1), but instead through its impact on the cost of education α_C.

So far, no firm conclusions have been made as to the magnitude of the impact of locus of control on education decisions and overall wages. In the following Section 5.2, the simulations we conduct make it possible to unravel and quantify the actual impact of locus of control on the different outcomes of interest.

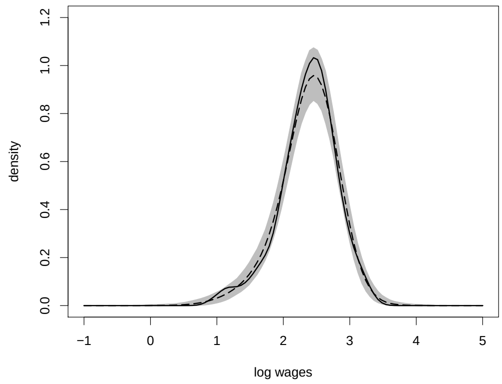
Model fit to actual data. Our model provides a good fit to the data, and especially to the distribution of wages. Figure 1 displays the observed distribution of wages, along with their posterior predictive distribution for the different specifications. The actual distribution is quite well approximated by the posterior predictive distribution, particularly in the case where the two schooling groups are pooled for the estimation of the wage equation (panels 1a and 1b). When the wage equation is estimated by level of schooling (panels 1c, 1d , 1e and 1f), the fit is somewhat less good. Nevertheless, the Kolmogorov-Smirnov tests we conduct to compare the actual distribution and the posterior predictive distribution never reject the null hypothesis of equal distribution. This result is in great part due to the use of normal mixtures for the error term, allowing for a flexible approximation of the true distribution.

Figure 1: Goodness-of-fit check for wages: posterior predictive (dashed) vs. actual distribution (solid) and Kolmogorov-Smirnov test for equal distributions.



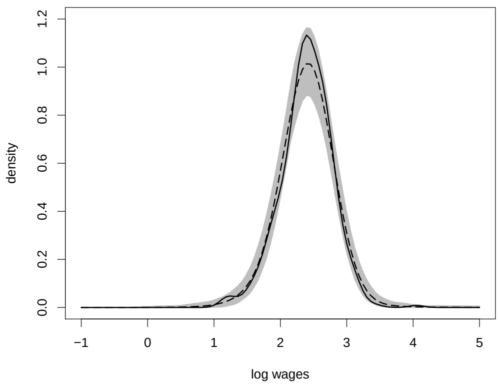
KS-test: 0.026 (0.745)

(a) Males, all education levels



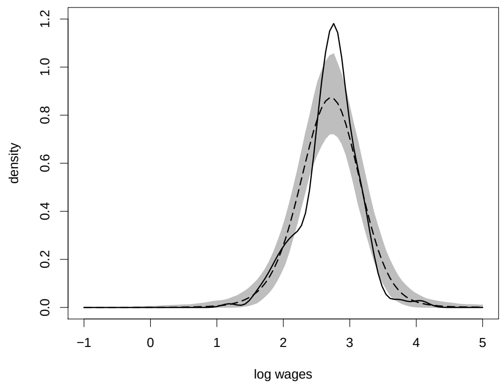
KS-test: 0.027 (0.799)

(b) Females, all education levels



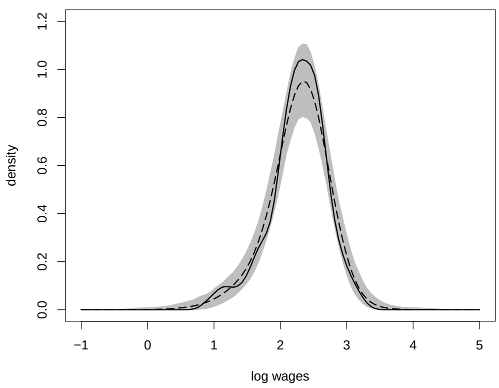
KS-test: 0.042 (0.418)

(c) Males, no higher education



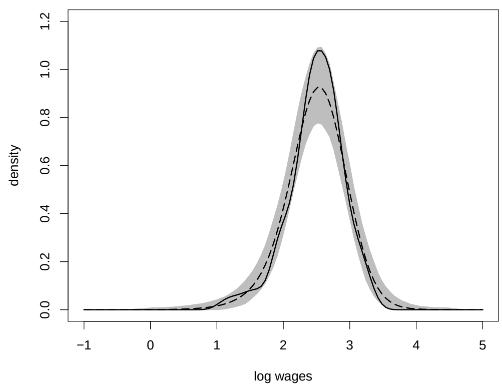
KS-test: 0.085 (0.072)

(d) Males, with higher education



KS-test: 0.047 (0.479)

(e) Females, no higher education

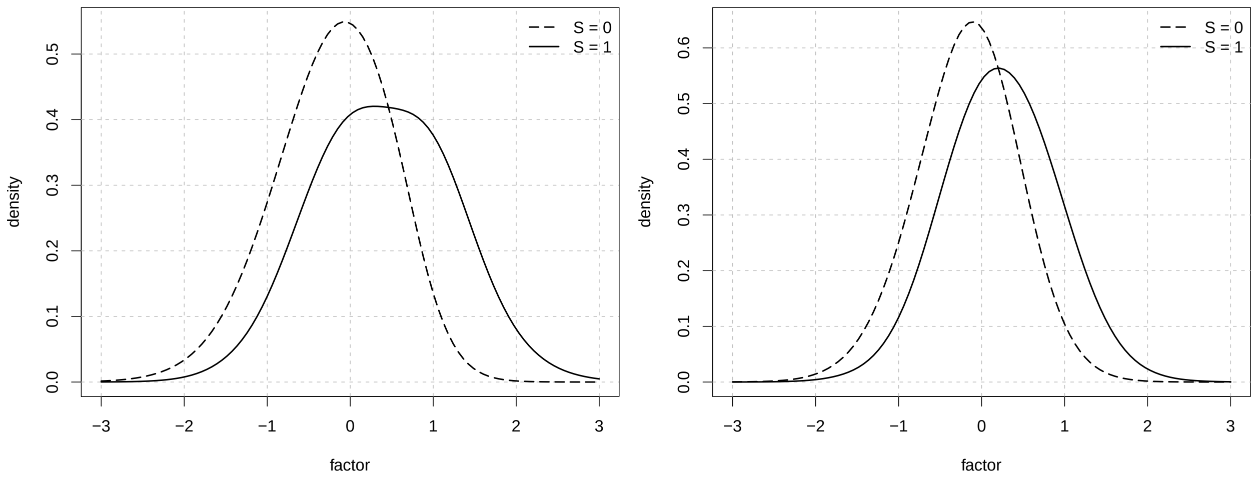


KS-test: 0.055 (0.398)

(f) Females, with higher education

Notes: Model estimated by conditioning labor market outcomes on education (panels 1c to 1f) and without conditioning on education (panels 1a and 1b). Kernel density estimation implemented using a Gaussian kernel with bandwidth selected using Silverman's rule of thumb (Silverman, 1986) with the variation proposed by Scott (1992). Wages predicted from their posterior distribution using 1,000 replications of the sample. Shaded area represents 95% confidence interval of posterior predictive distribution. Kolmogorov-Smirnov test: Two-sample KS-test with null hypothesis that the actual sample and the posterior predictive sample have the same distribution. p-values in brackets. Exact p-values could not be computed due to ties in the distribution of actual wages.

Figure 2: Latent factor distribution by levels of education: people with higher education ($S = 1$) and without higher education ($S = 0$).



KS-test: 0.298 (0.000)
(a) Males

KS-test: 0.242 (0.000)
(b) Females

Notes: Simulation from the estimates of the model using 1,000 replications of the posterior sample. Model estimated without conditioning labor market outcomes on education. Predicted levels of education used ($\Pr(S = 1) > .5$). Kernel density estimation implemented using a Gaussian kernel with bandwidth selected using Silverman's rule of thumb (Silverman, 1986) with the variation proposed by Scott (1992). Kolmogorov-Smirnov test: Two-sample KS-test with null hypothesis that the two distributions are the same. p-values in brackets. Exact p-values could not be computed due to ties in the distribution of the latent factor.

To assess the goodness of fit to the education decision, Table 4 shows the proportion of correct predictions of education achievement for each decile of the latent factor distribution. The fit appears good overall, especially for the lower deciles of the distribution.

5.2 Simulation of the model

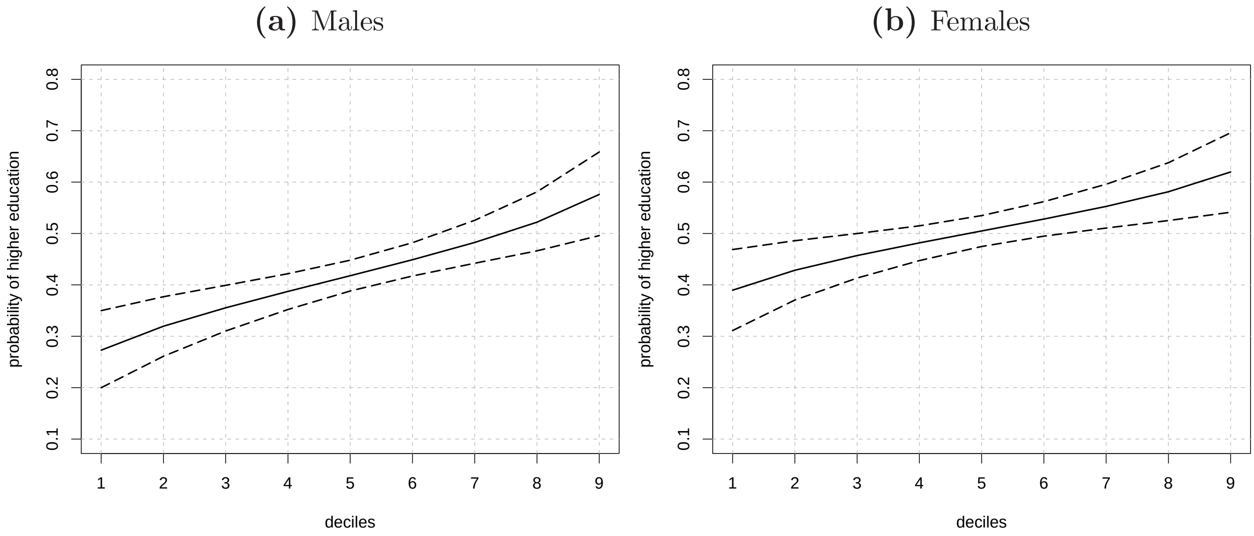
To shed more light on the implications of our model, we need to go beyond the mere interpretation of the factor loadings. Their statistical significance reveals an impact of locus of control on the outcomes, but is quite uninformative regarding the magnitude of this impact (McCloskey and Ziliak, 1996; Ziliak and McCloskey, 2004). Since the effects of premarket locus of control are intertwined and potentially operate through different channels on wages, the best way to understand our model is to simulate it.

Table 4: Goodness-of-fit check: proportion of correct predictions of education achievement for each decile of the latent factor distribution

		Deciles of latent factor distribution									
		10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Males	(1)	0.827	0.816	0.804	0.785	0.764	0.737	0.708	0.673	0.645	0.699
		(0.033)	(0.031)	(0.032)	(0.033)	(0.035)	(0.035)	(0.035)	(0.038)	(0.039)	(0.044)
	(2)	0.788	0.785	0.777	0.762	0.745	0.728	0.711	0.691	0.671	0.669
		(0.033)	(0.033)	(0.034)	(0.034)	(0.035)	(0.036)	(0.036)	(0.039)	(0.040)	(0.040)
Females	(3)	0.771	0.746	0.728	0.714	0.702	0.689	0.677	0.667	0.667	0.692
		(0.033)	(0.035)	(0.036)	(0.037)	(0.037)	(0.036)	(0.037)	(0.038)	(0.041)	(0.040)
	(4)	0.756	0.736	0.722	0.709	0.698	0.689	0.678	0.666	0.659	0.675
		(0.034)	(0.037)	(0.037)	(0.037)	(0.037)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)

Notes: Model estimated by conditioning labor market outcomes on education [(2) and (4)] and without conditioning [(1) and (3)]. Proportions of correct predictions computed for each MCMC replication, corresponding means and standard errors (in brackets) are reported.

Figure 3: Probability of achieving higher education for each decile of the factor distribution

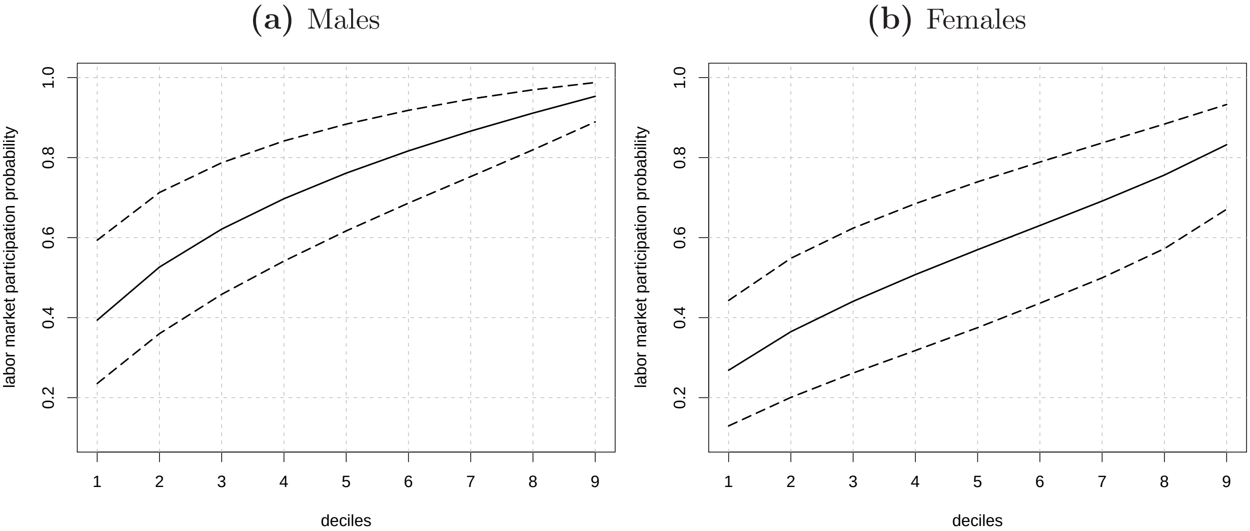


Notes: Simulation from the estimates of the model using 10,000 replications of the posterior sample. Model estimated conditioning labor market outcomes on education. 95% confidence band between dashed lines.

Figure 2 plots the estimated posterior distribution of the latent factor by levels of education, and shows that people who achieve higher education have a more internal locus of control. For males, the gap between the two schooling groups is even wider, revealing some gender differences in the way locus of control influences education decisions. The Kolmogorov-Smirnov test confirms that the discrepancy between the two distributions is statistically significant for both genders.

To get more insight on the impact of premarket locus of control on later outcomes, we can investigate how the wage of a given individual would be affected if she were exogenously moved along the distribution of the latent factor, for a given set of observed characteristics X_Y (Heckman et al., 2006b). For this purpose, we compute the expected wage for different quantiles of the distribution of the factor, conditional on a given set of covariates X_Y. The Gibbs algorithm we implement to estimate our model generates a sample of the model parameters from their conditional distribution that can be used as follows to approximate

Figure 4: Probability of labor market participation for people without higher education for each decile of the factor distribution



Notes: Simulation from the estimates of the model using 10,000 replications of the posterior sample. Model estimated conditioning labor market outcomes on education. 95% confidence band between dashed lines.

the expected wage for each quantile q_θ of the factor distribution:

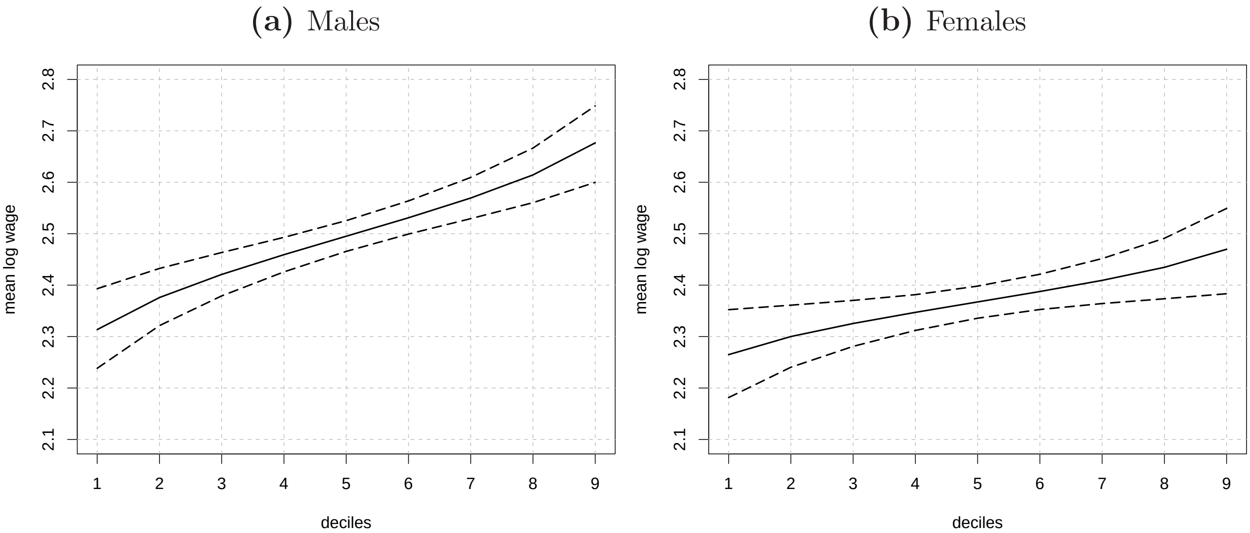
$$\frac{1}{M}\sum_{m=1}^{M}\left(X_Y\beta_Y^{(m)} + q_\theta^{(m)}\alpha_Y^{(m)}\right),$$

for a set of M simulated parameters $(\beta_Y^{(1)}, \alpha_Y^{(1)}), \ldots, (\beta_Y^{(M)}, \alpha_Y^{(M)})$. The quantile of the latent factor $q_\theta^{(m)}$ also has a superscript (m), since it depends on the variance of the factor $\sigma_\theta^{2(m)}$, and therefore varies during the MCMC sampling. Similarly, the schooling and labor market participation probabilities in the q^{th} quantile of the latent factor distribution can be approximated by:

$$\frac{1}{M}\sum_{m=1}^{M}\Phi\left(X_S\beta_S^{(m)} + q_\theta^{(m)}\alpha_S^{(m)}\right), \qquad \frac{1}{M}\sum_{m=1}^{M}\Phi\left(X_E\beta_E^{(m)} + q_\theta^{(m)}\alpha_E^{(m)}\right),$$

respectively, where $\Phi(\cdot)$ denotes the cdf of the standard normal distribution. More specifically, the simulations we present rely on the deciles of the distribution. In the following, our simulations are performed for the mean individual of the corresponding sample.

Figure 5: Mean log wage for each decile of the factor distribution



Notes: Simulation from the estimates of the model using 10,000 replications of the posterior sample. Model estimated without conditioning labor market outcomes on education. 95% confidence band between dashed lines.

From Figure 3, locus of control appears to have a large impact on the schooling decision, since moving the mean individual from the first to the last decile of the distribution results in a 0.30 point increase in the probability of achieving higher education for males, and a 0.23 point increase for females. Similarly, Figure 4 shows that in the group of people who did not achieve higher education, locus of control has a huge impact on labor market participation. This effect is more or less linear for females, whereas for males the concavity of the curve indicates that people in the low deciles are more affected than people in the higher deciles of the distribution. Concerning wages, Figure 5 shows that if the mean individual could be moved exogenously from the first to the 9^{th} decile of the locus of control distribution, this would corresponds to an increase in hourly wages of roughly 4.40 Euros for the mean male individual, and of roughly 2.20 Euros for the mean female individual.

At first sight, the effect of locus of control on education choice and labor market outcomes seems large. For instance, the mean male individual would earn 36% more in the last decile than in the first one. However, it is unrealistic to see an individual move all the way across the distribution. People are more likely to make small moves from one decile to the adjacent ones, and Figures 3 to 5 show that in the middle of the distribution, the locus of control effect is much smaller.

5.3 Some remarks on the results

In summary, we find an effect of locus of control on schooling probabilities, where males are more affected than females. Moving the mean individual in the distribution of the latent factor substantially changes her/his wage. However, this overall effect only operates through the channel of schooling. This finding that *premarket* locus of control influences schooling is in line with Coleman and DeLeire (2003), although in their paper the mechanism through which locus of control affects schooling is different, as it only works through wage expectations.

Our results seem somewhat contrary to the more direct link between locus of control and wages that been found in some of the literature (Heckman et al., 2006b; Heineck and Anger, 2010). Three different answers can be put forward to address this apparent contradiction. First, the term 'noncognitive skills' is very often used as a generic expression encompassing a lot of different personal abilities and traits, sometimes leading to confusion. A comparison of results is possible only if the same concept is used. For instance, Heckman et al. (2006b) find a significant effect of noncognitive skills on wages. However, they use a single underlying factor for noncognitive skills constructed from two psychometric tests, namely the Rosenberg self-esteem scale and the Rotter scale. This composite factor thus captures a different dimension than our factor, especially since it loads more on the self-esteem scale than on the locus of control scale in their empirical study. Second, and more importantly, we focus on *premarket* locus of control as a measure of locus of control that is independent of labor market experience. As a consequence, our findings differ from the results presented by Heineck and Anger (2010) who find a strong and significant impact of locus of control on wages, even after controlling for education. One reason could be that the authors do not estimate separate models by education level. More likely, however, the difference in results arises because of the use of contemporaneous measurements in their study, while we focus on the impact of *premarket* locus of control. Third, we only look at a sample of young labor market entrants. At this stage, wage setting is likely to be merely a function of formal qualifications. Hence, only after individuals have entered the labor market, a complex dynamic interaction process begins. While working on-the-job, individuals learn about their abilities, while at the same time employers adapt their knowledge about an individual's locus of control. As a result, a positive interdependence between locus of control and wages may arise (such as the one found by Heineck and Anger, 2010). Additional analyses not displayed in this paper show that the correlation between locus of control and wages does indeed increase with age and experience of the agents. Whether this is the result of reverse causality or learning of employers is an interesting topic left for future research. One explanation may be that although early locus of control does not influence wages directly, it may influence late locus of control which in turn is directly rewarded on the labor market. We leave it for future research to find out whether there exists a constant and invariable component to personality traits in general, and to locus of control in particular. Such a component may be extracted using dynamic factor models, and would require repeated measurements of locus of control over large parts of the life-cycle.

6 Conclusion

In this paper, we use Bayesian factor structure models to investigate how locus of control influences education decisions and wages. Using advanced econometric methods, we show that such recent methods can serve as a solution measurement error and endogeneity problems, especially if researchers are confronted with truncated life cycle data, as is very often the case for research at the intersection of psychology and economics.

We establish that an individual's *premarket* locus of control substantially raises the probability of choosing higher education. We also show that locus of control influences wages through schooling, but that there is no direct impact on wages once schooling is controlled for. Thus, in a framework where schooling decisions depend on relative lifetime earnings returns for each schooling level, net of the costs of obtaining either level of education, we can infer from our results that *premarket* locus of control, as measured at the age of 17, is not directly rewarded as a skill on the labor market. Instead, it is a personality trait that influences the non-pecuniary costs of education.

Our work conveys important policy implications. If some personality traits, such as locus of control, influence the cost of education but not outcomes directly, these individual characteristics may keep individuals from studying who, once they reach the labor market, are no less successful than other individuals. If these individuals are at high risk of dropping out of school, early personality tests and targeted mentoring of students with an external locus of control are a means to countervail skill shortages in society.

References

Andrisani, P. J. (1977): "Internal-External Attitudes, Personal Initiative, and the Labor Market Experience of Black and White Men," *Journal of Human Resources*, 12, 308–328.

——— (1981): "Internal-External Attitudes, Sense of Efficacy, and Labor Market Experience: A Reply to Duncan and Morgan," *Journal of Human Resources*, 16, 658–66.

Becker, G. S. (1964): *Human Capital: A Theoretical and Empirical Analysis, With Special Reference to Education*, New York: National Bureau of Economic Research.

Borghans, L., A. L. Duckworth, J. J. Heckman, and B. ter Weel (2008): "The Economics and Psychology of Personality Traits," *Journal of Human Resources*, 43, 972–1059.

Bowles, S. and H. Gintis (1976): *Schooling in Capitalist America: Educational Reform and the Contradictions of Economic Life*, Routledge.

——— (2002): "Schooling in Capitalist America Revisited," *Sociology of Education*, 75, 1–18.

Bowles, S., H. Gintis, and M. A. Osborne (2001): "The Determinants of Earnings: A Behavioral Approach," *Journal of Economic Literature*, 39, 1137–1176.

Caliendo, M., D. A. Cobb-Clark, and A. Uhlendorff (2010): "Locus of Control and Job Search Strategies," Institute for the Study of Labor (IZA) Discussion Paper No. 4750.

Card, D. (1999): "The causal effect of education on earnings," *Handbook of labor economics*, 3, 1801–1863.

Carneiro, P., K. Hansen, and J. J. Heckman (2003): "Estimating Distributions of Treatment Effects with an Application to the Returns to Schooling and Measurement of the Effects of Uncertainty on College Choice," *International Economic Review*, 44, 361–422.

Cebi, M. (2007): "Locus of Control and Human Capital Investment Revisited," *Journal of Human Resources*, 42, 919–932.

Coleman, J. S. (1968): "Equality of Educational Opportunity," *Equity & Excellence in Education*, 6, 19–28.

Coleman, M. and T. DeLeire (2003): "An Economic Model of Locus of Control and the Human Capital Investment Decision," *Journal of Human Resources*, 38, 701–721.

Cowles, M. K. (1996): "Accelerating Monte Carlo Markov Chain Convergence for Cumulative-Link Generalized Linear Models," *Statistics and Computing*, 6, 101–111.

Cunha, F. and J. J. Heckman (2008): "Formulating, Identifying and Estimating the Technology of Cognitive and Noncognitive Skill Formation," *Journal of Human Resources*, 43, 738–782.

Cunha, F., J. J. Heckman, and S. Navarro (2005): "Separating Uncertainty from Heterogeneity in Life Cycle Earnings," *Oxford Economic Papers*, 57, 191–261, The 2004 Hicks Lecture.

Dagsvik, J. K., T. Hægeland, and A. Raknerud (2010): "Estimating the Returns to Schooling: a Likelihood Approach Based on Normal Mixtures," *Journal of Applied Econometrics (forthcoming).*

Dohmen, T., U. Sunde, A. Falk, and D. Huffman (2010): "Are Risk Aversion and Impatience Related to Cognitive Ability?" *American Economic Review*, 100, 1238–1260.

Duncan, G. and J. Morgan (1981): "Sense of Efficacy and Subsequent Change in Earnings–A Replication," *Journal of Human Resources*, 16, 649–657.

Duncan, G. J. and R. Dunifon (1998): "Soft-Skills and Long-Run Labor Market Success," *Research in Labor Economics*, 17, 123–149.

Escobar, M. D. and M. West (1995): "Bayesian Density Estimation and Inference Using Mixtures," *Journal of the American Statistical Association*, 90, 577–588.

Falk, A., D. Huffman, and U. Sunde (2006): "Self-Confidence and Search," Institute for the Study of Labor (IZA) Discussion Paper No. 2525.

Ferguson, T. S. (1983): "Bayesian Density Estimation by Mixtures of Normal Distributions," in *Recent Advances in Statistics: Papers in Honor of Herman Chernoff on his Sixtieth Birthday*, ed. by H. Chernoff, M. Rizvi, J. Rustagi, and D. Siegmund, New York: Academic Press, 287–302.

Flossmann, A. and W. Pohlmeier (2006): "Causal Returns to Education: A Survey on Empirical Evidence for Germany," *Journal of Economics and Statistics*, 226, 6–23.

Flossmann, A. L., R. Piatek, and L. Wichert (2007): "Going Beyond Returns to Education: The Effect of Noncognitive Skills on Wages in Germany," Paper presented at the European Meeting of the Econometric Society, Budapest.

Frey, B. S. and S. Meier (2004): "Pro-Social Behavior, Reciprocity or Both?" *Journal* *of Economic Behavior and Organization*, 54, 65–68.

Gallo, W., J. Endrass, E. Bradley, D. Hell, and S. Kasl (2003): "The Influence of Internal Control on the Employment Status of German Workers," *Schmollers Jahrbuch*, 123, 71–81.

Gebel, M. and F. Pfeiffer (2010): "Educational expansion and its heterogeneous returns for wage workers," *Schmollers Jahrbuch*, 130, 19–42.

Gottschalk, P. (2005): "Can work alter welfare recipients' beliefs?" *Journal of Policy Analysis and Management*, 24, 485–498.

Hansen, K. T., J. J. Heckman, and K. J. Mullen (2004): "The Effect of Schooling and Ability on Achievement Test Scores," *Journal of Econometrics*, 121, 39–98.

Heckman, J., L. Lochner, and P. Todd (2006a): "Earnings Functions, Rates of Return and Treatment Effects: The Mincer Equation and Beyond," *Handbook of the Economics of Education*, 1, 307–458.

Heckman, J. J. (1979): "Sample Selection Bias as a Specification Error," *Econometrica*, 47, 153–161.

Heckman, J. J., J. Stixrud, and S. Urzua (2006b): "The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior," *Journal of Labor Economics*, 24, 411–482.

Heineck, G. and S. Anger (2010): "The Returns to Cognitive Abilities and Personality Traits in Germany," *Labour Economics*, 17, 535–546.

Hill, M. S. (1979): "The Wage Effects of Marital Status and Children," *Journal of Human Resources*, 14, 579–594.

Horny, G., R. Mendes, and G. Berg (2009): "Job Durations with Worker and Firm Specific Effects: MCMC Estimation with Longitudinal Employer-Employee Data," Institute for the Study of Labor (IZA) Discussion Paper No. 3992.

Jöreskog, K. G. and I. Moustaki (2001): "Factor Analysis of Ordinal Variables: A

Comparison of Three Approaches," *Multivariate Behavioral Research*, 36, 347–387.

Judge, T. A. and J. E. Bono (2001): "Relationship of Core Self-Evaluations Traits-Self-Esteem, Generalized Self-Efficacy, Locus of Control, and Emotional Stability-with Job Satisfaction and Job Performance: A Meta-Analysis," *Journal of Applied Psychology*, 86, 80–92.

Koop, G. and J. Tobias (2004): "Learning about heterogeneity in returns to schooling," *Journal of Applied Econometrics*, 19, 827–849.

Kotlarski, I. (1967): "On Characterizing the Gamma and the Normal Distribution," *Pacific Journal of Mathematics*, 20, 69–76.

Lauer, C. and V. Steiner (2000): "Private Erträge von Bildungsinvestitionen in Deutschland," *Applied Economics Quarterly*, 51, 71–101.

Li, M. (2006): "High school completion and future youth unemployment: new evidence from High School and Beyond," *Journal of Applied Econometrics*, 21, 23–53.

Liu, J. S. and C. Sabatti (2000): "Generalised Gibbs Sampler and Multigrid Monte Carlo for Bayesian Computation," *Biometrika*, 87, 353–369.

McCloskey, D. N. and S. T. Ziliak (1996): "The Standard Error of Regressions," *Journal of Economic Literature*, 34, 97–114.

Mincer, J. (1958): "Investment in Human Capital and Personal Income Distribution," *Journal of Political Economy*, 66, 281–302.

Nandram, B. and M.-H. Chen (1996): "Reparameterizing the Generalized Linear Model to Accelerate Gibbs Sampler Convergence," *Journal of Statistical Computation and Simulation*, 54, 129–144.

Osborne, M. A. (2000): "The Power of Personality: Labor Market Rewards and the Transmission of Earnings," Ph.D. thesis, University of Massachusetts.

Piatek, R. (2010): "Bayesian Inference for Factor Structure Models via Gibbs Sampling," *Unpublished technical report*.

Pischke, J. and T. Von Wachter (2008): "Zero returns to compulsory schooling in Germany: Evidence and interpretation," *The Review of Economics and Statistics*, 90, 592–598.

Psacharopoulos, G. (1981): "Returns to education: an updated international comparison," *Comparative Education*, 17, 321–341.

Rotter, J. B. (1966): "Generalized Expectancies for Internal versus External Control of Reinforcement," *Psychological Monographs: General & Applied*, 80, 1–28.

Scott, D. W. (1992): *Multivariate Density Estimation: Theory, Practice, and Visualization*, Wiley Interscience.

Silverman, B. W. (1986): *Density Estimation for Statistics and Data Analysis*, CRC Press.

Tanner, M. A. and W. H. Wong (1987): "The Calculation of Posterior Distributions by Data Augmentation," *Journal of the American Statistical Association*, 82, 528–540.

Trzcinski, E. and E. Holst (2010): "Interrelationship among Locus of Control and Years in Management and Unemployment: Differences by Gender," Discussion Papers of DIW Berlin 974, DIW Berlin, German Institute for Economic Research.

Uhlendorff, A. (2004): "Der Einfluss von Persönlichkeitseigenschaften und sozialen Ressourcen auf die Arbeitslosigkeitsdauer," *KZfSS Kölner Zeitschrift für Soziologie und Sozialpsychologie*, 56, 279–303.

van Dyk, D. A. and X.-L. Meng (2001): "The Art of Data Augmentation," *Journal of Computational & Graphical Statistics*, 10, 1–50.

Wagner, G., J. Frick, and J. Schupp (2007): "The German Socio-Economic Panel Study (SOEP)–Scope, Evolution and Enhancements," *Schmollers Jahrbuch: Journal of Applied Social Science Studies/Zeitschrift für Wirtschafts-und Sozialwissenschaften*, 127, 139–169.

Wagner, G., J. Goebel, P. Krause, R. Pischner, and I. Sieber (2008): "Das

Sozio-oekonomische Panel (SOEP): Multidisziplinaeres Haushaltspanel und Kohortenstudie fuer Deutschland–Eine Einfuehrung (fuer neue Datennutzer) mit einem Ausblick (fuer erfahrene Anwender)," *AStA Wirtschafts-und Sozialstatistisches Archiv*, 2, 301–328.

Ziliak, S. T. and D. N. McCloskey (2004): "Size Matters: the Standard Error of Regressions in the American Economic Review," *Journal of Socio-Economics*, 33, 527 – 546.

Appendix A Data addendum

Our data come from the German Socioeconomic Panel (SOEP), a representative longitudinal micro-dataset that contains a wide range of socio-economic information on individuals in Germany, comprising follow-ups for the years 1984-2008. Information was first collected from about 12,200 randomly selected adult respondents in West Germany in 1984. After German reunification in 1990, the SOEP was extended to around 4,500 persons from East Germany, and subsequently supplemented and expanded by additional samples. The data are well-suited for our analysis in that they allow us to exploit information on a wide range of background variables, locus of control and wages, for a representative panel of individuals. Furthermore, the inclusion of a special youth survey, comprising information on 17-year-olds, allows us to obtain background variables and locus of control measures for individuals who have not yet entered the labor market.

A.1 Combining samples

Our focus is to analyze the impact of locus of control and to purge our estimates of measurement error and endogeneity problems. Hence, to investigate how locus of control affects schooling decisions and wages, respectively, we would ideally need a sample of individuals for whom locus of control measures are collected at several points in time: first, at the time when individuals make education decisions, and second, at a time just before they start the respective job for which labor market returns can be observed. In this way, we would obtain locus of control measures that are truly exogenous, and not influenced by previous on-the-job labor market experience. However, we only have access to one measure of what we term 'premarket' locus of control. This measure is taken when individuals are 17 years of age, just after compulsory schooling, but before they enter the labor market.[15] We then

[15]Locus of control measures have also been collected for a cross section of young adults in 2007, but we disregard this information, as we suspect it to be flawed by previous labor market experience.

combine the sample of youth for which we have 'premarket' locus of control measures with a sample of young adults for whom we observe labor market outcomes. We draw our samples on the basis of selection criteria that are explained in the following.

A.1.1 Youth sample

Our youth sample is composed of 1,534 individuals born between 1984 and 1991, all of which are children of SOEP panel members. A comprehensive set of background variables, schooling choices, as well as locus of control measures of these individuals, have been collected in the years 2001-2008, when the subjects were 17 years of age. After the first interview at age 17, all subjects are subsequently interviewed on a yearly basis until early adulthood. For example, in 2008, the oldest youth are 24 years of age. An exception to the age rule was made for the 2001 wave, such that some subjects were already 18 or 19 years of age when first completing the questionnaire. We exclude these individuals from our sample. Besides, to ensure that our results are not flawed by post 1991 schooling and labor market adjustments, all individuals who went to school in East Germany (the former German Democratic Republic) have been excluded. Last, we exclude all individuals with missing locus of control measures, missing schooling information, or missing information among the covariates.

A.1.2 Adult sample

The adult sample used for our analysis comprises information on 1,192 individuals, aged 26-35, who are drawn from all West German representative subsamples We construct a cross-section of individuals based on the most recent information available from the waves 2004-2008. Hence, most of our information on the adult sample stems from the 2008 wave. However, if some important pieces of information on certain individuals in that wave are missing, they are filled up with information from 2007. If the information in the 2007 wave is also missing, information from 2006 is used, and so on.

We want to ensure that labor market outcomes and cognitive measures are not related to language problems, post 1991 adjustments, or discrimination. Hence, we exclude non-German citizens, individuals who did not live in West Germany at the time of reunification, as well as individuals whose parents do not speak German as a mother tongue. We also exclude handicapped individuals and individuals in vocational training. Furthermore, we exclude individuals with missing schooling information, because the schooling equation is crucial as it links our two samples and ensures identification. Also, individuals with missings among the control variables are dropped from the sample.

A.2 'Premarket' locus of control

In the SOEP, locus of control is measured by a 10-item questionnaire. However, the number of possible answers differs between the years 2001-2005, where a 7-point scale was used, and the years 2006-2008, where a 4-point item scale was used. To make the questionnaire comparable across samples, we transform the 7-point scale into a 4-point scale by assigning the middle category (4) either to category 2 or 3 of the 4-item scale, depending on the most probable answer. For example, if in the 2005 sample most youth answered "completely agree," people who answered "indifferent" in the 2006 sample are assumed to tend toward the "slightly agree" answer. After transforming answers to have the same scale, each question is answered on a Likert scale ranging from 1 ("completely disagree ") to 4 ("completely agree").

A.3 Schooling choice

We group schooling into two broad categories: higher education and lower education. Individuals are classified as being highly educated whenever they have some kind of academic qualification. That is, to qualify as highly educated, individuals need to have passed at least those exams that mark the completion of secondary schooling, and which are obtained in tracks with an academic orientation (German high school diploma (Abitur) obtained either at Gymnasium or Gesamtschule). To identify the level of schooling obtained, we use the international Comparative Analysis of Social Mobility in Industrial Nations (CASMIN) Classification, which is a generated variable available in the SOEP. We define individuals as being highly educated when their attained education level corresponds to CASMIN categories (2c, 3a, 3b). Similarly, individuals are low-educated if their education status is classified according to CASMIN classification categories (1b, 1c, 2a, 2b). Furthermore, for a subsample of youth who have not completed their education at the time of the last interview, we replace their final education status with their aspired (planned) level of education.

A.4 Wage construction and labor market participation

Wages are constructed by using most recent wage information available from the SOEP. Whenever occurring, missing wage information was substituted by wage information obtained in one of the earlier years. Wages have been inflation adjusted to match 2008 wage levels (inflation rates obtained from Eurostat). Wages are assigned a missing whenever the respective individual is indicating not to have a regular (full time or part time) job. We exclude other types of employment such as marginal employment, to ensure that we are not including typical student jobs.

Hourly wages have been constructed by dividing gross monthly wages by the actual number of hours worked in the last month before the interview. Log hourly wages are then obtained by taking the natural logarithm of the hourly wage variable. To account for outliers, we trim hourly wages below the first and above the ninety ninth percentiles. All individuals who indicate a positive wage and are full- or part-time employed are classified as labor market participants.

A.5 Covariates

In our measurements system, schooling equation and outcome equations, we control for a large set of background variables. The locus of control factor distribution is identified from the covariance structure of the unobservables of the model. Hence, any controls in the measurement system purge our measures of locus of control of any effects which are captured by the covariates. Thus, the covariates in place should be uncorrelated with the latent trait we want to capture, since in our model the latent factor has to be uncorrelated with these covariates by construction. In the following, a brief description of the different categories of covariates is provided.

A.5.1 Parental education and investment

Parental education variables have been constructed in the form of dummy variables for higher secondary degree (German Gymnasium), lower secondary degree (German Hauptschule or Realschule), dropout and other degree. This information was collected using the Biography Questionnaire, which every person answers when she is first interviewed in the SOEP.

Apart from parental education, *Parental investment* is proxied by two variables: broken home and number of siblings. Our broken home variable reflects the percentage of childhood time spent in a broken home until the age of 15. This information was also obtained from the Biography Questionnaire. Last, the number of siblings is obtained for the youth by counting the number of siblings living in the household. If an individual has many brothers and sisters, this may indicate that parental time is spread among more individuals, and that overall parental investment is lower.

A.5.2 Region dummies and city size

Because school quality and availability, culture and incomes may vary between large and small municipalities, we control for the size of the city where agents spent most of their childhood. Hence, we specify dummy variables for large city, medium city, small city and countryside. Furthermore, we specify four region variables to represent the current region of residence. Hereby, the German Länder are classified as follows:

- North: Berlin, Bremen, Hamburg, Lower Saxony, Schleswig-Holstein,
- South: Bavaria, Baden-Württemberg,
- West: Hessen, North Rhine-Westphalia, Rhineland-Palatinate, Saarland,
- East: Brandenburg, Mecklenburg Western Pomerania, Saxony, Saxony-Anhalt, Thuringia.

A.5.3 Unemployment rates

We construct unemployment rates at two different points in time. First, we use overall German unemployment at the time when individuals are 17, to have a rough measure of the business cycle when schooling decisions are made. Second, we use region (Länder) specific unemployment rates at the time when labor market outcomes are observed. The latter are important to explain the participation decision, as well as local wage rates. All local unemployment rates are obtained from the Federal Employment Office (Bundesagentur für Arbeit), and overall unemployment from the German Federal Statistical Agency (Bundesamt für Statistik).

A.5.4 Marital status and number of children

We construct a dummy variable for whether someone is married by looking at her current marital status. Furthermore, we identify the number of dependent children by counting all children for which child benefit payments (Kindergeld) are received by the household. These variables are important, because previous studies show that being married and the number of dependent children have a positive impact on labor market participation and wages for males, and a negative one for females (see, e.g., Hill, 1979, among others).

A.5.5 Track recommendation after elementary school

We acknowledge that both schooling decisions and locus of control measures may be correlated with cognitive skills. Hence, in order to proxy cognitive skills, and to account for the fact that schooling decisions may depend on prior track attendance, we include an individual's track recommendations after elementary school. In Germany, track recommendations are given to every student during 4^{th} grade by their elementary school teachers. In some of the German Länder, track recommendations are non-mandatory (but generally adhered to). In some other Länder, track recommendations are compulsory.

Appendix B Descriptive statistics

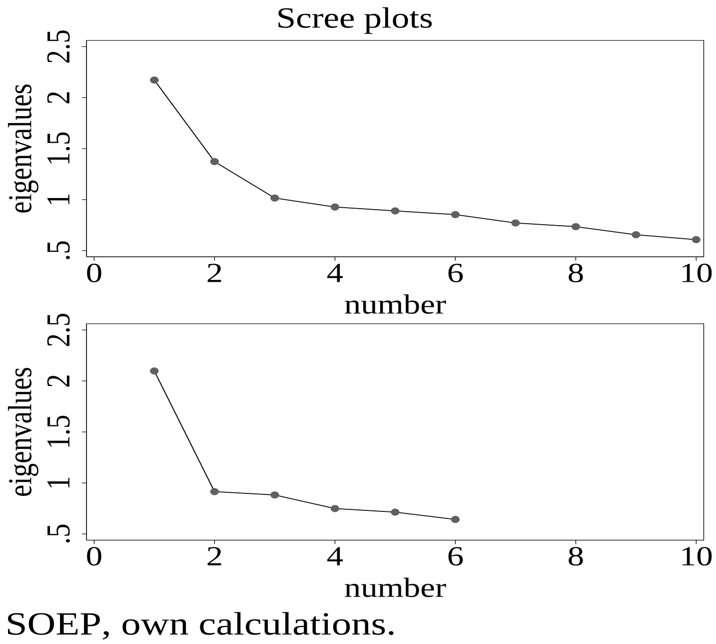


Figure B.1: Scree plot: all measurements versus 6 'external' items only

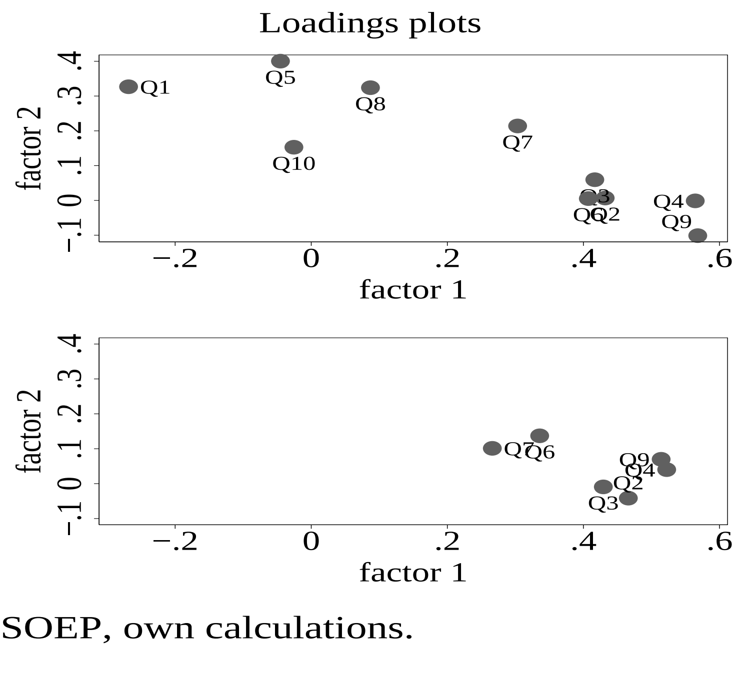


Figure B.2: Scatterplot of loadings: all measurements versus 6 'external' items only

Table B.1: Proportion of people with higher education (all samples)

Variables	**Mean**	**SD**	**N**
Females (youth sample)	0.518	0.500	774
Males (youth sample)	0.459	0.499	760
Females (adult sample)	0.461	0.499	592
Males (adult sample)	0.368	0.483	600

Table B.2: Descriptive statistics: labor market outcomes by schooling

	High education			**Low education**			
Variables	**Mean**	**SD**	**N**	**Mean**	**SD**	**N**	***p*-value**
Labor market participation (males)	0.49	0.50	472	0.71	0.45	617	0.00
Hourly wage (males)	16.03	7.16	228	11.58	4.67	435	0.00
Labor market participation (females)	0.49	0.50	553	0.58	0.49	558	0.00
Hourly wage (females)	12.89	4.86	269	10.35	4.00	316	0.00

Source: SOEP, cross section using most recent information from the waves 2004-2008. Own calculations.
Notes: p-values of a two-sided t-test for differences in means are reported.

Table B.3: Descriptive statistics: covariates in the measurement system

	Males		**Females**	
Variables	**Mean**	**SD**	**Mean**	**SD**
Childhood in large city	0.20	0.40	0.22	0.42
Childhood in medium city	0.19	0.40	0.19	0.40
Childhood in small city	0.29	0.45	0.25	0.44
North	0.26	0.44	0.24	0.43
South	0.31	0.46	0.34	0.47
Recommendation: grammar school	0.39	0.49	0.45	0.50
Recommendation: general secondary school	0.17	0.38	0.13	0.34
Number of siblings	0.98	1.27	1.01	1.22
Broken home	0.24	0.43	0.24	0.43
Father grammar school	0.29	0.45	0.33	0.47
Father dropout	0.03	0.16	0.04	0.19
Mother grammar school	0.23	0.42	0.25	0.44
Mothers dropout	0.01	0.10	0.03	0.16
# Observations	760		774	

Source: SOEP, cross section using most recent information from the waves 2004-2008. Own calculations.
Notes: p-values of a two-sided t-test for differences in means are reported.

Table B.4: Descriptive statistics: covariates in the outcome equations (by schooling)

	Males					**Females**				
	High education		Low education			High education		Low eduction		
Variables	**Mean**	**SD**	**Mean**	**SD**	p**-val**	**Mean**	**SD**	**Mean**	**SD**	p**-val**
Age	24.96	5.88	26.52	5.53	0.00	25.31	5.86	25.82	5.50	0.14
Broken home	0.14	0.35	0.18	0.39	0.07	0.17	0.37	0.22	0.41	0.03
Father grammar school	0.44	0.50	0.07	0.26	0.00	0.41	0.49	0.08	0.28	0.00
Father dropout	0.01	0.09	0.03	0.16	0.03	0.01	0.07	0.04	0.20	0.00
Mother grammar school	0.33	0.47	0.08	0.27	0.00	0.30	0.46	0.08	0.27	0.00
Mother dropout	0.00	0.07	0.02	0.14	0.03	0.01	0.11	0.03	0.17	0.06
Childhood in large city	0.24	0.43	0.18	0.38	0.01	0.21	0.40	0.20	0.40	0.71
Childhood in medium city	0.21	0.41	0.20	0.40	0.58	0.23	0.42	0.18	0.38	0.03
Childhood in small city	0.26	0.44	0.24	0.42	0.29	0.25	0.44	0.25	0.43	0.77
North	0.24	0.43	0.21	0.41	0.25	0.23	0.42	0.20	0.40	0.27
South	0.31	0.46	0.33	0.47	0.58	0.28	0.45	0.34	0.47	0.06
Unemployment at schooling decision	9.01	1.30	8.93	1.37	0.35	9.03	1.39	9.03	1.34	0.97
Unemployment	7.47	2.90	7.72	3.25	0.18	7.70	3.06	7.52	3.12	0.33
Married	0.16	0.37	0.23	0.42	0.01	0.18	0.38	0.27	0.45	0.00
Number of children	1.03	1.12	0.79	1.01	0.00	0.96	1.17	0.92	1.12	0.55
# Observations	472		617			553		558		

Source: SOEP, cross section using most recent information from the waves 2004-2008. Own calculations.
Notes: p-values of a two-sided t-test for differences in means are reported.