Abstract: Using detailed Norwegian data on earnings and education histories, we estimate a dynamic structural model of schooling and work decisions that captures our data’s rich patterns over the life-cycle. We validate the model against variation in schooling choices induced by a compulsory schooling reform. Our approach allows us to estimate the ex-ante returns to different schooling tracks at different stages of the life-cycle and quantify the contribution of option values. We find substantial heterogeneity in returns and establish crucial roles for option values and re-enrollment in determining schooling choices and the impact of schooling policies.

Keywords: sequential decisions, ex-ante returns, option values, reform evaluation

JEL code: J24, J31, D80

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1 Introduction

Standard models of human capital (Becker 1964; Mincer 1958) assume that individuals compare the potential future earnings streams at the beginning of their schooling career, choose the alternative with the highest net benefit, and subsequently complete their desired level of schooling. This view ignores both the sequential nature of human capital investments and the uncertainties embedded in this decision-making. The decision to take an additional year of schooling may open up further schooling opportunities as, for instance, a high school diploma is a stepping stone for a college education. And, individuals make such important decisions often facing considerable uncertainty about the associated costs and gains (see, e.g., Wiswall and Zafar (2015), Attanasio and Kaufmann (2017) and Wiswall and Zafar (2021)).

Our paper is motivated by two stylized facts about educational choices related to their sequential and uncertain nature. Firstly, across a wide range of settings, educational researchers have documented the prevalence of drop-out, re-enrollment, and track switching in educational histories. These patterns are present not only in countries with highly subsidized educational system like the Scandinavian countries and Germany, but also in the U.S., where students face high monetary costs of higher education. Secondly, a recurrent finding in the literature on compulsory schooling policies is that such policies tend to have so-called “inframarginal” impacts, i.e., educational choices beyond the minimum schooling requirements are impacted. In a seminal study of the compulsory attendance laws in the U.S., Lang and Kropp (1986) documented the prevalence of such impacts, while similar findings have echoed in later studies.

In this paper, we develop and estimate a dynamic structural model of educational choices in a life-cycle context that can accommodate and explain both of the above-mentioned features of educational careers. Agents in our model are forward-looking and make sequential decisions every period from age 15 to 58 on whether to attend school, and if so, the type of educational track to attend, to work, or to stay at home, while they face uncertainty in terms of their work productivity and tastes for schooling tracks, work and leisure, and also differ in terms of their}

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1 Heckman et al. (2006) and Card (1999) provide extensive reviews of this literature on returns to schooling based on the Becker-Mincer models of human capital investments.

2 For instance, according to data from the National Student Clearinghouse (NSC), thirty-six million Americans held some postsecondary schooling in 2019 without completing a college degree or being currently enrolled (Shapiro et al., 2019).

3 For the U.S., Acemoglu and Angrist (2000) provide further evidence on how the compulsory attendance laws affected the distribution of schooling, while Bedard (2001) provides evidence on how better university access increased high school drop-out rates. Relatedly, Meghir and Palme (2005) found evidence on “inframarginal” responses to a compulsory schooling reform in Sweden, while similar evidence for Norway is reported (though not emphasized) in Black et al. (2005). While these responses can reflect equilibrium adjustments to policy reforms in line with models of educational signaling (Spence 1973), these may also reflect the sequential and uncertain nature of educational decisions, as argued by Altonji (1993) and Heckman et al. (2018).
ability and a vector of latent types. Our model is able to generate a rich set of educational and work histories that feature (i) interruptions and re-enrollment in educational careers, (ii) persistence in choices across the life-cycle, (iii) costly switching between tracks, and (iv) heterogeneity across ability and latent types. The model is also able to re-produce “inframarginal” responses to actual and hypothetical compulsory schooling reforms, provide evidence on who is affected and inform about the potential economic mechanisms driving these patterns.

Using our model, we define and quantify two key objects related to educational choices. First, we consider the **ex-ante return** to each schooling track choice for a given state in our model. This object takes into account the sequential and uncertain nature of schooling choices and captures both the immediate wage and non-monetary rewards as well as the discounted lifetime rewards associated with a choice as compared to the best alternative choice. Unlike the monetary wage rewards that have been the focus of much of the returns to schooling literature (see, e.g., Card (1999) for a review), the ex-ante returns are the objects that drive the educational choices of agents in our model. To illustrate the role of uncertainty, we further contrast **ex-ante** and **ex-post** returns, where the latter depend on the realizations of productivity and taste shocks, while the former reflect agents’ expectations. Second, we consider the **option value** to each schooling track choice for a given state in our model. The sequential nature of schooling decisions generates this value, for instance, as completing a high school diploma generates the option to enroll in college, and college enrollment generates the option to obtain a college degree (Comay et al., 1973; Weisbrod, 1962). Non-linearities in the wage returns to schooling choices (Hungerford and Solon, 1987) and the sequential resolution of uncertainties embedded in these choices can further exacerbate the importance of option values (Trachter, 2015; Stange, 2012; Altonji, 1993). As we will show, these objects are crucial determinants of schooling decisions, essential in understanding the impacts of policy reforms, and under-appreciated in the existing literature.

We implement our modelling approach and provide evidence on the ex-ante returns and the option values of education using Norwegian administrative data with career-long earnings information and education histories. We combine these data with detailed demographic information, including measures on individual ability for males collected as part of the compulsory military recruitment testing. This dataset has several advantages, as this provides (i) complete annual information on educational track choices and earnings histories for selected cohorts across 44 years, (ii) allows us to capture several sources of persistent heterogeneity, and (iii) only suffers from natural sample attrition due to either death or out-migration. Our dataset further covers a compulsory schooling reform that increased the minimum requirement schooling from seven to nine years across different municipalities at different points in time (Black et al., 2005). The latter feature of our setting allows us to estimate our model on individuals that were not exposed to the reform and rely on the reform-induced variation to evaluate our model in an
out-of-sample validation and to shed light on “inframarginal” responses to educational policy reforms. Specifically, we compare the predictions about policy impacts based on the model estimated on pre-reform data to the observed impacts post-reform.\cite{Todd_and_Wolpin_2021}

Our analysis presents several insights. We find substantial heterogeneity in the ex-ante returns by the level of schooling, track choice and individual ability. The estimates of average ex-ante returns range from $-2\%$ for the 8th grade in the academic track for low-ability individuals up to $3\%$ for medium-ability for the 9th year in the vocational track.\footnote{Underlying this heterogeneity is a strong pattern of ability-related sorting into academic and vocational tracks. Indeed, the structure of the returns reflects the separation of the ability groups in the different schooling tracks at an early stage of the educational pathways. Decomposing the sources of ability-related sorting, we find that these patterns are explained by a combination of higher productivity-related rewards to academic track for high-ability types and distaste or weaker non-pecuniary rewards from vocational (academic) schooling for high-ability (low-ability) types. Moving beyond the averages, we document substantial heterogeneity in the distributions of ex-ante returns, with more dispersion in returns at the earlier stages of the educational careers, in the academic track and among high-ability individuals. Comparing the ex-ante and ex-post returns to schooling tracks, we find that around 10\% of individuals face regret, as the realized returns in their chosen track end up being negative.

Our evidence further shows that the option values make up a sizeable fraction of the overall values of educational choices, however, their contribution varies considerably by the stage of educational career, track and individual ability. Option values depend on the likelihood that an individual will continue to pursue schooling further and the rewards they accrue if they do so. A recurring finding is that the option value contribution is highest for the year of schooling right before the completion of an academic degree that entails considerable “diploma” effects. Intuitively, completing the schooling year right before the degree awarding year makes it more likely that individual will indeed pursue a degree and thus this choice holds a high option value. We also find important heterogeneity by ability and track. The option value contributions in the academic track tend to be highest for high-ability individuals, as they are also likely to benefit the most from the additional schooling opportunities. Indeed, we find that 82\% of the high-ability individuals facing the choice of attending the 11th year in academic track would not have completed this education had it not triggered the option of continuing further to attain a high school diploma. By contrast, in the vocational track, the option value contributions are

\footnote{The recent review by \cite{Galiani_and_Pantano_2021} also emphasizes the need for model validation and provides a structured review of the small literature.}

\footnote{A negative return to a choice alternative in our model reflects that an individual expects to receive a higher reward from another choice alternative; i.e., the respective choice alternative is thus not chosen.}
highest in the earliest years of schooling and relatively similar across ability groups.

Finally, we use our model to analyze the impacts of compulsory schooling reforms. Our model predicts that a compulsory schooling reform similar to the one actually implemented in Norway during the 1960s would increase the share of high school graduates by about 3% and college graduation by roughly 0.5% – predictions which are in-line with the actual reform-induced changes observed in our data. Option values provide an economic rationale for such “infra-marginal” responses. By forcing more schooling on individuals, who prior to the reform would have taken less schooling than the new minimum requirement, we also bring them closer to the margins of schooling choices that hold stronger rewards through diplomas or degrees, and as a result some of these individuals do indeed pursue further education. Another important mechanism that our model brings forth is that of re-enrollment opportunities. Even prior to the reform, a sizeable fraction of individuals would have attained the new minimum schooling requirement, but only after first dropping-out and re-enrolling at a large stage in their careers. Since the reform forces these individuals to take the new minimum schooling requirement in an uninterrupted manner, their educational trajectories are also impacted. Interestingly, some of these individuals now also go on to pursue further education, since they no longer face high re-enrollment costs, which further strengthens the patterns of “inframarginal” policy responses.

Our paper provides several contributions. We extend the empirical literature that acknowledges the sequential nature of schooling investments and emphasizes the roles of uncertainties and non-linearities. Eisenhauer et al. (2015), Lee et al. (2017), Trachter (2015) and Stange (2012) all study the role of uncertainty and option values in shaping schooling decisions in deliberately simplified settings. However, none of these studies analyze life-cycle decisions, or allow for heterogeneity by ability, re-enrollment, and track switching at the same time. Our work is closely related to Heckman et al. (2018), who develop a sequential educational choice model. However, they restrict their attention to ex-post returns of education, and avoid making specific assumptions about individuals’ expectations about costs and benefits of schooling. We impose additional structure on the decision process and are able to quantify ex-ante returns and option values. Our paper also relates to a large literature on compulsory schooling reforms (Brunello et al. 2009, Oreopoulou 2006), providing additional evidence on the impacts of such reforms along the distribution of schooling attainment and the potential mechanisms driving these patterns. Our paper further relates to the literature that emphasizes individual learning about their own ability and preferences as they progress in their schooling career (Arcidiacono et al. 2016, Stinebrickner and Stinebrickner 2014). We complement the literature that focuses on the optimal design of school aid policies in a life-cycle context (Colas et al. 2021, Stantcheva 2017).

The structure of our paper is as follows. We outline our structural model in Section 2.
describes our data and institutional setting, and discusses model implementation and provide evidence on model fit and validation. Section 4 presents our main findings. Section 5 concludes.

2 Model

We now present a model that takes the sequential and uncertain nature of schooling investments into account, besides allowing for nonlinearities in the rewards to such investments. Our model is an example of the Eckstein-Keane-Wolpin (EKW) class of models (Aguirregabiria and Mira, 2010), which are frequently used to study the mechanisms determining human capital investment decisions and to predict the effects of human capital policies (Blundell, 2017; Keane et al., 2011; Low and Meghir, 2017). The model exploits the richness of our data and captures essential features of the Norwegian school system. We start by describing the model setup, and then define our main objects of interest – the ex-ante returns and the option values of schooling.

2.1 Setup

We follow individuals over most of their working life from young adulthood at age 15 to the final period $T$ at age 58. The decision period $t = 15, \ldots, 58$ is a school year. Each period individuals observe the state of their choice environment $s_t$ and decide to take action $a_t \in A$. Individuals can decide whether to work ($a_t = W$), to attend an academic ($a_t = A$) or a vocational ($a_t = V$) schooling track, or to stay at home ($a_t = H$). The decision has two consequences: an individual receives an immediate utility $u(s_t, a_t)$ and the environment is updated to a new state $s_{t+1}$. The transition from $s_t$ to $s_{t+1}$ is affected by the action but remains partly uncertain. Individuals are forward-looking. Thus, they do not simply choose the alternative with the highest immediate utility. Instead, they take the future consequences of their current action into account.

Figure 1: Timing of Events.

A policy $\pi = (d_1, \ldots, d_T)$ provides the individual with instructions for choosing an action in any possible future state. It is a sequence of decision rules $d_t$ that specify the planned action
at a particular time \( t \) for any possible state \( s_t \). The implementation of a policy generates a sequence of utilities that depends on the transition probability distribution \( p(s_t, a_t) \) for the evolution of state \( s_t \) to \( s_{t+1} \) induced by the model. To fix ideas, Figure \[\] illustrates the timing of events in the model for two generic periods. At the beginning of period \( t \), an individual fully learns about each alternative’s immediate utility, chooses one of the alternatives, and receives its immediate utility. Then, the state evolves from \( s_t \) to \( s_{t+1} \) and the process is repeated in \( t+1 \).

Individuals make their decisions facing uncertainty about the future and seek to maximize their expected total discounted utilities over all remaining decision periods. They have rational expectations (Muth, 1961), so their subjective beliefs about the future agree with the objective probabilities for all possible future events determined by the model. Immediate utilities are separable between periods (Kahneman et al., 1997), and individuals discount future over immediate utilities by a discount factor \( \delta \) (Samuelson, 1937). Equation (1) provides the formal representation of an individual’s objective function. Given an initial state \( s_1 \), they implement a policy \( \pi^* \) from the set of all possible policies \( \Pi \) that maximizes the expected total discounted utilities over all decision periods given the information available at the time.

\[
\max_{\pi \in \Pi} \mathbb{E}_{s_1}^\pi \left[ \sum_{t=16}^{T} \delta^{t-16} u(s_t, d_t(s_t)) \right] \tag{1}
\]

When entering the model, all individuals have seven years of basic compulsory schooling, but they are one of the three \( J = \{1, 2, 3\} \) latent types that capture alternative-specific skill endowments \( e = (e_{j,a})_{J \times A} \) (Heckman and Singer, 1984). In addition, individuals can be of either low, medium, or high level of ability. Individuals know their own ability and latent type\(^6\). The immediate utility \( u(\cdot) \) of each alternative consists of a non-pecuniary utility \( \zeta_a(\cdot) \) and, for the working alternative, an additional monetary wage component \( w(\cdot) \). Both depend on an individual’s level of human capital as measured by work experience \( k_t \), years of completed schooling in each track \( h_t = (h_{a,t})_{a \in \{A,V\}} \), and the alternative-specific skill endowment \( e \). The immediate utilities are also influenced by the decision \( a_{t-1} \) in the previous period, a time trend

\[^6\]As researchers, we observe each individual’s ability group, but must infer their latent types based on choices. To classify individuals in ability groups, we rely on an IQ test score available in our data. See further details in Section 3.1 below. The ability measures capture observed heterogeneity while latent types capture persistent unobserved heterogeneity across individuals. The model is specified and estimated separately for each ability group but we refrain from making this distinction while outlining the model here to ease the exposition.
\( t \), and alternative-specific shocks \( \epsilon_t = (\epsilon_{a,t})_{a \in A} \). Their general form is given by:

\[
    u(\cdot) = \begin{cases} 
        \zeta W(k_t, h_t, t, a_{t-1}, e_{j,a}) + w(k_t, h_t, t, a_{t-1}, e_{j,a}, \epsilon_{a,t}) & \text{if } a = W \\
        \zeta_a(k_t, h_t, t, a_{t-1}, e_{j,a}, \epsilon_{a,t}) & \text{if } a \in \{A, V, H\}.
    \end{cases}
\]

Work experience \( k_t \) and years of completed schooling in each track \( h_t \) evolve deterministically. There is no uncertainty about grade completion (Altonji, 1993) and no part-time enrollment. Schooling is defined by time spent in school, not by formal credentials acquired. Once individuals reach a certain amount of schooling, they acquire a degree.

\[
    k_{t+1} = k_t + I[a_t = W] \\
    h_{a,t+1} = h_{a,t} + I[a_t = a] \quad \text{if } a \in \{A, V\}
\]

The productivity and preference shocks \( \epsilon_t \) are unknown to the individual in advance, and capture uncertainty about the returns and cost of future schooling. In our model setup, we specify these shocks \( \epsilon_t \) to be uncorrelated across time and follow a multivariate normal distribution with mean 0 and covariance \( \Sigma \). Given the structure of the utility functions and the distribution of the shocks, the state at time \( t \) is \( s_t = \{k_t, h_t, t, a_{t-1}, e, \epsilon_t\} \).

Individuals’ skill endowments \( e \) and their level of ability are the two sources of persistent heterogeneity in this model. All remaining differences in life-cycle decisions result from differences in the transitory shocks \( \epsilon_t \) over time. Thus, our setup allows for learning-by-doing (Altğuğ and Miller, 1998). In each period, individuals can increase their stock of human capital \( (k_t, h_t) \) by either working in the labor market or enrolling in school. However, we only incorporate individuals learning about themselves in a limited fashion (Miller, 1984). From the beginning, individuals are aware of their level of ability and alternative-specific skill endowments \( e \). They only learn about the realizations of shocks \( \epsilon_t \) at the beginning of each period. As the shocks are distributed independently over time, individuals do not update their prior beliefs about their productivity or alternative-specific tastes (Arcidiacono, 2004; Arcidiacono et al., 2016).

Previous research on the determinants of life-cycle wages and schooling decisions (Keane and Wolpin, 1997; Meghir and Pistaferri, 2011) informs our specification of the immediate utility functions. We specify the wage component \( w(\cdot) = r x(\cdot) \) in the immediate utility from working as the product of the market-equilibrium rental price \( r \) and a skill level \( x(\cdot) \). The skill level \( x(\cdot) \)

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\( \): While in principle, one could also allow persistence in these shocks over time, the estimation problem becomes computationally more cumbersome as this would increase the state space dramatically. However, as discussed below, since the model includes persistent heterogeneity and adjustment costs in moving across states, adding persistence in transitory shocks can also pose challenges for identification (Heckman and Singer, 1984).
is determined by a skill production function, which includes a deterministic component \( \Gamma(\cdot) \) and a multiplicative stochastic productivity shock \( \epsilon_{W,t} \), as follows:

\[
x(k_t, h_t, t, a_{t-1}, e_{j,W}, \epsilon_{W,t}) = \exp \left( \Gamma(k_t, h_t, t, a_{t-1}, e_{j,W}) \cdot \epsilon_{W,t} \right)
\]

The specification above leads to a standard logarithmic wage equation in which the constant term is the skill rental price \( \ln(r) \) and wages follow a log-normal distribution. Equation (2) shows the parametrization of the deterministic component \( \Gamma(\cdot) \) of the skill production function:

\[
\Gamma(k_t, h_t, t, a_{t-1}, e_{j,W}) = e_{j,W} + \beta_{1,w} \cdot h_A^t + \beta_{2,w} \cdot h_V^t + \beta_{3,w} \cdot k_t + \beta_{4,w} \cdot (k_t)^2
\]

\[+ \sum_{d \in \{9, 12, 16\}} \gamma_{d,w}^A \cdot I[h_A^t \geq d] + \sum_{d \in \{9, 12\}} \gamma_{d,w}^V \cdot I[h_V^t \geq d] \]

\[+ \eta_{1,w} \cdot I[a_{t-1} = W] + \nu_{1,w} \cdot (t - 15) + \nu_{2,w} \cdot I[t < 17] \]

The first part of the skill production function is motivated by Mincer (1974) and hence linear in years of completed schooling by track \( (\beta_{1,w}, \beta_{2,w}) \), quadratic in experience \( (\beta_{3,w}, \beta_{4,w}) \), and separable between the two of them. We include diploma effects \( (\gamma_{d,w}^A, \gamma_{d,w}^V) \) that capture the non-linear rewards associated with a degree \( d \) beyond the years of schooling (Hungerford and Solon 1987; Jaeger and Page 1996). Skills depreciate by \( \eta_1 \) if the individual didn’t work in the previous period. Finally, there is a time-trend \( \nu_1 \) and a penalty when working as a minor \( \nu_2 \).

In the following, we briefly highlight some salient aspects of how we parametrize the immediate non-pecuniary reward of working and the immediate utilities of attending academic and vocational schooling, and staying at home, respectively. The Appendix, Section A.1 provides more details on the parametrizations, while Section 3.3 discusses model solution and implementation.

We allow the immediate non-pecuniary reward (i.e., disutility) of work to depend on accumulated work experience \( k_t \) and years of completed schooling in each track \( h_t \), and allows for diploma effects as in equation [2]. Further, we include parameters that capture fixed costs of market entry (i.e., no past work experience). The immediate rewards of academic and vocational schooling include parameters capturing costs related to track switching, which can vary by the length of completed schooling in the other track, diploma effects as in equation (2), and indicators for residing in an area with a local high school capturing costs of geographic mobility or commuting to study. The utility of staying at home is allowed to depend on whether one is below age 17 and indicators for having completed a high school or an undergraduate degree.
2.2 Objects of Interest

We now define two primary objects of interest in our analysis within the framework of the above model, namely the ex-ante return to schooling and the option value of schooling. While in the empirical analysis, we will present evidence on these objects separately by academic and vocational schooling, we refer to a generic schooling choice $G \in \{A, V\}$ here to ease the exposition.

We define these objects in terms of value functions $v(s_t, a)$. The value functions are alternative- and state-specific and summarize the total value that individuals receive of choosing alternative $a$ for a given state $s_t$, including the immediate reward and the discounted future rewards, assuming that the optimal policy $\pi^*$ is followed in the future:

$$v(s_t, a) = u(s_t, a) + \delta E_{s_t} \left[ v^\pi(s_{t+1}) \right] \quad \forall \ a \in A$$

Accordingly, the total value of schooling $v(s_t, G)$ in state $s_t$ captures the immediate and expected future benefits from continuing one’s education in another period, subject to optimal policy $\pi^*$.

**Ex-ante Return** In Figure 2, we illustrate the choice alternatives that are needed to isolate the ex-ante return to an additional year of schooling. The thought-experiment we perform is to compare the total value of schooling $v(s_t, G)$ against the value of choosing the best alternative non-schooling choice. Notably, the alternative choice can also contain the option of taking more schooling at a later stage in the life-cycle through re-enrollment. Quantifying the ex-ante return requires making comparisons of counterfactuals as a given individual in state $s_t$ in the estimated model only chooses one of the available alternatives. We construct such counterfactuals through model simulations, where we require each individual to make alternative choices in state $s_t$, but restrict the realizations of shocks in each period to be held fixed across comparisons.

**Figure 2:** Choice Alternatives Isolating the Ex-ante Return to Schooling.

We denote by $ER(s_t)$ the ex-ante return capturing the value of an additional year of schooling against the best alternative choice in state $s_t$. Formally, we can express this object as follows:
\[
ER(s_t) = \frac{v^\pi(s_t, G) - \tilde{v}^\pi(s_t)}{\tilde{v}^\pi(s_t)}, \quad \text{where} \quad \tilde{v}^\pi(s_t) = \max_{a \in \{W,H\}} \{v^\pi(s_t, a)\}.
\] (3)

In our model, the ex-ante return is positive for all individuals who appear in state \( s_t \) that do enroll in school and negative for those that decide to work or stay at home instead.

**Option Value**  We are also interested in the option value of schooling \( OV(s_t) \). This object captures the part of the value of another year of schooling that can be attributed to having an opportunity to pursue further schooling in the future. This component arises due to the sequential nature of schooling investments. To compute the option value component, we perform another counterfactual comparison. We now compare the total value of schooling \( v^\pi(s_t, G) \) in state \( s_t \) to the value of the same alternative but with an optimal policy \( \hat{\pi} \) that does not allow one to increase schooling further beyond the next period. The latter is by construction a counterfactual scenario, unless one has already reached the maximum level of schooling.

\[
OV(s_t) = v^\pi(s_t, G) - v^{\hat{\pi}}(s_t, G)
\]

The option value of schooling is non-negative at all states and zero once an individual attains the maximum schooling level. The option value increases with the future benefits of pursuing higher education and the probability of doing so. Figure 3 shows the decision problem facing the individual for whom we calculate the option value. We compare the total value of continued schooling under the scenario that the individual may continue to increase their schooling level in the future periods and the counterfactual scenario where it is impossible to do so.

**Figure 3:** Choice Alternatives Isolating the Option Value of Schooling.

As a measure for the importance of the option value, we compute its contribution to the overall
value of a state by taking the following ratio:

\[ OVC(s_t) = \frac{OV(s_t)}{v^{\pi^*(s_t)}}. \]  

(4)

In the empirical analysis, we will report estimates of the option value contributions based on the above measure, which provides a decomposition of the total value of schooling in a state.

3 Data and Implementation

In this section, we first describe our data sources, then briefly describe the Norwegian education system and the compulsory schooling reform, before we discuss the implementation and estimation of our model on these data, and finally, provide evidence on model fit and validation.

3.1 Data Sources

Our empirical analysis uses several registry databases maintained by Statistics Norway. First, we use the Norwegian National Education Database, a comprehensive population-wide event-history dataset with information on the dates of enrollment, termination and completion of 6-digit educational courses for all residents since 1970. Second, we use a longitudinal dataset containing annual earnings and tax records for all Norwegians for every year from 1967 onwards. Third, we use demographic information (e.g., cohort of birth, gender and childhood municipality of residence) for all individuals ever registered in the Norwegian Central Population Register, established in 1964. Fourth, we are also able to access supplementary demographic data from the Decennial Population Censuses held in 1960 and 1970. Finally, we received information on IQ test scores from the Norwegian Armed Forces for male conscripts born in 1950 and later. Importantly, each of these datasets include unique personal identifiers which allow us to follow individuals' educational choices and earnings across time, and link a proxy of ability for males.

Sample construction We restrict our sample to Norwegian males born between 1955 and 1960. We can follow each of these individuals' educational choices and earnings from age 15 and up to age 58. Our initial sample consists of 176,804 Norwegian-born males. Dropping individuals with missing information on childhood municipality of residence, exposure to compulsory schooling reform and education enrollment or attainment, we retain 165,171 individuals. Further dropping individuals with missing information on IQ test scores in the Norwegian military records, we retain 136,292 individuals (i.e., around 77% of the initial sample). Using annual

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8We observe educational choices annually for birth cohort 1955 at age 15 and onwards since the National Education Database was established in 1970. Educational histories are partially observed for earlier cohorts.
information on individuals’ educational choices and earnings, we create a weakly-balanced panel of individuals entering our sample across 44 annual observations, which an individual can exit only due to natural attrition (i.e., death or out-migration). Our panel dataset thus consists of 5,840,243 person-year observations.

We further split the analytical sample in two parts, depending on the type of compulsory schooling system each individual was subject to, exploiting variation in the timing of a compulsory schooling reform across different municipalities in Norway (see details in Section 3.4). Specifically, there are 9,156 individuals in our sample (i.e., around 7%) who grew up in one of the 200 (out of 732) municipalities which hadn’t implemented the compulsory schooling reform by the year they turned age 14 (threshold age for completely compulsory schooling) and as such were subject to the pre-reform education system. We will utilize of this sample of 9,156 individuals and 392,941 person-year observations to estimate our structural model, accounting for key features of the pre-reform education system, and refer to this as the estimation sample. We will use the remaining sample of 127,136 post-reform individuals and 5,447,302 person-year observations to validate the structural model, and refer to this as the validation sample.

**Education**  Our education information is primarily based on the Norwegian National Education Database (NUDB), which is many respects is an ideal dataset to study the enrollment, drop-out and completion behavior of individuals across time. The NUDB is an event-history dataset providing population-wide information on the dates of each enrollment and exit within a 6-digit educational course code across all lower secondary educations to tertiary educations. The detailed classification of educational course codes allows distinguishing educations by the level of attainment, the standard length of each course/degree, and the type of field for secondary (vocational/academic) and tertiary educations. Each entry in this dataset further has information on the outcome of each enrollment, e.g., allowing the researcher to distinguish drop-out/early terminations and successful completions of a course, and whether the individual was enrolled as a part-time or as a full-time attendant in a specific course.

Combining information obtained from the NUDB and Statistics Norway’s Education Register, where the latter also comprises information on compulsory education attainment, we can classify individuals’ educational choices in a detailed manner across all education levels.\(^9\) Noteworthy, information in both the NUDB and the Education Register is based on the annual reports submitted by educational establishments for each of their attendants directly to Statis-

\(^9\)Earlier studies on the returns to education in Norway have relied on Statistics Norway’s Education Register and used information on an individual’s highest completed education level or the years of schooling corresponding to the highest level of education, see, e.g., Aryal et al. (2022), Bhuller et al. (2017) and Aakvik et al. (2010). Neither of these studies consider the ex-ante returns or the option value of educational choices.
Earnings Our earnings data are based on annual tax records. Our earnings measure is the sum of labor income (from wages and self-employment) and work-related cash transfers (such as unemployment benefits and short-term sickness benefits). This dataset have several advantages over those available in most countries. First, there is no attrition from the original sample other than natural attrition due to either death or out-migration. Second, our earnings data pertain to all individuals, and are not limited to some sectors or occupations. Third, we can construct long earnings histories that allow us estimate the returns to education across the life-cycle.

Ability An important measure we exploit in our analysis to capture observational heterogeneity is an IQ test score accessed from the Norwegian Armed Forces. In Norway, military service was compulsory for all able males in the birth cohorts we study. Before each male entered the service, his medical and psychological suitability was assessed. Most eligible Norwegian males in our sample took this test around their 18th birthday. The IQ test score is a composite unweighted mean from three speeded tests--arithmetics, word similarities, and figures (Sundet et al. (2004)). The score is reported in stanine (standard nine) units, a method of standardizing raw scores into a 9-point standard scale with a normal distribution, a mean of 5.8, and a standard deviation of 1.7. This score is strongly related to individuals’ actual completed education, with a correlation of around 0.5 with years of schooling in our analytical sample.

Descriptive Statistics Figure 4 provides descriptive statistics for key variables in our dataset. In each panel, we categorize individuals as either low (scores 1-4), medium (scores 5-6) or high (scores 7-9) ability. Panel (a) shows the distributions of final years of education, where we find clear associations between education and ability. Panel (b) shows the fraction of individuals enrolled in education at each age. Individuals are more likely to attend education during the early part of their life-cycle, with gradual declines in the enrollment rate up to age 30, and virtually no enrollment beyond age 33. Next, in panels (c)-(d), we consider the conditional exit and re-enrollment rates, focusing on the earlier part of the life-cycle. The exit rate is substantially higher among low- and medium-ability individuals, while high-ability individuals have consistently higher re-enrollment. Panel (e) illustrates the choices of academic and vocational tracks in middle and high school, reflecting clear ability-related differences in track choices.
Figure 4: Descriptive Statistics.

(a) Distribution of Final Years of Education  (b) Fraction Enrolled in Education by Age

(c) Exit Rate By Age  (d) Re-enrollment Rate by Age

(e) Track Choice in Middle/High School  (f) Fraction working by age

(g) Mean Earnings by Age  (h) Standard Deviation of Earnings by Age

Note: The sample consists of Norwegian males born 1955-1960, who grew up up in a municipality which hadn’t implemented the compulsory schooling reform by the year they turned age 14 (see details in Section 3.2). Individual are followed over ages 15–58, corresponding to calendar years 1970–2018, unless there is natural attrition due to death or out-migration. Individuals’ ability is split in three discrete categories, constructed as low (stanine IQ scores 1-4), medium (scores 5-6) and high (scores 7-9). N=9,143.
Next, panel (f) in Figure 4 shows the work-participation rates by ability. While low-ability individuals reach an employment rate of 96 percent already at age 20, high- and medium-ability individuals gradually increase their employment rates until age 30. Beyond age 30, the employment rates remain relatively stable across all groups, though low-ability have earlier labor market exits. Panels (g)-(h) show age-specific means and standard deviations of annual earnings (in 1000s, 2015-Norwegian Kroner) conditional on working, respectively, by ability. The age-earnings profiles are increasing for all ability groups up to age 45, aside from a temporary drop in earnings at ages 19/20 due to military service. Standard deviations of earnings are quite stable in the earlier parts of the life-cycle and relatively similar across ability groups, while there is a large increase after age 35, especially among high-ability individuals.

**Figure 5: Illustration of the Decision Tree and Transition Rates.**

Besides some of the key moments of our dataset that are illustrated in Figure 4, our model implementation will also rely crucially on the fractions of individuals who transit between different choices over their life-cycle. To illustrate the rich transition patterns present in our data, in Figure 5 we consider individuals who were enrolled in the vocational track at ages 15 to 16 after having completed compulsory schooling at age 14, and follow their transition histories over the following three years in our data. Around 79% of these individuals continue in the vocational track for a third year while 10% switch to an academic track. Only 8% enter the labor market, and 3% stay at home. Among the 3% that decide to stay at home for one period, roughly 8% re-enroll in an academic or vocational school. These rich patterns of (i) persistence in choices over time, (ii) presence of track switching, and (iii) re-enrollment after spells of work or home stay provide a motivation for the flexible modelling of schooling choices in Section 2.
3.2 The Norwegian Education System

We describe here the structure of the Norwegian education system that existed in the 1960s, which our model is specified to fit. This system had four main stages, as shown in Figure 6.

The first stage consisted of seven years of compulsory elementary education. The second stage involved tracking, where pupils could attend either a vocational middle school (framhaldsskole) or an academic middle school (realskole). The vocational middle school could be either one, two or three years, with most attending two years, while the academic middle school could be either two or three years, where the final year was only required for those who wanted to later pursue further academic education. The third stage corresponded to a high school education, which again was track-specific. After attending the academic middle school, students could move on to attend a academic high school (gymnas). In contrast, pupils attending the vocational middle school normally didn’t qualify for the academic high school, but could rather attend a vocational high school (yrkesskole). The academic high school was required to be three years, while the vocational high school could be of varying lengths, depending on the particular vocational field. Finally, the fourth stage involved higher education, leading up to an academic degree.

Figure 6: Illustration of the Norwegian Education System in 1960s.

Note: This figure illustrates the Norwegian education system following the 1959 legislation (Lov om folkeskolen 1959), when only seven years of elementary schooling was compulsory. Solid black arrows indicate the typical paths that pupils could take as they traverse through the school system, while dotted black (gray) arrows indicate switching between tracks (considered particularly difficult or associated with additional requirements). Following the subsequent legislation in 1969 (Lov om grunnskolen 1969), the compulsory schooling was extended to nine years, which was rolled-out in a staggered manner between 1960 and 1975 (see details in Section 3.4). Our baseline analysis uses individuals born between 1955-1960, who faced the pre-reform education system. In 1974, a new type of comprehensive high school (videregående skole) was introduced, which made track switching easier. The latter system remained in place up to the mid-1990s, when two reforms (Reform 94 and Reform 97) were enacted, which altered the structure of high school education and lowered the school starting age to six, respectively. See further details in Bertrand et al. (2021).
degree at a college or a university, enrollment to which was typically contingent on having completed the academic high school. There existed two main degrees in tertiary education; a 4 year degree (cand.mag) and a 6 year degree (hovedfag), while degrees of other durations also existed.

3.3 Model Implementation and Estimation

The model we described in Section 2 is set up as a standard Markov decision process (MDP), which can be solved by a simple backward induction procedure (Puterman 1994; White 1993; Rust 1994). In the final period T, there is no future to consider, and the optimal action is choosing the alternative with the highest immediate utility in each state. With the decision rule for the final period, we can determine all other optimal decisions recursively.

We use the method of simulated moments (Pakes and Pollard 1989; Duffie and Singelton 1993) to estimate the 61 parameters $\hat{\theta}$ of the model for each ability group, i.e., a total of $61 \times 3 = 183$ parameters. Equation 5 shows our criterion function. We select the parameterization for our analysis that minimizes the weighted squared distance between our specified set of moments computed on the observed $M_D$ and the simulated data $M_S(\theta)$. We weigh the moments with a diagonal matrix $W$ that contains the variances of the observed moments (Altonji and Segal 1996) and use a global version of the BOBYQA algorithm (Powell 2009) for the derivative-free optimization of the criterion function (Cartis et al. 2019). We simulate a sample of 50,000 individuals based on the candidate parameterizations of the model.

$$\hat{\theta} = \arg\min_{\theta \in \Theta} (M_D - M_S(\theta))W^{-1}(M_D - M_S(\theta))'$$ (5)

Table I provides an overview of the 1,692 empirical moments used in our estimation. These consist of aggregate moments of annual earnings (type I and II), aggregate annual choice proportions in each alternative (type III to VI), and the distribution of final years of schooling (type VII). Moments of type I to VI each have 264 moments that are calculated for each of the 44 periods in our model between ages 15 to 58, the three ability groups, and an indicator for residing in an area with a local high school during childhood, i.e., $44 \times 3 \times 2 = 264$ unique moments. Type VII captures the distribution of final years of schooling, which can take a total of 18 values between 7 and 25 years of completed schooling at the end of the life-cycle, calculated for the three ability groups by local high school availability, i.e., $18 \times 3 \times 2 = 108$ unique moments.\footnote{11}

\footnote{10}{We use our group’s open-source research code respy (Gabler and Raabe 2020) that allows for the flexible specification, simulation, and estimation of EKW models. Detailed documentation of our software and its numerical components is available at http://respy.readthedocs.io}

\footnote{11}{To ease the computational burden, we impose an upper limit of 25 years of completed schooling.}
These moments are selected to determine the various components of our model. While as described above all moments are used jointly in the estimation procedure, we can nonetheless provide some heuristic arguments for how these various moments aide identification. The information on average earnings in each period along with information on the proportion of individuals attending schooling by year in each track allows us to pin down the parameters of the wage component that determine the immediate pecuniary utility from working. Intuitively, the movements in aggregate wages across periods where people with more schooling enter the labor market allow us to identify the wage rewards to additional years of schooling. And, aggregate wages across periods where more high school graduates enter the labor market allow us to identify the wage rewards to a high school degree. Including the distribution of final years of schooling as an additional set of moments further allows recovering non-linearities in the wage-schooling relationship and associated bunching at specific degrees.\footnote{Note that we do not rely on the cross-sectional wage-schooling relationship directly in our estimation, as these moments usually suffer from problems related to endogeneity of schooling and sample selection bias. Using the distribution of final years of schooling and average earnings and choice shares by period, we can nonetheless recover the parameters of the wage-schooling relationship in a relatively flexible manner.} Similar arguments apply for the identification of wage rewards to additional years of labor market experience.

### Table 1: Summary of Moments Used in the Estimation.

| Type of Moment                                      | Number |
|-----------------------------------------------------|--------|
| I. Average of Annual Earnings Per Period             | 264    |
| II. Standard Deviation of Annual Earnings Per Period | 264    |
| III. Fraction in Academic Schooling Per Period       | 264    |
| IV. Fraction in Vocational Schooling Per Period      | 264    |
| V. Fraction Working Per Period                       | 264    |
| VI. Fraction Staying at Home Per Period              | 264    |
| VII. Distribution of Final Years of Schooling       | 108    |

*Note:* This table provides an overview of the 1,692 moments used in the estimation by the type of moment. Moments of type I to VI are each calculated for the 44 periods in our model between ages 15 to 58, high/medium/low ability type, and an indicator for residing in an area with a local high school during childhood, i.e., $44 \times 3 \times 2 = 264$ unique moments. Moments of type VII capture the distribution of final years of schooling, which can take a total of 18 values between 7 and 25 years of completed schooling, calculated for each of the three ability types and local high school availability, i.e., $18 \times 3 \times 2 = 108$ unique moments.

The non-pecuniary rewards associated with working are identified through variation in work choices across periods that cannot be fully captured by changes in annual earnings across periods. Similarly, non-pecuniary rewards of schooling are identified through variation in schooling choices across periods that cannot be fully captured by changes in annual earnings across peri-
ods. Allowing these moments to vary by local high school availability facilitates identification of the costs of geographic mobility or commuting, which enter the immediate rewards of academic and vocational schooling. By including all moments by ability, we can further allow each parameter to be heterogeneous. The distribution of shocks is identified by the dispersion in moments conditional on being in a state. For instance, residual variance in annual earnings that cannot be explained by observed heterogeneity helps us to identify the variance of productivity shocks. Similar arguments apply for the identification of taste shocks associated with the other alternatives. Finally, the latent heterogeneity types are identified as the set of discrete taste shifters that capture persistence in choices over time and minimize residual heterogeneity.

3.4 Model Validation

We now demonstrate our model’s credibility by discussing some selected parameter estimates and comparing them to the existing literature. We then report the estimated model’s in-sample model fit and discuss the results from an out-of-sample validation based on a schooling reform.

Parameter Estimates

All parameter estimates are reported in Appendix, Section A.2 along with the associated standard errors based on simulation-based inference. In the following, we discuss some of these estimates. Most of our parameter estimates are standard and in line with the previous literature [Eisenhauer et al., 2015; Keane and Wolpin, 1997]. The annual discount rate is about 4% for all ability levels. Returns to experience are concave and unobserved types play an important role in shaping schooling decisions even within ability groups. The cost of re-enrollment in school after dropping out is very high. There are interesting differences in the wage rewards to academic and vocational schooling by ability. For the vocational choice, the wage rewards are highest for low ability individuals where wages increase by 16% with an additional year compared to only 13% for high ability individuals. The pattern reverses for the academic choice, where the wage rewards are highest for high ability individuals, for whom another year of schooling increases wages by 18%, but only by 11% among low ability individuals. The associated non-pecuniary rewards reinforce the sorting of high-ability individuals into academic and low-ability individuals into a vocational school. For example, the non-pecuniary benefits from an academic education are negative for low ability individuals but positive for high ability.

In-Sample Model Fit

We now assess our model’s ability to reproduce the overall patterns of choices and earnings by comparing our simulated sample to the observed data. Figure 7 shows the shares of individuals deciding to either attend academic (panel a) or vocational (panel b) school, work (panel c) or stay at home (panel d). The model predictions (black solid lines) are closely aligned with the observed patterns in our data (dotted gray lines), but we fail to account for the stark drop in academic schooling at ages 19/20, which in the data is associated with compulsory military service not captured in our model. Next, we show the model fit for
Figure 7: Model Fit.

(a) Academic Schooling  
(b) Vocational Schooling  
(c) Working  
(d) Staying at Home  
(e) Average Earnings  
(f) Standard Deviation Earnings

Note: The figure is based on averaging across 10,000 simulated life-cycle profiles using the estimated model.

the average (panel e) and standard deviation (panel f) of annual earnings by age. Our model does an excellent job of reproducing these basic patterns over the life cycle as well.

Out-of-Sample Model Validation  We now assess the out-of-sample performance of our model. For this purpose, we rely on variation in schooling choices coming from a compulsory schooling reform. As discussed in Black et al. (2005), since 1959, seven years of elementary education had been compulsory in Norway. However, each municipality—the lowest level of local
administration—was allowed to enact nine years of compulsory school, i.e., *two additional years beyond the national minimum requirement*. In subsequent legislation in 1969, nine years of elementary education (*grunnskole*) was made compulsory throughout Norway. Due to the lack of resources some municipalities nevertheless didn’t enforce nine years of compulsory education before 1974. These features led to substantial geographic variation in compulsory education across Norway between 1960 and 1975. For more than a decade, Norwegian schools were divided into two separate systems, where the length of compulsory schooling depended on the birth year and the municipality of residence at age 14, i.e., the childhood municipality.

**Figure 8:** Out-of-Sample Validation Using Compulsory Schooling Reform.

![Graph showing simulated and observed changes in final schooling years.](image)

*Note:* The figure is based on two samples of 10,000 simulated schooling careers based on the estimated model. We first simulate the model with seven years of compulsory schooling, as in our baseline simulations. Next, we rerun the simulation but impose nine years of compulsory schooling. Throughout, we keep the random realizations of the productivity and taste shocks $\epsilon_t$ fixed, and we are thus able to compare the schooling decisions of the same individual under the two different regimes. The black bars *Simulated change* show the percentage points differences in the fraction of individuals that leave school with twelve years of final schooling and those that leave with sixteen years of final schooling, respectively. The gray bars *Observed change* show the same difference in the observed data before and after the reform. We do not distinguish between vocational and academic tracks in this calculation.

We exploit the Norwegian compulsory schooling reform to validate our model in the following manner. First, as described in Section 3.1, our model is estimated solely using data on individuals born 1955–1960 who were subject to the pre-reform education system, and is geared to capture the schooling system that exited pre-reform. Second, for the purposes of model validation, we constraint the choice sets in a modified version of our model where individuals cannot leave schooling before nine years to reflect the implementation of a nine year compulsory

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13 The staggered roll-out of the compulsory schooling reform in Norway has led to extensive literature relying on quasi-experimental designs to study the causal effects of schooling on various outcomes, see, e.g., Black et al. (2005), Monstad et al. (2008), Aakvik et al. (2010), Machin et al. (2012), Bhuller et al. (2017), and Aryal et al. (2022). None of these studies consider the ex-ante returns or the option values of schooling choices.
schooling. We then compare the predicted changes in education choices in our model to the observed differences in education choices across pre- and post-reform cohorts born 1955–1960, respectively. Finally, in order to provide an insightful and strong validation of our model, we focus on “inframarginal” responses beyond the new minimum schooling requirement. We focus on such responses as the reform is mechanically expected to induce increases in educational attainment up to the new minimum schooling requirement among those who otherwise would have had less than nine years of schooling, both in the observed data and in our model, while it is less clear how educational choices beyond the new minimum schooling requirement are affected.

Figure 8 provides the results of our validation exercise. We compare the predicted changes in the fractions of individuals leaving with 12 years (high school degree) of schooling and 16 years (college), respectively, in model simulations pre- and post-reform to the corresponding changes observed in actual data. This exercise highlights the main motivation of our modelling approach as there are indeed changes in the distribution of education attainment across margins that are not directly affected by the policy reform, and the model does predict that there will be such “inframarginal” responses. We predict an increase in graduation rates of 3.2% for high school and 0.3% for college. In the validation sample, the share of individuals with a high school degree increases by 2.5% and the share of college graduates by 0.3%. Thus, our model predictions slightly exceed the increase in high school graduates, while we are spot-on for college graduation. In a nutshell, the predictions from our model line up with the observed changes. We return to these findings in Section 4.3, where we provide additional evidence on economic mechanisms from our model that shed more light on the nature of these responses.

4 Empirical Results

We now present our empirical findings based on the estimated model. We first document heterogeneity in ex-ante returns by year of schooling, choices of academic and vocational track, and ability, before we consider the importance of option values in schooling decisions, and finally investigate the impacts of alternative schooling reforms. In these calculations, we simulate life-cycle histories for 10,000 individuals for each ability group using the estimated model.

4.1 Evidence on Ex-ante Returns

To construct measures of ex-ante returns to schooling, we will compare the discounted lifetime value of attending schooling in a particular track in a given period in our model to the corresponding value associated with the best alternative choice. Notably, since our model allows for re-enrollment in a flexible manner, the best alternative choice can include the possibility of
attending more education at a later stage in the life-cycle. Individuals can thus reach a given level of final schooling at the end of their life-cycle through many different paths due to the opportunities of track switching and re-enrollment. To ease interpretation and tractability of our findings, we will therefore focus on individuals who in our model have had uninterrupted schooling careers in given track up to the period where we explore the ex-ante returns associated with different schooling choices. To avoid our results to be driven by a small number of individuals, we will drop particular transitions in our expositions for groups who have less than 0.5% chance of reaching such transitions (e.g., low ability individuals attending college).

**Ex-ante Returns By Track and Ability** Figure 9 shows our main evidence on the ex-ante returns to continue schooling in academic or vocational track for another year and individual ability type. The returns are shown for each year of schooling along the horizontal axis and are computed for individuals that have reached this particular stage and are faced with the decision to continue schooling, i.e., the bars at 10 years illustrate the average ex-ante returns of attending the 10th grade by track and ability for individuals who have completed 9 years of schooling in this track in an uninterrupted spell. As we move towards right in each panel, the illustrate returns pertain to only individuals who actually reach those stages in our model. At each stage, these returns capture both the immediate rewards and the discounted future rewards. In this sense, the model allows us to estimate the average dynamic treatment effect for those facing this treatment choice (Heckman et al., 2016; Heckman and Navarro, 2007).

Figure 9: Average Ex-ante Returns to Academic and Vocational Schooling.

(a) Academic Schooling

(b) Vocational Schooling

*Note:* The figure is based on samples of 10,000 simulated schooling careers for each ability group based on the estimated model. This figure contains average ex-ante returns for each year-track-ability cell. The left figure shows how ex-ante returns to academic schooling develop over time for each group while the right figure shows the same for the vocational track. Each bar shows the average ex-ante return to a particular year of schooling for the individuals in the respective ability group that reaches the relevant transition in our model. For instance, the bar for the high-ability group in the academic panel in year 11 shows the average ex-ante return of the 11th overall high-ability individuals that have had an uninterrupted academic schooling career until the 10th year. We compute the ex-ante return as defined in Equation (3). Whenever there are only a few people of a particular ability group that reach a particular transition we do omit this group from the calculation.

We find substantial heterogeneity in the average ex-ante returns by ability, track choice and
year of schooling. The returns range from $-2\%$ for the 8th grade in the academic track for low-ability individuals up to $3\%$ for medium-ability for the 9th year in the vocational track. Underlying this heterogeneity is a strong pattern of sorting into academic and vocational tracks by ability, which in our model is both caused by differences in wage rewards and preference heterogeneity. Indeed, the structure of the 8th grade returns reflects the separation of the ability groups in the different schooling tracks at an early stage of the educational pathways, consistent with the descriptive evidence in Figure 4 panel (e). The average return to vocational track at the 8th year is negative at $-1\%$ for high-ability individuals, so the majority of them never enter vocational school. The opposite is true for low-ability individuals, for whom the returns to an academic track are negative initially, pushing them into vocational schooling instead. Indeed, about $83\%$ of low-ability individuals never attend an academic school. As we move towards right in panel (a), we notice that the returns to academic schooling remain consistently positive only for high-ability individuals. In each track, we find the highest returns for transitions that entail a middle school degree at the 9th year, with gradually decreasing returns as we progress further.

**The Distributions of Ex-ante Returns** The average returns in Figure 9 can mask considerable heterogeneity in returns by track choice across individuals with the same ability facing identical choices. For instance, Wiswall and Zafar (2015) and Attanasio and Kaufmann (2017) document substantial heterogeneity in ex-ante returns using survey data on subjective expectations. In our model, heterogeneous returns across observationally similar individuals, i.e., those from the same ability group who have reached the same stage of the decision tree after an uninterrupted spell, are represented through the presence of heterogeneous latent types and different realizations of shocks to productivity and tastes associated with different choices.

To illustrate heterogeneity in ex-ante returns, we now focus in Figure 10 on individuals in each ability group who in our model faced the choices of 11th and 15th year of academic schooling and 8th and 11th year of vocational schooling, respectively. In panel (b), we see that the average return of the 11th year of academic schooling is positive for both high- and medium-ability groups, but also that a considerable share within each group has negative returns. In our model, all individuals with negative returns to academic schooling would decide not to attend academic schooling as this choice is (in expectation) dominated by the best alternative choice. They might, however, pursue academic school later as this does not rule out the possibility of re-enrollment. In panel (b), we also see that the distributions overlap, so there are many individuals of medium-ability for whom returns to the 11th year of academic schooling are higher than for high-ability individuals. Overall, the distribution of returns is more spread out among high-ability individuals at that transition. In panel (a), we see the distributions of returns to the 15th year of academic schooling are more similar across ability groups, reflecting that
fewer among the high-ability group go on to attend the 15th year as compared to the 11th year.

**Figure 10:** Distributions of Ex-Ante Returns to Academic and Vocational Schooling.

(a) Academic Schooling at 15th Year

(b) Academic Schooling at 11th Year

(c) Vocational Schooling at 11th Year

(d) Vocational Schooling at 8th Year

*Note:* The figure is based on samples of 10,000 simulated schooling careers for each ability group based on the estimated model. Each panel shows the distribution of ex-ante returns to a particular schooling choice by ability who those with an uninterrupted schooling career up to that point who have reached this transition. For instance, in panel (a), we show the distribution of ex-ante returns to the 15th year of academic schooling for all individuals with uninterrupted schooling careers up to that point. We compute the ex-ante return as defined in Equation (3). The heterogeneity in returns follow from the permanent differences across latent types $e$ and the realizations of transitory shocks $\epsilon_t$. Whenever there are only a few people of a particular ability group that reach a particular transition we do omit this group from the calculation.

Next, in Figure 10 panels (c)-(d), we consider the distributions of returns to 11th and 8th year of vocational schooling, respectively. In these plots, we include all three ability groups as sufficiently many from each group are present at these transitions in our model. We find interesting ability-related patterns in panel (d), where the majority of low-ability individuals have positive returns to 8th year of vocational schooling, while the majority of high-ability individuals have negative returns. These results reflect the strong patterns of ability-related sorting at the 8th year schooling tracks. By contrast, the distributions of returns are much more similar in panel (c), reflecting that conditional on having reached the 10th year of vocational schooling, the transition rates to 11th year of vocational school do not differ substantially across ability groups. This finding may reflect that there are latent types among high- and medium-ability individuals with a high propensity to attend vocational schooling, and these types stay in vo-
The Role of Re-enrollment. A salient aspect of our model—crucial in interpreting the results above—is the individuals’ ability to re-enroll in school after having exited and undergone a non-schooling spell. Indeed, the relatively low average ex-ante returns in Figure 9 can be partly attributed to the fact that many individuals come back to school to pursue more education. In an attempt to illustrate this feature of our model, we show the final schooling level for individuals that initially leave school after the 8th grade in either track by ability in Figure 11. Among low ability individuals, dropping out at that stage determines the final schooling level for about 90%. Only 10% do still acquire their middle school degree at a later stage. For high-ability individuals, however, the large majority do continue their schooling at some point. Roughly 85% do eventually end up with at least a middle school degree, and 30% even continue to obtain at least a high school degree. We need to keep this feature of our model in mind when interpreting average ex-ante returns at each transition that are presented above.

Figure 11: The Final Years of Schooling for those Exiting School at the 8th Grade.

Note: The figure is based on samples of 10,000 simulated schooling careers for each ability group based on the estimated model. We further restrict the sample to 1,580 individuals who continue their schooling for only one additional year and then initially drop out of school at the 8th year of schooling, i.e., early drop-outs. We determine an individual’s final schooling level as the sum of the years spent in academic and vocational school.

The Role of Shocks to Productivity and Tastes. Given the evidence on strong ability-related sorting into different tracks, substantial heterogeneity in ex-ante returns within ability types by track and the wide prevalence of interruptions and re-enrollments in education careers, it is natural to consider the extent to which these patterns are related to the transitory shocks to productivity and tastes. To shed light on these aspects through the lens of our model, we
perform a series of comparative statics, where we re-compute average ex-ante returns by ability and track shutting off various sources of shocks and compare the findings to our baseline model.

Figure 12 summarizes our findings from these exercises. To facilitate comparison, panel A reports estimates of average ex-ante returns by ability and track from our baseline model (as in Figure 9), while panel B shows the corresponding estimates from a version of the model where we remove shocks to productivity (i.e., no wage risk), while in panel C we further also remove unobserved transitory shocks related to tastes for schooling, working or staying at home. This illustration provides a few additional insights. While high-ability individuals have the highest ex-ante returns to academic schooling across all panels, the returns to the 8th year of academic (vocational) schooling for low (high) ability individuals are no longer negative once productivity shocks are turned off (panel B). This pattern becomes even stronger once we also remove taste shocks (panel C). These comparative statics imply that the strong patterns of ability-related sorting into tracks in the early stage of educational careers in our model are partly explained by (i) positive returns to academic schooling for high-ability types, irrespective of their taste preferences or presence of wage risk, (ii) negative returns to academic schooling for low-ability types stemming from a combination of taste and productivity shocks, and (iii) negative returns to vocational schooling for high-ability types stemming from a combination of taste and productivity shocks. Indeed, when both taste and productivity shocks are removed, the returns to vocational schooling are relatively homogeneous across ability groups (panel C).

**Ex-ante and Ex-post Returns** The preceding analysis have been focused on ex-ante returns, i.e., the relative rewards that agents in our model base their decisions on. We now contrast our estimates of ex-ante returns to another set of objects which we refer to as ex-post returns. The latter returns are based on our baseline model with taste and productivity shocks turned on, but where we use the actual realizations of shocks rather than the agents’ expectations about these to calculate their returns to difference choices. Since our model assumes rational expectations, on average, ex-ante and ex-post returns must agree. However, there does exist a non-degenerate joint distribution of ex-ante and ex-post returns across agents. To construct measures of ex-post returns, we limit attention to individuals in our model who ended up selecting specific schooling choices and retain the realization of shocks they were exposed to as they traversed through their decision trees. By construction, the ex-ante returns for these individuals for the set of schooling choices they ended up making are strictly positive. To provide a comparison of the ex-ante and ex-post returns, we compare both the expected and the realized utility flows to the expected values of the next best alternatives the individuals faced.

Figure 13 presents the joint distribution of ex-ante and ex-post returns for a random set of 500
Figure 12: Average Ex-ante Returns – The Role of Shocks to Productivity and Tastes.

Panel A. Baseline Model

(A-1) Academic Schooling

(B-1) Academic Schooling

Panel B. No Shocks to Productivity

(A-2) Vocational Schooling

(B-2) Vocational Schooling

Panel C. No Shocks to Productivity and Tastes

(C-1) Academic Schooling

(C-2) Vocational Schooling

Note: The figure is based on samples of 10,000 simulated schooling careers for each ability group based on the estimated model under different specifications of transitory shocks. Each panel contains average ex-ante returns for each year-track-ability cell for alternative model specifications. Panel A shows results based on the baseline model, while panel B removes shocks to productivity (i.e., no wage risk) and panel C further also removes taste shocks. In each panel, the left figure shows how ex-ante returns to academic schooling develop over time for each group while the right figure shows the same for the vocational track. Each bar shows the average ex-ante return to a particular year of schooling for the subset of the respective ability group that has reached the relevant transition in our model. For instance, the bar for the high-ability group in the academic panel in year 11 shows the average ex-ante return of the 11th year for those that have had an uninterrupted academic schooling career until the 10th year. We compute the ex-ante return as defined in Equation (3). Whenever there are only a few people of a particular ability group that reaches a particular transition we do omit this group from the calculation.
Figure 13: Joint Distributions of Ex-Ante and Ex-post Returns.

(a) Academic Schooling at 15th Year

(b) Academic Schooling at 11th Year

(c) Vocational Schooling at 11th Year

(d) Vocational Schooling at 8th Year

Note: The figure is based on samples of 10,000 simulated schooling careers for each ability group based on the estimated model. We then restrict the sample to 500 random individuals with uninterrupted careers in the respective period for a particular track. Each panel shows the joint distributions of ex-ante and ex-post returns to a particular schooling choice in either academic or vocational track. Ex-post returns are the realized total discounted utilities over the remaining decision periods relative to the value function of the best alternative. The gray area shows all points where the realized return is smaller than the expected return from the second best option. Ex-ante return as defined in Equation (3). Whenever there are only a few people of a particular ability group that reaches a particular transition we do omit this group from the calculation.

individuals from our model at each transition. As expected, the ex-ante return are always positive by construction in each panel. However, the shaded areas indicate that the ex-post returns from pursuing an education were negative for some individuals, i.e., they faced regret due to the actual shock realizations. We also note that the ex-post returns to the 8th year of vocational schooling are relatively dispersed. As this decision made early in the life-cycle, agents face very different life-time trajectories subject to the future shock realizations and choices. By contrast, the ex-post returns to the 15th year of academic schooling are relatively compressed. As most individuals would go on to attend the 16th year to attain a college degree and then enter the labor market, these ex-post returns are associated with more similar life-time trajectories. These findings also demonstrate how uncertainty is highest at the beginning of the life-cycle and the choices made early on are more consequential in a dynamic setting like ours.
4.2 Evidence on Option Values

Part of the overall value to a schooling choice is the option to continue schooling further. We now provide evidence on such option values based on our model. To construct measures of option values to schooling, we will compare the discounted lifetime value of attending schooling in a particular track in a given period in our model to the corresponding value of the same schooling track under a counterfactual policy where the individual is prohibited from making a schooling choice in any future period. As earlier, we will focus on individuals who in our model have had uninterrupted schooling careers in given track up to the period where we explore the option values associated with a schooling track choice.

Option Value Contributions By Track and Ability

Figure 14 shows the contribution of the option value to the overall value of a schooling track by the year of schooling and ability. The option value contributions in the academic track range from 7% for the 11th year to almost zero beyond the 15th year of schooling. A recurring pattern is that the option value contribution is always the highest for the year of schooling right before the completion of an academic degree that entails considerable “diploma” effects. We also find sizeable heterogeneity by ability level. The option value contributions in the academic track tend to be the highest for high-ability individuals, as they are also likely to benefit the most from the additional schooling opportunities that open up from taking an extra year of schooling. By contrast, in the vocational track, the option value contributions are the highest at the 8th year of schooling and of a comparable order of magnitude across ability groups. This pattern may reflect that most attending this track go on to complete the 9th year in vocational school, irrespective of ability. Among those who progress further in vocational schooling, we again find a strong ability gradient. This likely reflects that among this group, also the high-ability individuals have the highest gain from attending the 10th and 11th year, and reach a vocational high school degree.

While the previous illustration provides evidence on the option value contributions, measured as a fraction of the overall value of a choice, we now provide more direct evidence on how the option value channel can play a crucial role in shaping schooling careers. To get at this, we perform counterfactual experiments based on our model where we turn on and off the option value of a choice and characterize the schooling decisions made by the agents in our model under each scenario. Based on these comparisons and inspired by the IV/LATE complier characterizations done in the program evaluation literature (e.g., Angrist et al. (1996)), we perform a characterization of agents into three groups; always-takers, never-takers and marginal agents (or compliers). Agents that always (never) decide to take another year of schooling when faced with this choice, irrespective of the option value, are characterized as always-takers (never-takers). While, agents that decide to take another year of schooling when the option value is
Figure 14: The Option Value Contributions of Academic and Vocational Schooling.

(a) Academic Schooling

(b) Vocational Schooling

Note: The figure is based on samples of 10,000 simulated schooling careers for each ability group based on the estimated model. We restrict the sample to individuals with uninterrupted schooling careers up the relevant transition using the estimated model. The left figure shows how option value contributions for academic schooling develop over time for each group while the right figure shows the same for the vocational track. The option value contribution is defined in Equation (4). Whenever there are only a few people of a particular ability group that reaches a particular transition we do omit this group from the calculation.

turned on but not when it is off are characterized as marginal (i.e., compliers). By construction, monotonicity is satisfied, as for given shock realizations, agents in our model are never more likely to take more schooling when the option value is turned off compared to when it is on.

Figure 15 illustrates our evidence based on the complier characterizations described above. In panels (a)-(b), we focus on high-ability individuals who faced the decision to continue their schooling for the 11th and 12th year in the academic track. These figures provide interesting illustrations of how important option values can be close to the degree-rewarding schooling choices. Among those facing the decision to continue their academic schooling in the 11th year, we find that a large majority at 82% among the high-ability individuals consists of marginal compliers, i.e., individuals who continue for another year of schooling only because of the option value stemming from being able to complete a high school degree right afterwards. By contrast, fewer than 1% are always-takers, who move ahead with their schooling even when no future schooling opportunities are available, and about 18% are never-takers, who drop out regardless. The picture is somewhat different at the 12th year of academic schooling. The fraction of always-takers rises drastically to 29% as completing the high school degree provides immediate considerable wage rewards. For 53% the option value of the high school diploma is crucial to complete the 12th year, as receiving this diploma opens up the possibility of attending college. Still, 18% drop-out and do not complete high school regardless of the option value.

Next, in panels (c)-(d) of Figure 15 we consider all individuals (irrespective of ability) who faced the decision to continue their schooling for the 8th and 9th year in the vocational track. Option values in the vocational track arise primarily at the 8th year of schooling as this gives
**Figure 15:** ‘Complier’ Characterization – Switching Off the Option Value.

(a) Academic Schooling at 11th Year (b) Academic Schooling at 12th Year

(c) Vocational Schooling at 8th Year (d) Vocational Schooling at 9th Year

**Note:** The figure is based on samples of 10,000 simulated schooling careers for each ability group based on the estimated model. Panels (a)-(b) are restricted to high-ability individuals, while panels (c)-(d) average across all ability groups. Each panel provides a complier characterization based on model simulations where we turn off the option value of a particular schooling choice. This calculation compares the total value of schooling and the value of schooling net of the option value contribution to the next best alternative. The option value contribution is defined in Equation (4). Always-takers (never-takers) always (never) choose to continue with another year of schooling, irrespective of the option value contribution, while marginal individuals take the additional year only because of the option value contribution. Whenever there are only a few people of a particular ability group that reaches a particular transition we do omit this group from the calculation.

the option to continue later on with the 9th year of vocational schooling, i.e., receive a two-year vocational diploma. At the 9th year of vocational schooling, the large majority at 72% of individuals facing this choice are characterized as always-takers, who attend this year due to the immediate wage gains associated with this choice, while the option value associated with the possibility to continue with a vocational high school matters for only 10% of individuals.

**Uncertainty and the Option Value Contributions** In our model, transitory shocks to productivity (i.e., wage risk) and tastes for alternative schooling-work-home choices give rise to uncertainty in agents’ decision-making. We now consider how these sources of uncertainty con-
As in Figure 12, we now perform a series of comparative statics to assess the role of such uncertainty, where we re-compute option values shutting off the various sources of shocks in our model.

**Figure 16:** Option Value Contributions – The Role of Shocks to Productivity and Tastes.

(a) Academic Schooling at 11th Year (Medium)  
(b) Vocational Schooling at 8th Year (Low)

Note: The figure is based on samples of 10,000 simulated schooling careers for each ability group based on alternative model specifications. The left panel shows the different option value contributions for medium-ability individuals for the 11th year of academic schooling, while the right panel shows the option value contributions for low-ability individuals for the 8th year of vocational schooling. The option value contribution is defined in Equation (4). The bars correspond to different model specification; the first bar corresponds to the estimated model, the medium bar corresponds to an adapted version of the estimated model where productivity shocks (i.e., wage risk) is turned off and the final bar to a model where both productivity and taste shocks are turned off. Whenever there are only a few people of a particular ability group that reaches a particular transition we do omit this group from the calculation.

We present in Figure 16 two different scenarios where the presence of transitory shocks has opposite signed effects on the option value contribution in our model. In panel (a), we consider the option value of the 11th year in the academic track for individuals of medium ability under different sources of uncertainty. We first turn off the productivity shocks and then also turn off the taste shocks. In the baseline model, the option value contribution amounts to about 3.2% as most individuals of medium ability continue to at least a high school degree. When we turn off the productivity shocks alone, the option value contribution shrinks by about 0.3 percentage points. It further decreases to about 2.1% in a scenario without any uncertainty. This pattern reflects that the continuation of schooling becomes less likely when we reduce the extent of uncertainty. Specifically, for some of the medium-ability individuals facing the decision to

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**Footnote 14:** The existing literature on learning and educational choices in dynamic settings actually emphasizes uncertainty as the primary source of option values, i.e., individual learn about their own ability and preferences as they progress in their schooling career (Arcidiacono et al., 2016; Trachter, 2015; Stinebrickner and Stinebrickner, 2014; Stange, 2012). As the shocks in our model are distributed independently over time, individuals do not update their prior beliefs about their productivity or alternative-specific tastes, i.e., our model does not feature learning over time. We rather focus on the overall value attached to a schooling choice stemming from the possibility of pursuing further education, and not only the value associated with resolution of uncertainty and learning. The presence of transitory shocks may nonetheless affect individuals’ schooling choices and alter the likelihood of attending further schooling, i.e., option values can depend on the presence of shocks.
attend 11th year of academic schooling, the decision to further attend college is driven by the realization of productivity and/or taste shocks. These individuals decide to attend college only as a result of receiving a low productivity shock, thus facing low opportunity cost of continued schooling, or a high taste shock for schooling. As we successively remove these realizations, the option value of attending the 11th academic year thus declines for these individuals.

In panel (b) of Figure 16, we consider another scenario showing how the presence of transitory shocks affects the option value contribution in our model. Here, we consider the option value of the 8th year in the vocational track for individuals of low ability under different sources of uncertainty. In the baseline model, the option value contribution is sizeable at above 4%. When we turn off the productivity shocks alone, the option value remains almost unchanged, but when we remove taste shocks this value increase to almost 7%. This pattern reflects that some among the low-ability individuals in our baseline model who drop-out at the 8th year of vocational schooling do so due to the realization of taste shocks. Once we remove these shocks from our model, their likelihood of continuing beyond the 8th year increases even further, so that the option value of this choices increases further.

4.3 Policy Evaluation

We now use our model to analyze the impacts of compulsory schooling reforms. First, we provide further evidence on compliance to the Norwegian compulsory schooling reform that we earlier used to validate our model. We show who is affected by the policy along the distribution of schooling by ability and by early drop-out status. Second, we investigate the impacts of a high school enrollment policy, which requires everyone to attend ten years of schooling.

The Norwegian Compulsory Schooling Reform As described in Section 3.4, the Norwegian compulsory schooling reform increased the minimum schooling requirement from seven to nine years, and was gradually introduced in different municipalities in different years. In our analysis thus far we used individuals born 1955-1960 who were not exposed to the reform and relied on the reform variation in an out-of-sample validation of our model. We now use our estimated model to shed light on the compliance to this reform by ability and early drop-out status. In panel (a) of Figure 17, we show the fractions of individuals by their final year of schooling in the baseline scenario (i.e., pre-reform) along the horizontal axis that change their schooling choices due to the reform. By construction, since the post-reform compulsory schooling is nine years, all individuals that previously decided to stop after seven or eight years are affected. Notably, as discussed in Section 3.4, some of these individuals even increase their schooling beyond the new minimum requirement. Such “inframarginal” responses in our model can be explained by
the presence of option values; by forcing individuals to attend nine years of schooling, we also bring them closer to transitions that make a high school diploma within reach.\footnote{Indeed, we relied on the extent of such “inframarginal” responses for the model validation in Section 3.4}

**Figure 17:** Compliance to the Norwegian Compulsory Schooling Reform.

(a) By Ability

(b) By Ability, Among Early Drop-outs

*Note:* The figure is based on two samples of 10,000 simulated schooling careers for each ability group under alternative scenarios. Using the point estimates, we first simulate the model with the original seven years of compulsory schooling. Next, we rerun the simulation but impose nine years of compulsory schooling. Throughout, we keep the random realizations of the productivity and taste shocks $\epsilon_t$ fixed, and we are thus able to compare the schooling decisions of the same individual under the two different regimes. In panel (a), we plot the fractions of individuals who change their schooling decisions for varying levels of final schooling in the baseline scenario along the horizontal axis. In panel (b), we restrict our sample to individuals who initially dropped out after the 8th year of uninterrupted schooling in the baseline scenario and then illustrate the distribution of observed increases in their final schooling due to the policy reform.

More interestingly, our model also predicts alterations in the educational trajectories among those who in the baseline scenario actually had attended nine or more years of schooling. While the presence of option values can trigger the “inframarginal” responses discussed above among those with less than nine years of schooling, an additional mechanism of re-enrollment possibilities is at play when we consider those having nine or more years of schooling pre-reform. Prior of the reform, 10% of individuals had dropped out either after the 7th or 8th grade but then re-enrolled at a later time. Since the reform rules out any interruptions between 7th and 9th year of schooling, the educational trajectories individuals who earlier dropped out after the 7th or 8th grade and re-enrolled are also affected. Indeed, about 40% of those who end up with only nine years of schooling in the baseline scenario increase their final schooling level after the reform. They do so because they no longer face the considerable re-enrollment costs they had to incur in the baseline scenario where they dropped out after the 7th or 8th year.

In panel (b) of Figure 17, we show that the compulsory schooling reform affects individuals who initially dropped out after the 8th year of schooling in our model. Around 20% of the early drop-outs with medium- and high-ability do not increase their final years of schooling.
post reform; these individuals all re-enrolled even in the baseline scenario and attained at least nine years of schooling in the end. Around 30% increase their schooling by one year and thus only meet the new requirement, while around 25% increase their schooling level by four years and thus attain a high school degree after the reform. Taken together, option values and re-enrollment are important channels that are useful to explain these compliance patterns.

**Compulsory High School Enrollment Policy** Another policy we consider next is the introduction of compulsory high school enrollment, which requires all individuals to attend ten years of schooling, i.e., one more year than the Norwegian compulsory schooling reform. Figure 18 compares the distributions of final years of schooling in our model between the simulated reform with the nine year of compulsory schooling (‘Reform 9’) and the compulsory high school enrollment policy (‘Reform 10’). On average, the latter policy increases schooling by yet another 0.5 years and has impacts along the distribution of schooling.

**Figure 18: Compliance to Compulsory High School Enrollment (‘Reform 10’).**

![Figure 18: Compliance to Compulsory High School Enrollment (‘Reform 10’).](image)

*Note:* The figure is based on two samples of 10,000 simulated schooling careers under alternative policies. Using the point estimates, we first simulate the model with the nine years of compulsory schooling (‘Reform 9’). Next, we rerun the simulation but impose ten years of compulsory schooling to illustrate the compulsory high school enrollment policy (‘Reform 10’). Throughout, we keep the random realizations of the productivity and taste shocks $\epsilon_t$ fixed, and we are thus able to compare the schooling decisions of the same individual under the two different regimes. Finally, we illustrate the distributions of final years of schooling under each policy simulation.

Interestingly, we again find evidence of strong “inframarginal” responses; most individuals that are induced to change their schooling level by the compulsory high school enrollment policy indeed go on to complete a high school degree. Overall, the fraction of individuals with at least 12 years of schooling increases from 68% to more than 83%. Most of these increases come from low-ability individuals who increase their graduation rate from about 40% to 63%. By contrast, there are negligible changes in the fractions attending only 10 or 11 years of schooling; those
induced to attend the 10th year due to the policy have a substantial option value of a high school degree and thus go beyond the new minimum requirement.

5 Conclusion

This paper has attempted to provide evidence on the ex-ante returns and option values to educational choices. To achieve this, we devised a dynamic model of schooling decisions in a life-cycle context that acknowledges uncertainty and sequential nature of schooling decisions. We estimated this model using Norwegian population panel data with nearly career-long earnings histories, and validated this against variation in schooling choices induced by a compulsory schooling reform. Finally, we used the structure of our model to learn about the rich patterns of compliance observed in our data and the potential economic mechanisms driving these.

Our analysis gave several interesting insights. The ex-ante returns to schooling vary across the different stages of educational careers, depend on the choice of track and the ability of individuals. Underlying these heterogeneities is a strong pattern of ability-related sorting into different educational tracks. We also find that option values play a dominant role in shaping schooling decisions at several points in the educational career. We also documented how the presence of option values and re-enrollment opportunities could explain the “inframarginal” impacts of compulsory schooling reforms across the distribution of schooling attainment.

While our paper provides several contributions, some shortcomings can be mentioned. Recent studies have emphasized the role of “experimentation” in educational decisions, where individuals make such decisions in view of the returns generated through the subsequent resolution of uncertainty that they are initially faced with (see, e.g., Arcidiacono et al. (2016) and references therein). We regard this as an important stream of research, which highlights another channel for why option values can matter in educational decisions. Our model however does not feature learning and updating of individuals’ prior beliefs, but instead has focused on the analyzing educational decisions in a life-cycle context with many periods, while the existing literature focused on learning typically involves models with two or three periods. We leave it for future work to develop a modelling framework for educational choices with learning where agents receive noisy signals and update their beliefs in a life-cycle context.

Another shortcoming of our modelling approach is that we have provided a relatively simple representation of individuals’ work choices. By contrast, seminal contributions like Keane and Wolpin (1997) and Miller (1984) allow agents to make heterogeneous occupational choices. This limitation is mainly driven by our narrow focus on agents’ heterogeneous educational choices and their associated returns, and in future work one may aim to analyze agents’ choices of
heterogeneous educations and occupations jointly within a life-cycle framework.

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Appendix

A.1 Specifications of Immediate Reward Functions

We present here the parametrizations of immediate rewards functions in our model. In the estimation, all parameters are allowed to vary freely across three observed ability types.

**Choice Alternative: Work**

The immediate reward of work consists of a wage and a non-pecuniary component:

\[
\zeta_W(k_t, h_t, t, a_{t-1}, e_{j,W}) + w(k_t, h_t, t, a_{t-1}, e_{j,W}, \epsilon_{W,t})
\]

**Wage Component**

\[
w(k_t, h_t, t, a_{t-1}, e_{j,W}, \epsilon_{W,t}) = r \cdot x(k_t, h_t, t, a_{t-1}, e_{j,W}, \epsilon_{W,t})
\]

\[
x(k_t, h_t, t, a_{t-1}, e_{j,W}, \epsilon_{W,t}) = \exp \left\{ \Gamma(k_t, h_t, t, a_{t-1}, e_{j,W}) \cdot \epsilon_{W,t} \right\}
\]

\[
\Gamma(k_t, h_t, t, a_{t-1}, e_{j,W}) = e_{j,W} + \beta_{1,w} \cdot h_t^A + \beta_{2,w} \cdot h_t^V + \beta_{3,w} \cdot k_t + \beta_{4,w} \cdot (k_t)^2
\]

\[
+ \sum_{d \in \{9, 12, 16\}} \gamma_{d,w} \cdot I[h_t^A \geq d] + \sum_{d \in \{9, 12\}} \gamma_{d,w} \cdot I[h_t^V \geq d]
\]

\[
+ \eta_{1,w} \cdot I[a_{t-1} = W]
\]

\[
+ \nu_{1,w} \cdot (t - 15) + \nu_{2,w} \cdot I[t < 17]
\]

**Non-Pecuniary Component**

\[
\zeta_w(k_t, h_t, t, a_{t-1}, e_{j,W}) = e_{j,W} + \beta_{2,w} \cdot I[k_t > 0] + \beta_{3,w} \cdot I[t < 17]
\]

\[
+ \beta_{4,w} \cdot k_t + \beta_{5,w} \cdot h_t^A + \beta_{6,w} \cdot h_t^V
\]

\[
+ \sum_{d \in \{9, 12, 16\}} \varphi_{d,w}^A \cdot I[h_t^A \geq d]
\]

\[
+ \sum_{d \in \{9, 12\}} \varphi_{d,w}^V \cdot I[h_t^V \geq d]
\]
Choice Alternative: Academic Schooling

\[ \zeta_A(k_t, h_t, t, a_{t-1}, e_{j,A}, \epsilon_{A,t}) = e_{j,A} + \beta_{1,A} \cdot I[a_{t-1} = A] + \beta_{2,A} \cdot I[a_{t-1} = V] + \beta_{3,A} \cdot (t - 15) + \beta_{4,A} \cdot (h^V_t - 7) + \beta_{6,A} \cdot I[a_{t-1} = A] \cdot I[h^A_t \geq 12] + \beta_{7,A} \cdot I[\text{HS Proximity} = 1] + \sum_{d \in \{9, 12, 16\}} \vartheta^A_{d,A} \cdot I[h^A_t \geq d] + \epsilon_{A,t} \]

Choice Alternative: Vocational Schooling

\[ \zeta_V(k_t, h_t, t, a_{t-1}, e_{j,V}, \epsilon_{V,t}) = e_{j,V} + \beta_{1,V} \cdot I[a_{t-1} = A] + \beta_{2,V} \cdot I[a_{t-1} = V] + \beta_{3,V} \cdot (t - 15) + \beta_{4,V} \cdot (h^A_t - 7) + \beta_{7,V} \cdot I[\text{HS Proximity} = 1] + \sum_{d \in \{9, 12\}} \vartheta^V_{d,V} \cdot I[h^V_t \geq d] + \epsilon_{V,t} \]

Choice Alternative: Staying at Home

\[ \zeta_H(k_t, h_t, t, a_{t-1}, e_{j,H}, \epsilon_{H,t}) = e_{j,H} + \beta_{1,H} \cdot I[t < 17] + \sum_{d \in \{12, 16\}} \vartheta^H_{d,H} \cdot I[h^A_t \geq d] + \vartheta^V_{12,H} \cdot I[h^V_t \geq 12] + \epsilon_{H,t} \]
A.2 Estimation Results

Choice Alternative: Work

Table A.1 presents the point estimates and the standard errors for the parameters in the wage component, while Table A.2 presents the point estimates and the standard errors for the parameters in the specification of non-pecuniary component.

|                           | Low Ability | Medium Ability | High Ability |
|---------------------------|-------------|----------------|--------------|
| **Constant Term**         | 10.3        | 10.1           | 9.7          |
|                           | (0.00074)   | (0.00077)      | (0.00085)    |
| **Years of Academic Schooling** | β_{1,w} 0.11372 | 0.15632        | 0.18123      |
|                           | (0.00007)   | (0.00002)      | (0.00003)    |
| **Years of Vocational Schooling** | β_{2,w} 0.16168 | 0.13436        | 0.13707      |
|                           | (0.00007)   | (0.00005)      | (0.00002)    |
| **Academic Middle School Diploma** | γ_{9,w}^{A} 0.09542 | 0.05577        | 0.06588      |
|                           | (0.00025)   | (0.00021)      | (0.00015)    |
| **Vocational Middle School Diploma** | γ_{9,w}^{V} 0.00862 | 0.01748        | 0.02278      |
|                           | (0.00033)   | (0.00013)      | (0.00014)    |
| **Academic High School Diploma** | γ_{12,w}^{A} -0.05320 | 0.10376        | -0.05320     |
|                           | (-) (0.00024) | (0.00020)      | (0.00020)    |
| **Vocational High School Diploma** | γ_{12,w}^{V} 0.02199 | 0.00614        | 0.11436      |
|                           | (0.00021)   | (0.00011)      | (0.00016)    |
| **College Degree**        | γ_{15,w}^{A} -0.00940 | 0.05349        | -0.00940     |
|                           | (0.00034)   | (0.00021)      | (0.00021)    |
| **Years of Work Experience** | β_{3,w} 0.10725 | 0.13831        | 0.15012      |
|                           | (0.00005)   | (0.00003)      | (0.00004)    |
| **Years of Work Experience Squared** | β_{4,w} -0.05463 | -0.07934       | -0.10123     |
|                           | (-) (0.00011) | (0.00009)      | (0.00010)    |
| **Period**                | ν_{1,w} -0.07726 | -0.09627       | -0.10092     |
|                           | (0.00003)   | (0.00001)      | (0.00001)    |
| **Lagged Choice: Work**   | η_{1,w} 0.34907 | 0.32721        | 0.22061      |
|                           | (0.00046)   | (0.00031)      | (0.00058)    |
| **Latent Type 1**         | e_{1,w} -0.00454 | -0.00107       | 0.15594      |
|                           | (0.00099)   | (0.00112)      | (0.00096)    |
| **Latent Type 2**         | e_{2,w} -0.02594 | 0.00379        | -0.08258     |
|                           | (0.00085)   | (0.00097)      | (0.00093)    |
| Table A.2: Choice Alternative: Work – Non-Pecuniary Component. |
|---------------------------------------------------------------|
|                                                             |
|                                                              |
| **Constant Term**                                            | **Low** Ability | **Medium** Ability | **High** Ability |
|                                                              | 172902.6        | 149525.8           | 189391.9         |
|                                                              | (521.6)         | (350.9)            | (443.9)          |
| **Years of Academic Schooling**                              | **β₅₋₆,₃**     | **β₆₋₆,₃**        | **β₆₋₆,₃**      |
|                                                              | 1401.4          | -1473.3            | 13073.3          |
|                                                              | (52.5)          | (36.3)             | (43.1)           |
| **Years of Vocational Schooling**                            | **β₆₋₆,₃**     | **β₆₋₆,₃**        | **β₆₋₆,₃**      |
|                                                              | 11101.5         | 13889.9            | 12560.2          |
|                                                              | (33.4)          | (30.7)             | (36.2)           |
| **Academic Middle School Diploma**                           | **ϑ₉₋₆,₃**     | **ϑ₉₋₆,₃**        | **ϑ₉₋₆,₃**      |
|                                                              | 1854.0          | -14817.8           | -5530.7          |
|                                                              | (111.0)         | (86.0)             | (71.9)           |
| **Vocational Middle School Diploma**                         | **ϑ₉₋₆,₃**     | **ϑ₉₋₆,₃**        | **ϑ₉₋₆,₃**      |
|                                                              | -1400.6         | 3053.7             | 12320.1          |
|                                                              | (123.1)         | (64.6)             | (61.5)           |
| **Academic High School Diploma**                             | **ϑ₁₀₋₆,₃**    | **ϑ₁₀₋₆,₃**       | **ϑ₁₀₋₆,₃**     |
|                                                              | -1356.1         | 27757.1            | 14234.4          |
|                                                              | (115.0)         | (68.9)             | (67.9)           |
| **Vocational High School Diploma**                           | **ϑ₁₀₋₆,₃**    | **ϑ₁₀₋₆,₃**       | **ϑ₁₀₋₆,₃**     |
|                                                              | -1356.1         | 27757.1            | 14234.4          |
|                                                              | (115.0)         | (68.9)             | (67.9)           |
| **College Degree**                                           | **ϑ₁₆₋₆,₃**    | **ϑ₁₆₋₆,₃**       | **ϑ₁₆₋₆,₃**     |
|                                                              | -1356.1         | 27757.1            | 14234.4          |
|                                                              | (115.0)         | (68.9)             | (67.9)           |
| **Years of Work Experience**                                 | **β₄₋₆,₃**     | **β₄₋₆,₃**        | **β₄₋₆,₃**      |
|                                                              | 117431.5        | 116545.1           | 81132.1          |
|                                                              | (400.3)         | (298.4)            | (302.0)          |
| **Any Past Work Experience**                                 | **β₂₋₆,₃**     | **β₂₋₆,₃**        | **β₂₋₆,₃**      |
|                                                              | 117431.5        | 116545.1           | 81132.1          |
|                                                              | (400.3)         | (298.4)            | (302.0)          |
| **Latent Type 1**                                            | **e₁₋₆,₃**     | **e₁₋₆,₃**        | **e₁₋₆,₃**      |
|                                                              | 3375.7          | 2306.1             | -15816.0         |
|                                                              | (949.2)         | (560.4)            | (865.9)          |
| **Latent Type 2**                                            | **e₂₋₆,₃**     | **e₂₋₆,₃**        | **e₂₋₆,₃**      |
|                                                              | -11346.0        | 1865.5             | 2609.0           |
|                                                              | (1096.6)        | (635.5)            | (476.3)          |
Table A.3 presents the point estimates and the standard errors for the parameters determining the immediate utility from academic schooling.

| Choice Alternative: Academic Schooling | Low Ability | Medium Ability | High Ability |
|----------------------------------------|-------------|----------------|--------------|
| Constant Term                          | -83055.2    | 45869.0        | -39418.3     |
|                                        | (442.5)     | (428.8)        | (343.8)      |
| Academic High School Diploma            | $\theta_{12,A}$ | 103657.6 | 110434.9 |
|                                        | (-)         | (883.4)        | (454.3)      |
| Academic Middle School Diploma          | $\theta_{9,A}$ | 52943.8   | 87702.0     |
|                                        | (-)         | (221.4)        | (522.8)      |
| Post High School Diploma Return         | $\beta_{6,A}$ | 17196.0    | 41794.8     |
|                                        | (-)         | (439.9)        | (289.1)      |
| College Degree                          | $\theta_{16,A}$ | 135069.8 | 146769.2   |
|                                        | (-)         | (1910.9)       | (475.5)      |
| Lagged Choice: Academic Schooling       | $\beta_{1,A}$ | 47152.9   | 56605.9     |
|                                        | (577.2)     | (268.5)       | (153.8)      |
| Lagged Choice: Vocational Schooling     | $\beta_{2,A}$ | -550.9    | -11344.4    |
|                                        | (1448.4)    | (1083.2)      | (727.4)      |
| Years of Vocational Schooling, Lagged  | $\beta_{4,A}$ | -38108.7  | -89136.7    | -
|                                        | (457.8)     | (550.7)       | (-)          |
| Local High School Proximity             | $\beta_{7,A}$ | 17157.6   | 21213.7     |
|                                        | (429.1)     | (283.4)       | (238.3)      |
| Period                                  | $\beta_{3,A}$ | -17150.2  | -11194.6    | -53514.6    |
|                                        | (107.9)     | (52.1)        | (80.4)       |
| Type 1                                  | $e_{1,A}$   | -3080.6     | -2304.3     |
|                                        | (1115.5)    | (870.2)       | (845.2)      |
| Type 2                                  | $e_{2,A}$   | -9954.3     | 2433.7      |
|                                        | (992.4)     | (702.1)       | (622.3)      |
**Choice Alternative: Vocational Schooling**

Table A.4 presents the point estimates and the standard errors for the parameters determining the immediate utility from vocational schooling.

|                                | Low Ability | Medium Ability | High Ability |
|--------------------------------|-------------|----------------|--------------|
| Constant Term                  | -75784.9    | 127841.7       | 71896.0      |
| (390.2)                        | (431.2)     | (240.2)        |
| Academic Middle School Diploma | $\varphi_{12,V}^A$ | - | 403.6 | -79761.2 |
| (-)                             | (969.2)     | (456.2)        |
| Vocational Middle School Diploma| $\varphi_{9,V}^V$ | 148182.7 | 141612.1 | 72891.7 |
| (278.1)                        | (397.5)     | (253.3)        |
| Lagged Choice: Academic Schooling| $\beta_{1,V}^V$ | -29296.9 | -1804.2 | -618.8 |
| (1543.7)                       | (508.3)     | (284.6)        |
| Lagged Choice: Vocational Schooling| $\beta_{2,V}^V$ | 242.4 | 18929.3 | 8292.2 |
| (221.0)                        | (91.2)      | (139.0)        |
| Years of Academic Schooling, Lagged| $\beta_{4,V}^V$ | -40518.4 | -92163.6 | - |
| (417.2)                        | (590.0)     | (-)            |
| Local High School Proximity    | $\beta_{7,V}^V$ | 15296.4 | 17331.1 | 16711.1 |
| (307.1)                        | (146.4)     | (205.1)        |
| Period                         | $\beta_{3,V}^V$ | -25015.3 | -29593.6 | -14764.7 |
| (127.1)                        | (24.5)      | (39.9)         |
| Latent Type 1                  | $e_{1,V}^V$ | 3131.0        | -3837.6      | -3158.5 |
| (1032.4)                       | (664.3)     | (945.8)        |
| Latent Type 2                  | $e_{2,V}^V$ | 654.7         | -1666.8      | 7432.9  |
| (840.7)                        | (609.1)     | (462.5)        |
Choice Alternative: Staying at Home

Table A.5 presents the point estimates and the standard errors for the parameters determining the immediate utility of staying at home.

| Choice Alternative: Staying at Home |
|-------------------------------------|
| **Table A.5**: Choice Alternative: Staying at Home. |
| | Low Ability | Medium Ability | High Ability |
| Constant Term | -58833.5 | -31032.1 | -27323.8 |
| | (281.4) | (163.9) | (344.3) |
| Minor (Age < 17) | $\beta_{1,H}$ | 151586.6 | 78733.0 | 66323.2 |
| | | (1140.1) | (963.6) | (908.6) |
| Academic High School Diploma | $\vartheta_{12,H}^A$ | -923.8 | 1906.5 | 45719.0 |
| | | (654.8) | (226.1) | (309.7) |
| Vocational High School Diploma | $\vartheta_{12,H}^V$ | -164321.3 | 65120.2 |
| | | (-) | (1054.3) | (667.3) |
| College Degree | $\vartheta_{16,H}^A$ | - | 67766.7 | 60369.5 |
| | | (-) | (9557.1) | (1833.4) |
| Period | $\beta_{2,H}$ | 9119.3 | - | - |
| | | (33.8) | (-) | (-) |
| Latent Type 1 | $e_{1,H}$ | -195.0 | 1314.7 | -1136.9 |
| | | (1053.5) | (735.6) | (1793.0) |
| Latent Type 2 | $e_{2,H}$ | 3632.8 | -1218.1 | 3872.9 |
| | | (718.4) | (739.4) | (618.8) |

Time Preferences and the Distribution of Shocks

Table A.6 presents the point estimates and the standard errors for the parameters determining the discount rate and distribution of the shocks.

| Choice Alternative: Staying at Home |
|-------------------------------------|
| **Table A.6**: Time Preferences and Distribution of Shocks. |
| | Low Ability | Medium Ability | High Ability |
| Discount Rate | 0.96586 | 0.95933 | 0.95850 |
| | (0.00006) | (0.00005) | (0.00003) |
| Shock SD Work | 0.30237 | 0.33056 | 0.15257 |
| | (0.00066) | (0.00053) | (0.00041) |
| Shock SD Academic | 263544.4 | 244771.0 | 366191.6 |
| | (0.00099) | (0.00042) | (0.00045) |
| Shock SD Vocational | 143429.8 | 183672.8 | 154709.2 |
| | (0.00041) | (0.00017) | (0.00030) |
| Shock SD Home | 1008774.6 | 916222.1 | 789137.5 |
| | (0.00026) | (0.00024) | (0.00023) |