Persistent Inequality & Education Policy during Adolescence.

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Individuals from low-income backgrounds perform worse than their higher-income peers early in their schooling career. Later on, they are more likely to enter university after having worked or completed vocational training. Policy that attempts to address persistent inequality thus needs to consider alternative paths to university. This paper asks how institutional features of the education system, such as the organization of vocational training and income subsidies during higher education, affect university graduation and future wages of low-income individuals. I extend previous contributions on this topic by explicitly accounting for existing achievement gaps and alternative paths to university. To reach this goal, I specify a dynamic model of education that follows low-income individuals in the Netherlands during adolescence and early adulthood. The model shows that despite initial achievement gaps, many low-income backgrounds have high returns from finishing a bachelor's degree later. They, however, face substantial dropout risk when entering higher education. Alternative paths to university are essential as many low-income individuals only discover they want to enter university later. Making the tracking system more flexible and decreasing the duration of vocational programs would reduce inequality across socioeconomic status.

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1 Introduction

Children from lower-income backgrounds perform worse than their higher-income peers in school(OECD, 2019). This achievement gap persists in future educational careers and has a lasting impact on future outcomes of individuals from low-income households. Low-income individuals are more likely to dropout of high school to work or pursue vocational training. Later in life, many low-income individuals enter higher education despite earlier achievement gaps. Consistent with these earlier achievement gaps, they are more likely to do so after finishing vocational training or dropping out of high school before. Prior literature has treated nonacademic degrees or high school dropouts as terminal states and abstracted from alternative routes to higher education despite their importance for low-income individuals. This paper asks how institutional features of the education system, such as the organization of vocational training and income subsidies during higher education, affect university graduation and future wages of low-income individuals. I extend previous contributions on this topic by explicitly accounting for existing achievement gaps and alternative paths to university.

The exact way achievement gaps affect low-income individuals' educational careers varies by country's education system. In many European countries, individuals are separated into different school types based on achievement, which I will refer to as tracking in this analysis. Low-income individuals are particularly likely to be selected into vocational schools, which are shorter than other school types and prepare individuals for vocational training (OECD, 2020). Most countries offer pathways to university for individuals who graduate from vocational training. In the United States, where all students are kept together until high school graduation, low-income individuals are likelier to drop out of secondary schooling (OECD, 2012). After dropping out of high school, individuals can obtain a GED certification and enter university(see, e.g., (Maralani, 2011)).

I begin by documenting two stylized facts about education in the Netherlands. First, most low-income individuals are enrolled in vocational school, consistent with evidence of achievement gaps. Secondly, university graduates from low-income backgrounds are twice as likely to have entered university after completing vocational training. Motivated by this observation, I analyze the educational careers of graduates of vocational schools in the Netherlands. More precisely, I estimate a dynamic model of educational choices and analyze a recent reform to student income subsidies.

I first introduce a dynamic discrete choice model in the spirit of Keane and Wolpin (1997) that follows graduates of vocational school[1]. After graduating from vocational school, individuals can enroll in

[1] I focus on graduates of the technical branch of vocational school (VMBO-T) in this application. This is the largest branch with the most options after graduation, so I focus on it.

vocational training or enter high school[2]. Whether individuals can enter high school depends on their grades and location, as high schools have their own rules for admitting graduates of vocational school. After that, individuals can enter applied university[3] after graduating from high school or a higher vocational program. Finishing a vocational program takes longer and contains no explicit preparation for higher education. Individuals who pursue the vocational path to university are thus older and potentially less prepared when they enter applied university.

I leverage data on schooling careers, enrollment, and wage outcomes to estimate key model parameters. One challenge in identifying the model is endogenous selection into different schooling careers. I leverage differences in rules across schools to identify the nature of selection in the model. Unobserved characteristics will differ across school choice combinations as schools employ different rules for transitioning to high school. I can thus use differences in outcomes across individuals from different schools who took the same choice to identify the importance of unobserved factors in the model.

Having estimated the model, I first summarize the estimated parameters and discuss their policy implications. The estimated parameters show that wage returns to applied university differ substantially across the population. At age thirty, some people receive substantial returns to having a bachelor's degree, while others earn negative returns. However, wages of applied university graduates increase substantially after thirty such that most people have substantial positive returns from holding a bachelor's degree at age forty. Dropout risk is the most important factor generating inequality in outcomes across individuals with different characteristics in the model. Particularly, individuals with low grades face substantial risk at applied university.

Next, I run several simulations to predict the effect of counterfactual policies. I find that enforcing higher acceptance rates of vocational graduates at high school increases graduation by three percent. Decreasing the length of vocational programs to three years would increase the number of university graduates by around two percent. Finally, I remove the option to enter university after finishing vocational education while decreasing transition costs to high school. Removing the option to enter university after finishing vocational education while decreasing transition costs to high school would significantly reduce the number of individuals holding bachelor's degrees. This is because many individuals do not know yet know that they want to study at age sixteen.

In the final part of the paper, I investigate the effect of income subsidies in the presence of achievement

[2]The Netherlands has three different education tracks. The academic track (VWO) prepares individuals for academic university and takes six years. The mid-level track (HAVO) prepares individuals for applied university and takes five years. The vocational track (VMBO) prepares individuals for vocational programs and takes five years. Under some circumstances, graduates of VMBO can also transit to the fourth year of HAVO

[3]The Netherlands has two types of higher education institutions: academic and Applied Universities. Applied Universities are less abstract and include more practical training for future jobs. If graduates of vocational middle school enter higher education, it is most likely at an applied University. Thus, I focus on these institutions throughout.

gaps and different paths to university. I use the model and a recent reform to student income subsidies in the Netherlands.

The Dutch government pays income subsidies to students to increase the accessibility of higher education. A reform in 2015 has abolished privileges for individuals who moved out of their parental home while studying and has completely removed grants for higher income individuals[4]. Low-income individuals who would have studied and stayed at their parental home before the reform was introduced are unaffected and can thus be used as a control group. I use machine learning techniques to identify the control group and run a difference in difference specification with the results. I find that reform has decreased applied university enrollment among graduates of vocational training by four percent. Degree completion has also decreased but much less strongly, which implies that complier had a relatively large dropout risk on average. The reform's substantial effect shows that vocational training graduates are particularly sensitive to the costs of higher education. This may be caused by the fact that graduates of vocational training are older and from lower-income backgrounds than graduates of high school. Policymakers should explicitly consider alternative paths to university when designing income subsidies in higher education.

The model predicts a smaller decline in enrollment. This is because the treated group differs from the broad population and because the model includes no consumption component and no risk aversion. If I simulate an alternative model with a similar effect on enrollment as the reform has, the model reproduces the characteristics reform complier. While the model cannot precisely reproduce the reform, it gets the selection right, which increases confidence in the other policy simulations.

I contribute to different branches of the literature. First, I contribute to a literature investigating education choices under uncertainty and limited information. Bhuller et al. (2022), Lee et al. (2015), Trachter (2015), Stange (2012) and Heckman et al. (2018) derive ex-ante and ex-post returns to education using dynamic discrete choice models. They find that uncertainty creates a rift between ex-ante and ex-post returns that is important to consider when evaluating actual choices. Stinebrickner and Stinebrickner (2012), Proctor (2022) and Arcidiacono et al. (2016) emphasize the role of learning about own ability. Wiswall and Zafar (2015), Attanasio and Kaufmann (2017) and Ehrmantraut et al. (2020) document uncertainty about returns to higher education. They find that uncertainty about one's ability drives common phenomena such as dropout or re-enrollment. In contrast to earlier models, my model explicitly accounts for nonacademic education and alternative routes to university. Adding these features yields two crucial insights. Providing nonacademic education improves outcomes for individuals who face considerable dropout risk. At the same time, it diverts some people who would

[4]See section 4 for a detailed description.

have high returns from higher education but do not yet know they want to study at sixteen. Providing flexibility between different education options allows one to reap the benefits of providing different options while keeping the losses due to wrong choices under uncertainty at a young age limited.

The second branch I contribute is a growing literature investigating returns to vocational education. Hanushek et al. (2017),Birkelund and van de Werfhorst (2022), Bertrand et al. (2021) and Silliman and Virtanen (2022) analyze returns to vocational programs against different alternatives. Matthewes and Ventura (2022) considers returns of vocational training against the next best alternative and finds that returns vary by the second-best option individuals have. Eckardt (2019) investigates the consequences of uncertainty in vocational program choice and quantifies the costs of a mismatch between vocational training and occupation. I extend this literature in two ways. I estimate a fully structural model, which requires more assumptions but allows me to simulate the effect of policies. Furthermore, I consider further education choices after individuals have completed a vocational program. My analysis highlights how the returns to vocational programs depend on further educational careers of vocational graduates.

Another literature I speak to seeks to identify the effect of income subsidies and scholarships on university enrollment and graduation of low-income individuals (See, e.g., Kane (2006),Deming and Dynarski (2010) for summaries.). Castleman and Long (2016) analyze the effect of need-based financial aid in Florida on enrollment and graduation. They find that access to financial aid increases both enrollment and university graduation. Cohodes and Goodman (2014) documents diversion effects of subsidy schemes that only subsidize studying certain institutions. I expand this literature in two ways. First, I consider a particularly policy-relevant population consisting of low-income individuals who are older on average compared to regular university entrants. Secondly, I analyze a subsidy scheme that explicitly subsidizes individuals who move out of their parental home. My results show that many low-income individuals face a double burden at university. They have a lower capacity to stay at home since they are older on average and receive fewer parental transfers since they are poorer on average. Particularly in the presence of rising housing costs, it is thus essential to consider how housing may inhibit college entry for low-income individuals.

2 Setting & Stylized Facts

In this section, I explain relevant features of the Dutch education system, show stylized facts motivating the subsequent analysis, and summarize all the options that graduates of vocational school have.

2.1 Tracking in the Netherlands

The Dutch education system separates individuals at age twelve based on grades and teacher evaluations and sends them to different secondary schools. Each school sets a different focus and prepares for a different post-secondary education. I focus on the vocational schooling track (VMBO), which receives individuals with the lowest assessed academic potential and prepares students for vocational training. I will refer to the vocational schooling track as vocational school in this paper. Vocational training comes after vocational school prepares individuals for particular occupations. I will describe different career options for graduates of vocational school in section 2.4. The other two tracks are more academic and prepare individuals for applied university and academic, respectively. Higher education in the Netherlands differentiates between applied universities, which are more practical and academic universities. I will abstract from academic university and master's degrees in this context as most of the graduates of vocational school never enroll in either.

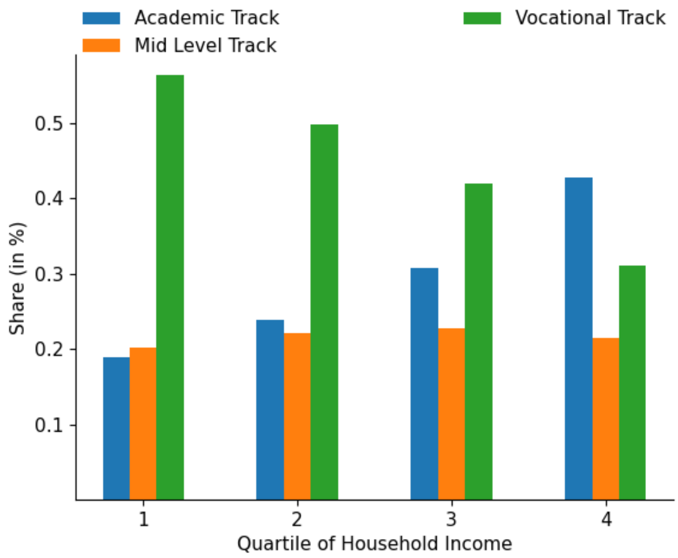
2.2 Data

I use Dutch administrative records to follow graduates of vocational schools. I combine information on educational careers, grades in middle school, the economic situation of their parents, school characteristics, place of residence, and future labor market outcomes. I use the constructed data to obtain characteristics of an individual's school and the immediate neighborhood in which an individual lives. I will focus on graduates of vocational school and their future outcomes for the structural models. The reform evaluation will focus on graduates of vocational training who are primarily between 18 and 22.

2.3 Stylized Facts

Low-income individuals are most likely to be in the vocational track: Figure 1 summarizes the gradient in track choice after primary school. Lower-income individuals are most likely to be selected for vocational school. Track assignment is decided by teacher evaluations and a centralized test individuals take at the end of primary school. Grade differences at the end of primary school can explain a substantial part of the differences in track choice. Zumbuehl et al. (2022) show that low-income backgrounds, however, receive lower track recommendations even after controlling for grades and cog-

Figure 1: Track Assignment by Parental Income



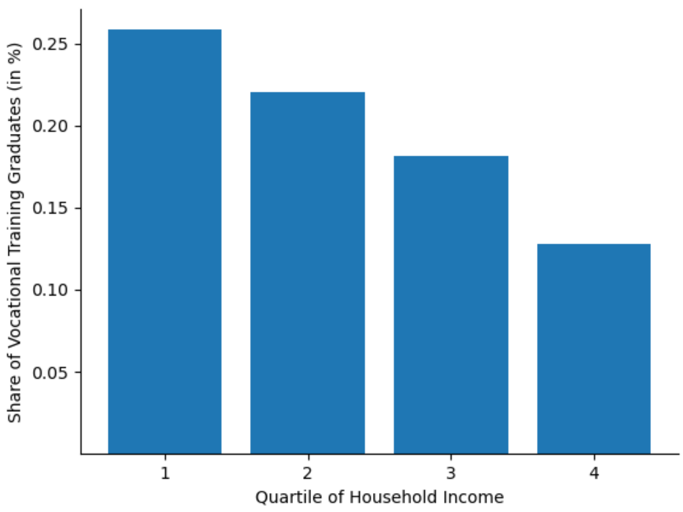
Note: This figure shows track assignment by quartile of parental household income. The vocational track includes all branches of VMBO. The figure is based on the dataset described in 2.2 and contains data from 2008-2010.

nitive skills. The misallocation is thus potentially worse among low-income individuals than their higher-income peers. The picture shows that addressing persistent inequality in education requires that at least some low-income individuals in vocational school need to complete higher education later in their life.

Alternative Paths to education are more common among low-income individuals: I now consider all individuals who at least hold an applied university degree. Figure 2 shows the proportion of university graduates that have completed vocational training before. Conditional on reaching a tertiary degree, individuals from low socioeconomic backgrounds are twice as likely to have entered higher education after vocational training. Entering university after finishing vocational training is a well-established career in the Netherlands that is particularly important for low-income individuals. Graduates of vocational education are older and have received less academic education when they consider entering university.

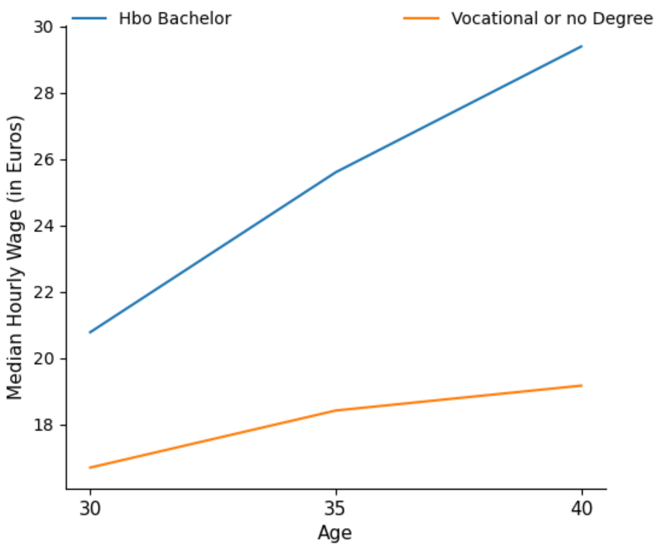
The wage gap between vocational and academic schooling increases over the life cycle: Wage gaps between individuals with bachelor's degrees from applied universities and those without university degrees are growing quickly. Figure 3 shows median wages for individuals with applied university degrees and those without university degrees between the ages of thirty and forty.

Figure 2: Fraction of University Graduates who finished Vocational Training



Note: This figure shows the fraction of university graduates who have completed vocational training before entering university. University graduates include everyone with at least an applied university bachelor's degree. Individuals with an academic university bachelor's degree or any master's degree are also included. Note that these proportions are not synchronized with figure 1, where I show individuals enrolled in different schooling tracks. This figure shows how many individuals graduated from vocational training and went to university afterward. Vocational training comes after vocational school, and some vocational school graduates also choose to enroll in high school, as I explain in section 2.4. The figure is based on the dataset described in 2.2 and contains data from 2008-2010.

Figure 3: Wage Inequality over Time



Note: This figure shows the evolution of average hourly wages for individuals with and without applied university degrees. I only include individuals who work full-time. The applied university category only includes individuals with bachelor's degrees. The data is obtained from a cross section of hourly wages in 2019.

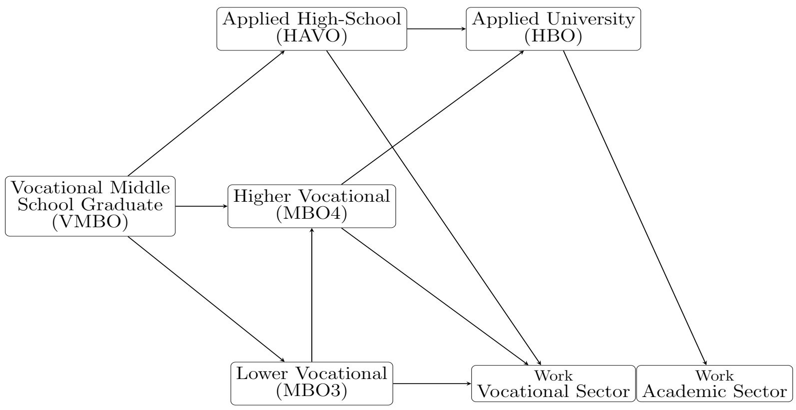
The wage gap is modest at age thirty but grows quickly after that. Understanding how much of these differences are driven by selection and actual returns to applied university degrees is important.

Increasing applied university graduation among low-income individuals will contribute to narrowing the wage gap if substantial returns remain after accounting for selection. The decision tree that agents face in the model.

2.4 Pathways to University

Having demonstrated that low-income individuals are most likely to be in vocational school, I now present all possible future pathways for graduates of vocational school. From now on, I focus on graduates of the technical branch of vocational school[5]. I focus on this branch because it is the largest and because graduates of this branch have the widest choice options. Hence, there is more variation in choices among technical graduates, allowing me to explore the effect of different educational options. The effect of policy on the other branches is likely similar to that of policy at the bottom of the grade distribution in the technical branch, as the technical branch receives individuals with the highest grades. 4 illustrates pathways that vocational graduates can pursue after graduation. After graduation, individuals can enroll in different vocational programs or switch up to the schooling track that prepares for applied university, which I consider high school for simplicity. Once individuals graduate from high school or a higher vocational program, they can enter university. If they hold a

Figure 4: Pathways for graduates of vocational school



Note: This figure summarizes educational careers individuals can pursue after graduating from a vocational school.

lower vocational degree, they can pursue a higher vocational degree to enter university in the third period. Individuals can leave education and work at each point in the decision tree, which is terminal in this context. 4 includes few simplifications. Lower vocational programs contain several options. Most graduates of the technical branch, however, choose MBO3 and none of the other options. There are also different options to receive a high school degree, but none of the alternative options plays an

[5]Vocational school is split into four different branches. The technical branch receives the students with the highest assessed academic ability within the branch.

important role. Finally, individuals can also enroll in academic university or pursue a master's degree. Both options are not particularly relevant for vocational graduates as most pursue applied university degrees if they enroll in tertiary education.

School Types: The transition to high school is not organized centrally. High Schools have employed their own rules for admitting students from vocational school(Van Esch and J., 2010). The number of individuals that transfer to high school from a particular middle school thus varies by the specific rules that high schools in the area use and by the amount of assistance that the school offers students for their transition to high school.

3 A model of further education.

I now introduce a structural model of education. I will first explain the model, then show how to solve the model, and finally, I show how to identify and estimate the model.

3.1 Sample & Decision Tree

The model is based on the summary of pathways introduced in 4 last section. Individuals can first choose between higher and lower vocational training and high school. After that, they can enter university after high school or after graduating from higher vocational training. Vocational training takes longer and contains less preparation for university. The sample of individuals the model is estimated with consists of all graduates of the technical branch of vocational school, as described in the last section. I focus on the years 2008-2010 as there is insufficient information for individuals who graduated before and because there are no long-term outcomes for individuals who graduated after that. Individuals with very uncommon careers and individuals with missing spells are excluded. Moreover, I abstract from part-time work and only use full-time work spells to estimate wage processes.

3.2 Model Organization & Decision Period

Contrary to prior dynamic discrete choice models of education, individuals do not make a new decision each year. I chose this alternative way of specifying the model to reduce the computational complexity. Using decision periods allows me to substantially reduce the number of states because I do not have to include experiences for each choice in the state space. After individuals enroll in a particular education program, they stick with this decision for a potentially stochastic number of years until they either graduate or fail to do so. A spell denotes the number of years an individual spends in a particular education due to their prior decision. Once the current spell is over, they make a new decision based on their current state. I thus distinguish between periods and decision periods in the model. A period $t \in \{0, 1, 2, 3, 4\}$ denotes the number of years that have passed since the onset of the model. A decision period $\tau \in \{0, 1, 2, 3, 4\}$ represents the number of choices that the individual has already taken.

3.3 States & Fixed Hetereogeneity

Each individual is characterized by fixed characteristics and dynamic states. Fixed characteristics include observable ability G, unobserved ability θ, parental income Y, and school type U. Observable ability G_i is individual i's quartile of vocational school grades. Y_i denotes the quartile of parental household income of individual i. School Type U denotes the type of transit policy in the individual i's school. This variable captures that transitioning to high school after graduating from vocational school is easier at some schools than others. I identify school types by grouping school fixed effects obtained from a regression of schools and individual characteristics on high school attendance. Unobserved ability ν is assumed to be one-dimensional and supposed to capture the remaining dependence between choices and outcomes. Dynamic states include age A, current level of schooling E, and lagged choice $d_{\tau-1}$.

One state is a tuple that consists of all fixed characteristics and dynamic states $s_\tau = (A_\tau, E_\tau, C^{\tau-1}, G_i, \nu_i, Y_i)$. Individuals start the model at age 16.

3.4 Choices & Timing

Let $d_{i,\tau}$ denote the choice of individual i at decision period τ. At each decision period, an individual makes a choice. Afterward, the individual stays with that choice for a potentially stochastic number of periods. After the spell is over, the individual takes the next decision.

$C(s_\tau)$ maps a state into a set of admissible choices. This function is consistent with the decision tree above. An individual who has, for example, just finished a higher vocational program can either enroll in university or leave education and work. Moreover, individuals are not allowed to enroll in the same program repeatedly. This is why the lagged choice is part of the state space. Individuals decide between academic schooling and vocational programs in the first stage and between university and work in the second stage.

If individuals enroll in a particular schooling program, they are not guaranteed to finish it. Schooling programs are associated with varying levels of dropout risk and uncertain length. Depending on their choice and the realization of academic risk, they will transit to a new stage. The stochastic function $T(s_\tau, d_{i,\tau})$ maps a state and a choice into a state at the end of the current spell.

Taking a decision thus has the following consequences. First, the transition function realizes and determines the state that an individual will end up in. Function $N(s_\tau, s_{\tau+1})$ determines all the states in between the state of departure and the state of arrival and $n(s_\tau, s_{\tau+1})$ is the number of states between s_τ and $s_{\tau+1}$. After that, the individual receives utility for each state and makes a new decision in the arrival state, corresponding to the next decision period. Suppose the transition function, for example, determines that an individual enrolled in a higher vocational program will graduate within four years. In that case, the individual will receive utility for these four years and make a new decision after she graduates from the vocational program.

If an individual leaves education and starts working, the choice is terminal. Individuals receive the discounted lifetime income associated with their characteristics and final education.

3.5 Transitions & Uncertainty

Individuals face two types of uncertainty: they can potentially dropout and not graduate from a particular education program, or they can graduate but with a delay.

Degree risk is represented by a logit model of individual characteristics on an indicator of graduation. The equations' coefficients are model objects estimated jointly with all other parameters.

$$Logit(P(E_{\tau+1} = d_\tau))(G, \theta, Y) = \beta^R_{0,d} + \xi^R_{1,d} * G + \xi^R_{2,d} * \theta + \xi^R_{3,d} * Y + \nu_d \tag{1}$$

If an individual i completes a degree successfully, she faces a poison process that determines the duration of her degree:

$$T_d^{E_{\tau+1}=d_\tau}(G, \theta, Y) \sim Poisson(min, \beta^D_{0,d} + \xi^D_{1,d} * G + \xi^D_{1,d} * \theta + \xi^D_{3,d} * Y) \tag{2}$$

If the individual drops out the length, she will still spend a stochastic number of periods in the education program. The length is determined by:

$$T_{di}^{E_{\tau+1} \neq d_{i\tau}} \sim Poisson(min, \beta_0) \tag{3}$$

The exact parametrization differs between the programs and can be found in the appendix.

Agents additionally face taste shocks $\nu_{i,\tau}(d)$ to their utility. Taste shocks are modeled as an extreme value type one distribution. They are independent and identically distributed across all individuals and all choices.

3.6 Wages & Nonpecuniary Preferences

Wages are modeled as two separate mincer equations for individuals with higher education diplomas and individuals without. Once students enter the labor market, they receive income for the rest of their life. I estimate a mincer regression for log wages and assume that everyone works full time after they leave school. Let k_t,k_t be work experience at time t and let E^C be the combination of degrees that an individual holds. Log wages for the vocational sector look as follows:

$$\begin{aligned} w_v(E, A_t, k_{t,v}, G, \theta, Y) =& \beta^W_{0,v} + \beta^W_{1,v} * E + \beta^W_{2,v} * k_{t,v} + \beta^W_{3,v} * k^2_{t,v} + \beta^W_{4,v} * A_t + \beta^W_{5,v} * k_{t,v} * E \\ &+ \xi^W_{1,v} * G + \xi^W_{2,v} * \theta + \xi^W_{3,v} * Y + \epsilon_{v,t} \end{aligned} \tag{4}$$

Log wages depend on experience, age, parental income, ability, type, highest degree completed, and highest degree completed interacted with experience. Wages for the academic sector are modeled separately to allow for a flexible form of the college premium. Wages in the academic sector look as follows:

$$\begin{aligned} w_a(E^C, A_t, k_{t,v}, G, \theta, Y) =& \beta^W_{0,a} + \beta^W_{1,a} * E^C + \beta^W_{2,a} * k_t + \beta^W_{3,a} * k_t^2 + \beta^W_{3,a} * A_t + \xi^W_{1,a} * G + \xi^W_{2,a} * \theta \\ &+ \xi^W_{3,a} * Y + \epsilon_{a,t} \end{aligned} \tag{5}$$

They depend on experience, age, parental income, ability, type, and educational career. Similar to Keane and Wolpin (1997), every choice is associated with nonpecuniary utility that is measured on the same scale as wages. I allow nonpecuniary returns $F(S_i, d_{i,t})$ to depend on parental income, type, and dynamic characteristics such as experience or age. Observed grades are only part of nonpecuniary rewards for high school, where higher grades may be associated with lower transition costs. I include transition to high school $T(U)$ to capture differences across school types. 6 shows the utility that is associated with taking a decision d in state s. All education choices only have a nonpecuniary component, and transition costs are only incurred during the first year of high school

$$U^d(s) = F_d(s) + e^{w_d(s)} + T \tag{6}$$

7 denotes the discounted lifetime utility from working if an agent reaches a terminal state.

$$\sum_{t \in \{s,..T\}} \beta^t U^w(s) \tag{7}$$

3.7 The Agent's Problem & Solution Algorithm

Expected utility is the weighted average over all possible paths a decision could lead to. One needs to sum over all states that could be reached from a particular state choice combination. Let $R(s_\tau, d_{i\tau})$ be the range of potential outcomes one can reach from state s_τ and decision $d_{i\tau}$ and let $P_{s_\tau, d_{i\tau}}(s_{\tau+1})$ be a probability distribution over the range of outcomes. Formula 8 shows the optimization problem of an individual in the model at state s_τ.

$$\max_{d \in C(s_\tau)} \sum_{s_{\tau+1} \in R(s_\tau, d)} \sum_{s \in N(s_\tau, s_{\tau+1})} (\beta^{n(s_\tau, s)} U(s)) + \beta^t V(s_{\tau+1}) + \nu_{i,\tau}(d) \tag{8}$$

I solve the model by backward induction. Let $V(s)$ be the expected continuation value from reaching state s, let $V(s, d)$ be the expected continuation value from choosing d in state s, and let $V(s, d, \hat{s})$ be the expected continuation value of choosing d in state s and reaching $\hat{s}$. To find this model, I proceed as follows. I start with the highest age at which agents can make decisions in the model. I then follow the following steps for each age that I iterate backward through:

1. Collect all possible state choice combinations (s, d) of age t

2. For all terminal state choice combinations, assign the continuation value

$$C(s, d) = \sum_{t \in \{s,..T\}} \beta^t U^w(s)$$

3. For all non-terminal combinations:

   a) Collect all reachable states $\hat{s} \in R(s, d)$ and their probability $P_{s,d}(\hat{s})$

   b) Collect the expected continuation value from reaching $\hat{s}$: $V(\hat{s})$

   c) Now combine the expected continuation value with the flow utility on the path from s to $\hat{s}$:

$$V(s, d, \hat{s}) = \sum_{\widetilde{s} \in N(s,\hat{s})} \beta^{n(s,\widetilde{s})} U(\widetilde{s}, d) + \beta^{n(s,\hat{s})} V(\hat{s})$$

   d) Get the continuation value of (s, d) by taking the expected value over $\hat{s}$:

$$V(s, d) = \sum_{\hat{s} \in R(s,d)} P_{s,d}(\hat{s}) V(s, d, \hat{s})$$

4. Now get $V(s)$ by getting the expected value of the maximum of $V(s, d)$: $V(s) = E[max\{V(s, d\}] = \sigma log(\sum_d e^{\frac{V(s,d)}{\sigma}})$ where σ is the scale of the extreme value taste shocks.

3.8 Estimation & Identification

Estimation: I use indirect inference to estimate 117 parameters $\hat{\theta}$. Equation **??** shows the criterion function. I select the parametrization that minimizes the weighted squared distance between the specified set of moments computed on the observed M_D and the simulated data $M_S(\theta)$. I weigh the statistics with a diagonal matrix W that contains the variances of the observed moments (**?**). I use a package for the estimation of scientific models by Gabler (2022) for the optimization of the criterion function[6].

$$\hat{\theta} = argmin_{\theta \in \Theta} \left(M_D - M_S(\theta)\right) W^{-1} \left(M_D - M_S(\theta)\right)' \tag{9}$$

[6] I use a global version of the BOBYQA algorithm within the package(**?**).

Identification: Table 1 provides an overview of all 353 statistics used in the model estimation. The enrollment percentage for a particular program indicates how many people have been enrolled in that respective program. By grade and by income mean that this set of proportions is included for each quartile of parental income and grades. By school type x grade means the statistic is included for all 12 combinations of school types and grades at the end of vocational school. The final degree combination indicates all post middle school degrees an individual receives before starting work. If a person first graduates from a vocational program and then graduates from an applied university, her degree will be higher vocational & bachelor. I combined some programs and removed some individuals with very uncommon careers. Furthermore, I include the last schooling age for all observed ability and income groups. The last schooling age is when an individual is done with education and starts to work. This moment is included for all ability and income groups. Final schooling age helps to identify the degree-length process. Since I do not allow re-enrollment, there is always one age where individuals leave education. In practice, I allow individuals to take a gap of one year between spells, which will be part of the degree duration. Wage quartiles over time are wage quartiles for individuals with and without an applied university degree at ages 30, 35, and 40. Finally, I match the coefficients of three separate wage equations. Two are wage regressions for individuals with and without bachelor's degrees. The last equation regresses controls and school-type indicators on future wages.

Table 1: Summary of Moments Used in the Estimation.

Type of Moment	**Number**
I. Percentage enrolled in each program by income, grade & school type x grade	80
II. Degree combination by income, grade, school type	160
III. Fraction in Academic Schooling Per Period	80
IV. Last schooling age by income, grade	24
V. Wage quartiles over time	18
VI. Coefficients of wage equations	53

Note: This table summarizes all 353 moments used to estimate the model. The left column indicates a particular category of statistics, and the right column indicates the number of moments the respective category has.

The set of statistics is chosen to identify all components of the model. While the moments are used jointly, I will provide some heuristic arguments of how each category of moments aids identification. Coefficients of wage equations and wage quartiles pin down components of the wage equation. The discrepancy between enrollment and graduation in each program identifies academic risk. The distribution of final schooling ages pins down the distribution of degree duration. Non-pecuniary returns to work and education programs are pinned down by residual variation in choices across characteristics that wage returns can not explain. The distribution of taste shocks is pinned down by variation in choices, holding all characteristics fixed. Transition costs to high school by school type are identified by differences in choices and outcomes of individuals who chose not to enroll in high school. Latent types are identified in two ways. First, they are identified by all moments jointly as they introduce persistence in choices over time, which minimizes residual heterogeneity. Secondly, the differences in transition costs across schools lead to differences in the joint distribution of unobserved characteristics and choices across schools. The degree to which outcomes differ across schools holding observed characteristics and the degree of selection fixed helps to identify latent types.

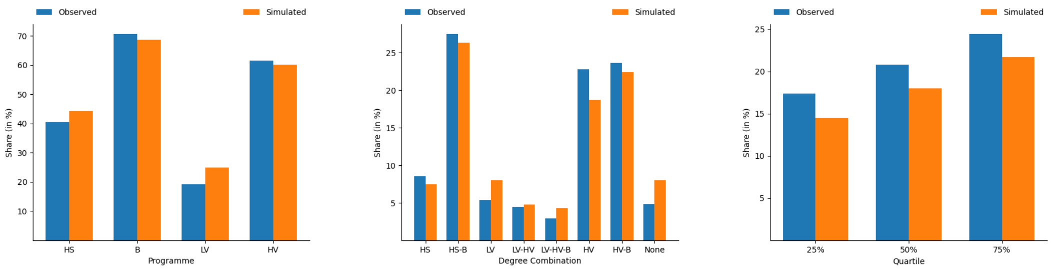
4 Results

I now present the empirical findings of the structural model. First, I present the model fit of the simulated moments, and then I discuss estimated parameters and their implication for education policy. After that, I simulate three explicit policies and discuss the resulting predictions.

4.1 Estimation & Model Fit

Figure 5 briefly summarizes the model fit. A more detailed summary can be found in the appendix. The first two panels show the fit of enrollment proportions and degree combinations for individuals with high grades. Both sets of simulated moments are closely aligned with their observed counterparts. The third panel shows wage quartiles at age 30 for individuals with an applied university degree. The model slightly underestimates quartiles at age 30. The components of the wage equation are not rich enough to accurately reproduce every feature of the wage distribution. The estimated model, however, provides a good approximation as most statistics are closely aligned.

Figure 5: Summary of Model Fit



(a) Enrollment Proportion (b) Degree Combination (c) Wage Quantiles Academics 30

Note: This figure summarizes the model fit. The figures compare observed moments based on the dataset described in 2.2 and simulated moments from a model with the estimated parameters. The blue bars show the observed moments, and the orange bars show simulated moments. The x-axis labels for the first two figures correspond to education programs specified in Figure 4. Each label in the first figure is an abbreviation for an education program that appears in the figure. LV and HV correspond to lower and higher vocational programs; HS corresponds to high school; B to applied university bachelor. Labels in the second figure represent paths through the decision tree specified in Figure 4. HS-B, for example, indicates that an individual graduates from high school first and from an applied university after that.

4.2 Mechanisms

Estimated parameters contain information about the distribution of wage returns to university and characteristics of academic risk.

Wage Returns to Applied University: The model parameters show that wage returns to applied university are substantial. The most crucial difference between the wage process in the academic and vocational sector are returns to experience. Individuals with bachelor's degrees enjoy substantially larger returns to experience than those without. The college wage premium increases particularly strongly between the ages of thirty and forty. To understand how expected returns to university are distributed, I calculate returns for each combination of observed and unobserved characteristics in the model. Table 2 shows the percentile of the distribution of wage returns to applied university. Returns to applied university differ substantially across the population. Most individuals receive negative at age thirty, while some receive positive returns. It is essential to note that individuals without applied university degrees have accumulated more experience at age thirty. This may explain why returns at age thirty are negative for many individuals. Most individuals receive positive returns at age forty, while others receive significant returns. The distribution of wage returns highlights that understanding

Table 2: Distribution of returns to applied university.

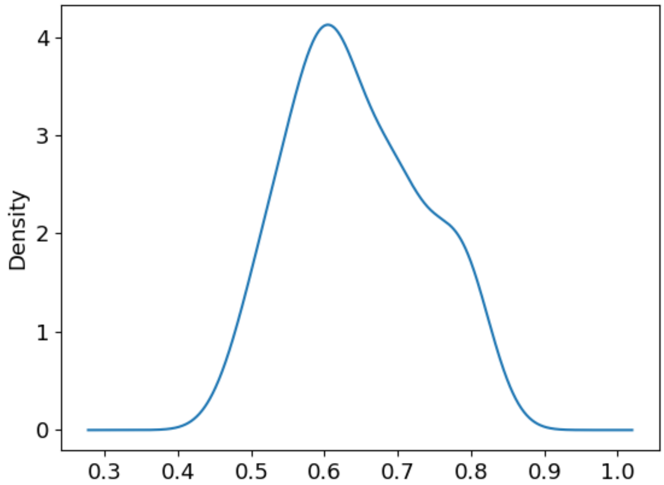
Percentile	**Return Age 30**	**Return Age 40**
25th percentile	-3.5	3.8
50th percentile	-3	4.6
75th percentile	2.9	14.4

Note: This table summarizes the distributions of returns to applied universities at age thirty and forty. The returns are expressed in Euros per hour worked. The returns are obtained by calculating average returns across all groups with distinct observable and unobservable characteristics in the simulated model.

the long-term effect of policy requires understanding what kind of individuals are shifted. Returns to applied university do not substantially differ by parental income. Increasing the number of low-income individuals with an applied university degree thus narrows the income gap across socioeconomic backgrounds. Wages also differ by the non-academic degree an individual pursues. Quitting school after graduating from vocational school is associated with substantially lower wages than holding a high school or vocational degree. Graduates from a vocational program tend to earn more than those with a high school degree. Individuals may choose a vocational degree before they enter university as it is associated with a higher-paying outside option if they dropout of university. The gap is, however, small and declines over time.

Dropout Risk: Heterogenous dropout risk across people is the most dominant factor generating heterogeneity in outcomes across individuals in the model. Considering that the model suggests that returns to applied university are substantial for most of the population, the relevant question is what factors drive significant differences in applied university graduation. Parameter estimates suggest that differences in dropout risk, as opposed to differences in other unexplained preferences, are particularly important. Figure 6 shows the distribution of dropout risk in the population. The figure shows that degree risk is significant and that some groups only graduate from university with a chance of 50 percent. The most important difference in academic risk is along grades. Individuals who enter university from vocational education are slightly more likely to dropout than those who enter high school. Individuals are explicitly prepared for university during high school, while vocational

Figure 6: distribution of dropout risk

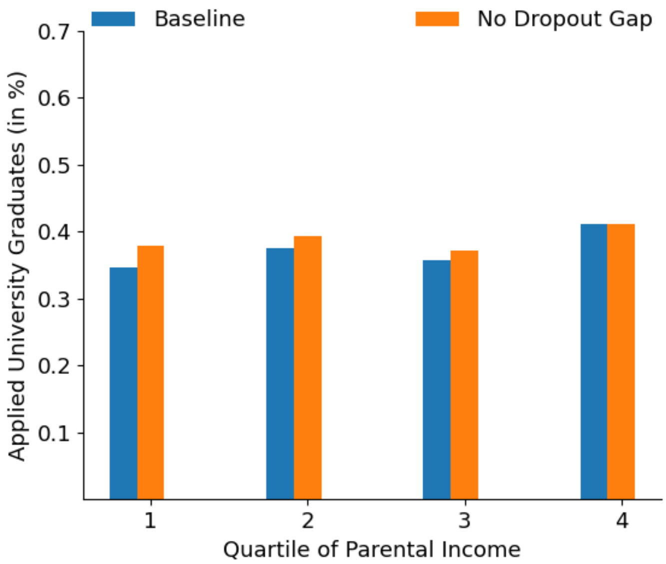


Note: This figure shows a histogram visualizing the distribution of dropout risk. This figure is obtained by calculating the fraction of dropouts out of all individuals that enrolled in university for each combination of observed and unobserved characteristics in the model.

programs usually set a different focus. The difference in dropout rates is, however, relatively small. This finding is remarkable since it shows that pursuing more practical education for some time does not significantly affect eventual success at an applied university. Unobserved factors also matter for dropout risk. Individuals with significant returns to applied universities also have a higher probability of passing applied universities. It is thus even more important to understand which individuals are shifted by a particular policy. If people with modest returns and significant risks are marginal for a specific reform, the effect on wages will be substantially smaller.

Dropout Gap by Parental Income: Parental income is associated with substantially larger dropout risk even after controlling for all previous factors. Particularly, individuals from the lowest income quartile are more likely to dropout of university, holding other factors fixed. Figure 7 shows how applied university graduation would change if the risk gap between students from different socioeconomic backgrounds were removed. The applied university graduation rate among individuals from low-income backgrounds would increase substantially. There could be several reasons for the estimated risk gap. Individuals from low-income backgrounds may have to work on the side or face more economic risk, making them more likely to dropout after receiving an initial shock. Another potential reason is that they have less information and have a more challenging time choosing a university subject

Figure 7: Gradient in dropout risk



Note: This figure shows how graduation rates would change if there were no dropout gaps by parental income. The blue bars show the estimated model's graduation rates for parental income quartiles. The orange bars show graduation rates in an alternative model without a dropout gap by parental income.

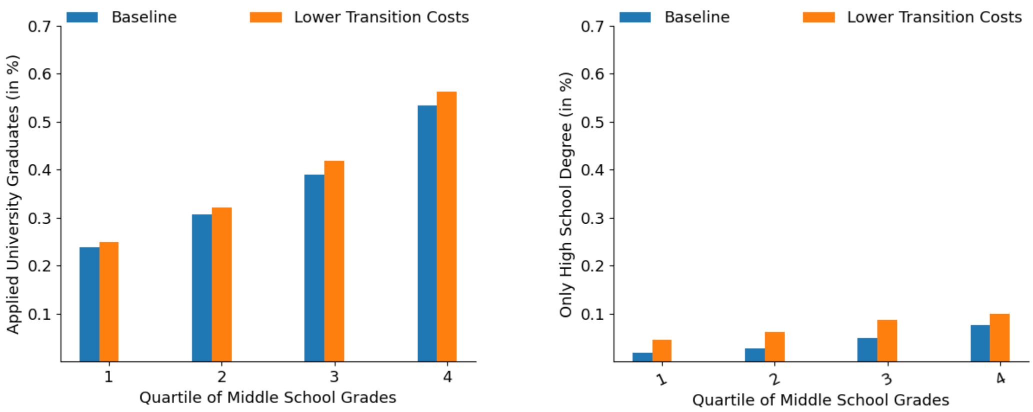
that suits them. Understanding which factors are driving this gap and how policy can address it is essential.

4.3 Counterfactuals

I use the estimated model to run several counterfactual policies. I estimate the impact of changing tracking policies, removing the vocational path to university, and modifying program characteristics. For each policy, I compare an alternative model to the estimated model. Figures show differences in outcomes for groups of observable ability because the impact of policy varies most strongly along this dimension. Whenever patterns differ substantially between individuals from lower and higher income backgrounds, I discuss these differences.

Transition Costs Transition costs to applied high school are substantial and constitute a barrier to higher education for individuals with high grades. I change two aspects of the model to understand how a more flexible tracking system would shift outcomes. I abolish school types and simulate a world where every school is part of the class of the most liberal schools. Secondly, I decrease costs for individuals with lower grades since these individuals are facing more barriers to transit to high school. Figure 8 shows how the simulated policy would change graduation. I plot the change in university graduation and high school graduation for each group of observed ability. The policy increases applied university graduation by around two percent. The policy also increases the amount of people who only complete a high school degree. Individuals with low observed ability see a smaller increase in university graduations but a more significant increase in individuals who only hold a high school degree. Many of them thus dropout of university or do not enroll in university after graduating from mid level high school.

Figure 8: The effect of enforcing higher acceptance rates at high school.



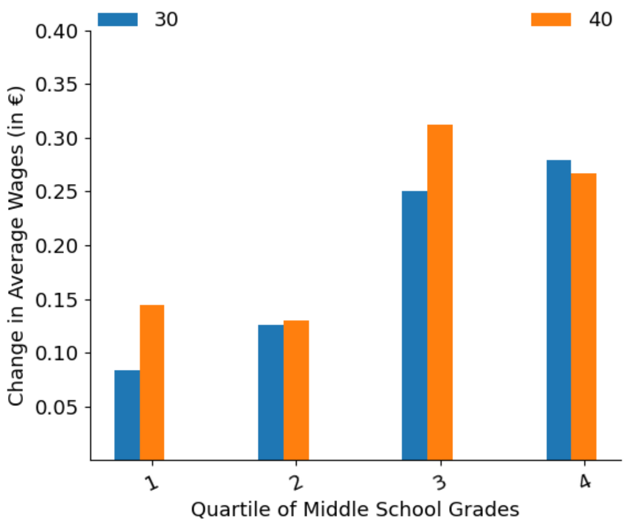
(a) University Graduates (b) HAVO only

Note: This figure shows how enforcing higher acceptance rates at high school would affect the number of university graduates and individuals who only hold a high school degree. The blue bar shows proportions in the baseline model. In contrast, the orange bar shows the proportion in the counterfactual scenario where all schools behave like the most lenient schools and individuals with low grades face lower barriers.

Figure 9 shows changes in average hourly wages caused by the reform. Individuals with higher grades benefit more than individuals with lower grades. This is because low-grade individuals contain a higher fraction that is induced to enter high school by the policy but fail to finish college. Increasing flexibility for individuals with higher grades is associated with higher graduation and average wages.

Vocational path to university: Without any uncertainty, there would be no value to the vocational path to university. Entering university from vocational education usually takes longer and is associated with a slightly higher dropout risk. However, the vocational path plays two crucial roles in an uncertain world. First of all, it allows individuals to manage risk. If they directly proceed to high school and dropout of university later, they only have a high school degree, which is associated with lower labor market returns. Moreover, there is also a substantial risk of dropout out of high school, possibly costing people years. Vocational programs are associated with lower dropout rates and higher labor market returns than high school degrees. If an individual thus faces substantial academic risk, it may make sense to pursue a vocational degree first and continue to try entering university afterward. Another reason is that some individuals may only discover their interest in academic education later. In particular, if they are not from an academic background, they may not know whether they would like higher education at 16. Figure 10 shows a simulated model without a vocational path to university

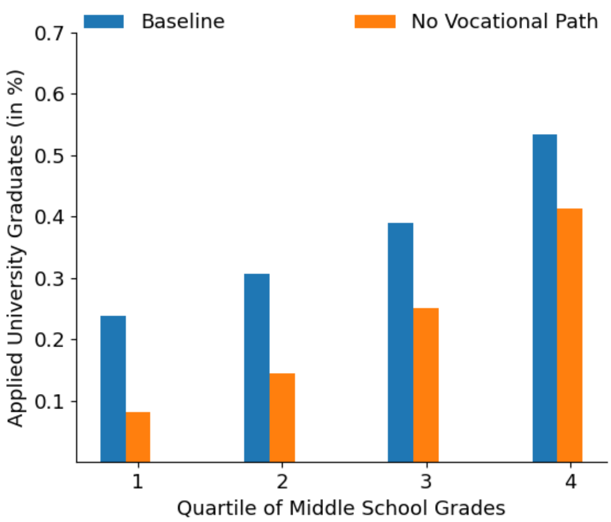
Figure 9: The effect of enforcing higher acceptance rates at high school.



Note: This figure shows how enforcing higher acceptance rates at applied universities would affect average wages. The blue bars show the difference in wages across the baseline and a counterfactual scenario where all schools behave like the most lenient schools and individuals with low grades face lower barriers at age 30. The orange bar shows the same difference at age 40.

but with lower transition costs to high school. The figure shows that university graduation would fall drastically across all grade levels. The vocational path to university increases university graduation by allowing individuals to hedge risk and reconsider their initial decision. The model parameters suggest that being able to reconsider drives most of the effect in 10 as returns to high school are similar to returns to vocational training. There could be a lot of motives behind changing your mind

Figure 10: Change in Graduation if there was no vocational path to Applied University.

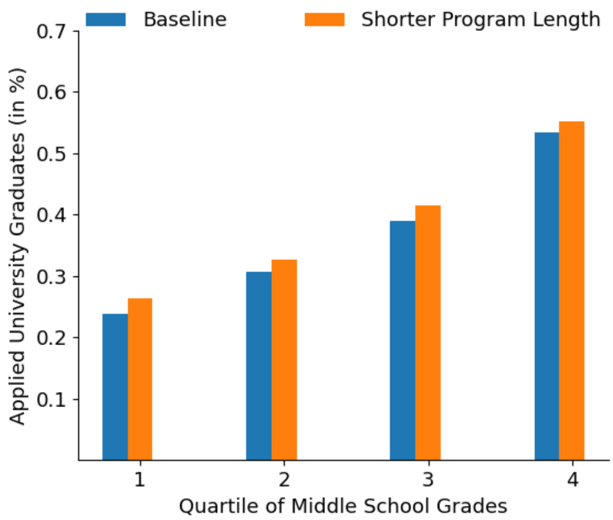


Note: This figure shows how removing the vocational path to applied university would affect applied university graduation. The blue bar shows proportions in the baseline model, while the orange bar shows the proportion in the counterfactual scenario without a vocational path to applied university.

about wanting to go to university. Having a limited amount of information about applied university could be a reason. Maturing over time could also be necessary. In particular, children from academic households are more likely to get pressured into academic education than children from non-academic households. Another reason could be learning about returns or one's ability over time. It is beyond the scope of the model to separate these factors. The results show, however, that this block of reasons is essential for individual decisions.

Changing Program Characteristics To understand the effect of shorter program duration, I simulate a model where vocational programs only take three years. It is essential to mention that many programs already offer the option to get a vocational degree within three years. Many people, however, take longer, between four and six years. This may also be partly due to individuals switching or repeating classes. It is thus likely not possible to implement this policy exactly. The results, however, show the effects of measures that would decrease the time until graduation in vocational education. To

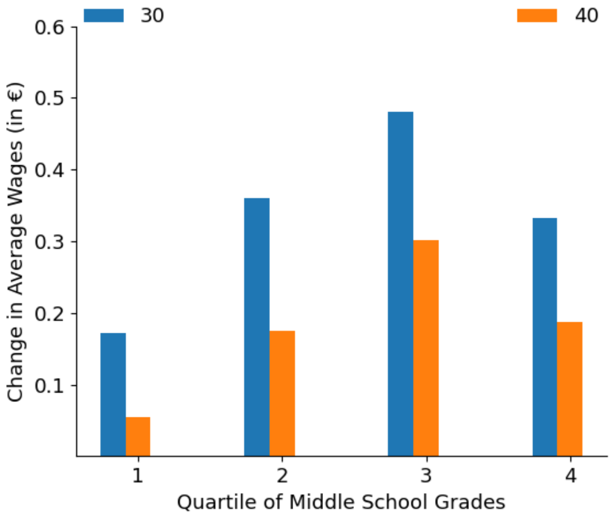
Figure 11: effect of shorter vocational programs.



Note: This figure shows how decreasing the duration of vocational programs would affect applied university graduation. The blue bar shows proportions in the baseline model, while the orange bar shows the proportion in the counterfactual scenario where higher vocational programs only take three years.

understand the effect of shorter program duration, I simulate a model where vocational programs only take three years. It is essential to mention that many programs offer the option to get a vocational degree within three years. Many people, however, take between four and six years to finish vocational training. This may also be partly due to individuals switching or repeating classes. It is thus likely not possible to implement this policy exactly. The results, however, show the effects of measures that would decrease the time until graduation in vocational education. The effect is more significant at age 30 because individuals in the simulated data also graduate earlier, leading to more experience at any given time. The effect on average wages, however, remains substantial at age 40. Decreasing time spent until obtaining a vocational degree may thus facilitate more university degrees. While it may not be possible to make everyone graduate within three years, policymakers should trade off the volume of programs with the fact that people may want to proceed to university afterward.

Figure 12: ..



Note: This figure shows how decreasing the duration of vocational programs would affect applied university graduation. The blue bar shows proportions in the baseline model, while the orange bar shows the proportion in the counterfactual scenario where higher vocational programs only take three years.

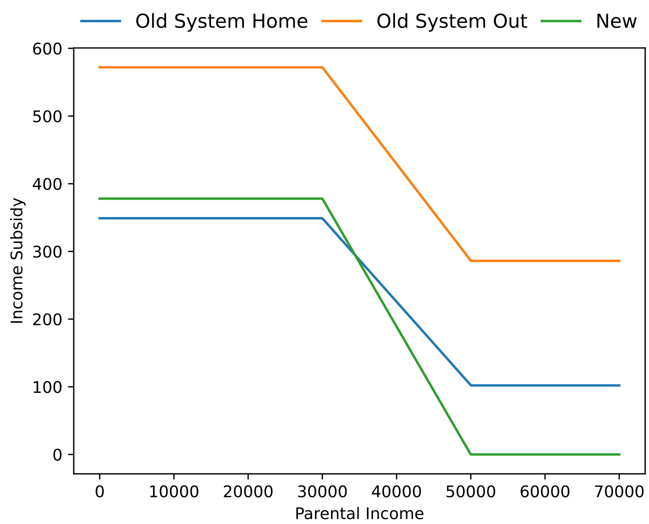
5 The Effect of Income Subsidies

I now discuss the impact of income subsidies. I first introduce a recent reform to student income subsidies. Then, I present the empirical strategy and, finally, the results.

5.1 A Reform to Student Income Subsidies

The Dutch government pays monthly loans to university students converted to grants upon graduation. Initially, individuals who moved out of their parental homes received higher payments. In 2015, the Dutch government introduced a reform to the subsidy scheme. Figure 13 summarizes the changes that have been introduced. Subsidies for individuals from higher-income households have been removed completely. Furthermore, the reform has abolished privileges for individuals who enter university and move out. Low-income individuals who would have studied and moved out under the initial subsidy scheme have lost 200 euros, while individuals who would have stayed home have lost nothing. Individuals who entered university before 2015 could keep the old subsidy scheme until graduation.

Figure 13: Incidence of the reform



Note: This figure shows the impact of the income subsidy reform in 2015. The x-axis shows parental income, and the y-axis shows the subsidy amount over different spells. Note that this shows the amount of subsidies for individuals without siblings. If an individual has one more sibling still dependent on the parents, all lines are shifted to the right by varying amounts.

5.2 Empirical Strategy

I now summarize the empirical strategy to derive treatment effects from the reform I have just introduced. I will first characterize a latent control group. After that, I will introduce a method to identify this latent group, and finally, I will show how I use this information to obtain the effect of the reform.

Characterization of a latent control group: Individuals who would not have moved out and entered university before the reform are not affected and can thus be used as a control group. Figure 3 shows that the reform has only changed subsidies for people who would have moved out and entered university. Let $d_i = (h_i, e_i)$ be the joint housing and education decision of an individual, where $h_i \in \{0, 1\}$ denotes the decision to remain at home and $e_i \in \{0, 1\}$ indicates the decision to attend university. Let $T(d)$ be a function that maps a joint decision d into a monthly subsidy amount. Let T_{pre} refer to the old subsidy scheme and T_{post} to the reformed scheme since 2015. Individual i picks the combination of housing and education that maximizes her utility depending on the subsidy scheme she faces $d_i(T_t)$. Figure 13 shows that low-income individuals who would have studied and stayed at home before the reform receive slightly higher subsidies after the reform. People who would not have been attending university will not change their decision because of the reform since it makes studying less attractive. I will only focus on individuals from lower-income backgrounds since higher-income individuals have lost out in either case. Formula 10 formally defines the latent control group. One who would not have studied and moved under the old reform scheme will keep their decision under the new scheme.

$$d_i(T_0) = d_i(T_1) \text{ for any } d_i(T_0) \neq (0, 1) \tag{10}$$

Additionally, I assume that treatment assignment is stable over time in formula 11.

$$d_{i,t}(T) = d_{i,t+n}(T) = d_i(T) \tag{11}$$

If both conditions hold, one can compare enrollment changes across the latent control and treatment groups to identify the reform's effect.

Empirical approximation of latent treatment: Potential choices under the old subsidy scheme $d_i(T_{pre})$ cannot be observed after the reform is introduced, which implies that one cannot directly compare the treatment and control group. Instead, I predict latent treatment status with observable characteristics retrieved from administrative data. It is difficult to predict the joint decision d with observable characteristics directly. To overcome this problem, I predict the probability that an individual would stay at home conditional on going to university. Later, when I compare individuals with different treatment probabilities, I will control for an individual's probability of enrollment to account for varying enrollment rates across observables. Let X_i be a vector of observables and let $P_d(X) = P(d_i(T_{pre}) = (1, 1)|e_i(T_{pre}) = 1, X_i = X)$ be the probability that an individual with characteristics X would stay at home if she would attend university. I can observe X for all individuals and $d_i(T_{pre})$ only for individuals who graduated before the reform was introduced. To predict $P_d(X)$, I train a gradient-boosting regressor on individuals who enrolled in university before the reform was introduced. X includes spatial factors, personal characteristics, family situation data, and prior schooling career information. I leave out individuals who graduated in 2014 and use them to test the algorithm's predictions.

Parallel Trends: I need to make a parallel trends assumption to derive treatment effects from differences across individuals with a high and low probability of being treated. Let Z_i be a vector of individual level controls and let Y_i be an individual level outcome such as university enrollment or graduation. Let $Y_{i,pre}$ denote the value of Y_i before the introduction and $Y_{i,post}$ denote the value after the introduction. Figure 12 shows my parallel trends assumption. Trends need to be parallel between latent treatment groups and between individuals with different probabilities of receiving the latent treatment. I need to adapt the usual parallel trends assumption because I only approximate the treatment status of individuals. The identification thus comes from comparing individuals who have been treated and have a high probability of being treated and individuals who have not been treated and have a low probability of being treated.

$$\begin{aligned}&E[Y_{i,post}(T_{pre}) - d_{i,pre}(T_{pre})|d_i(T_{pre}) \neq (0,1), P_H, Z_i] =\\&E[d_{i,t}(T_{post}) - d_{i,t-1}(T_{pre})|d_{i,pre} = (0,1), P_L, Z_i]\end{aligned} \tag{12}$$

In practice, I will assume that this holds if individuals with a high and low probability of treatment exhibit parallel trends before the reform. The amount of people who have a high probability of being part of the treated group and are not actually will not be significant. Observed trends will be close to trends across latent treatment groups with different treatment probabilities.

Comparing Individuals with High and Low Probability: The parallel trends assumption allows me to express differences across individuals with a high and low probability of being treated in terms of treatment effect on the treated conditional on controls and treatment probabilities. A more detailed composition of the effect is provided in section 7.4 of the appendix. The differences in differences across groups can be written as the difference between two terms. The first term is proportional to the treatment effect on treated individuals with a high probability of being treated. The second term is proportional to the treatment effect on treated individuals with a low probability of being treated. As long as the probability of treatment is high in the predicted treatment group and low in the predicted control group, the whole term is close to the treatment effect on treated individuals with a high probability of being treated. In the appendix derivation, I use the probability of being treated given someone's observables. However, the same decomposition also works if I plug in an estimate of this probability instead. In the estimation, I will use the predicted $\hat{P}_d(X)$ that I described last section. An alternative way to derive the effects of the reform would be to run a continuous two-way fixed effects regression where the coefficient of interest is the interaction between time and the continuous predicted probability. However, using a continuous treatment indicator requires strong assumptions (Callaway et al., 2021).

Empirical Strategy: I now present the specification I estimate to derive the reform's effect on enrollment and university graduation. I consider individuals treated if their predicted probability of staying at home conditional on going to university is below twenty-five percent: $\hat{P}_{T_0}(X_i) \leq 25$. Individuals belong to the control group if their expected probability of staying at home conditional on going to university is above seventy-five percent: $\hat{P}_{T_0}(X_i) \geq 75\%$. I chose these cutoffs as they leave me with a sufficiently large sample and still only contain people with a high probability of being in the control or treatment groups. Let γ_i be a treatment fixed effect. First, I consider the effect of the reform on university enrollment. To account for different enrollment rates across people with high and low propensities to be treated, I control for an individual's probability of entering university $P_E(X_i)$. I predict $\hat{P}_E(X_i)$ the same way as I get the probability of treatment. Furthermore, θ denotes year fixed effects, and Y_i denotes a vector of observables containing gender, the duration of vocational training, and the type of vocational program that individual i has pursued before graduation. I then estimate the following linear probability model:

$$E_i = \beta_0 + \theta_i * \gamma_i + \theta_i + \beta_1\gamma_i + \beta_2\hat{P}_E(X_i) + \beta_3 Y_i + \epsilon_i \tag{13}$$

Running a two-way fixed effects regression may be problematic as the weighting across control variables may not sum to one. It is, however, essential to keep the probability of going to university fixed across the comparison groups. To derive the reform's effect on graduation, I include the probability of graduating from university $P_G(X_i)$ instead of the probability of enrolling in university. I again obtain $\hat{P}_G(X_i)$ by training a gradient boosting algorithm on pre-reform data. The final specification for graduation looks as follows:

$$G_i = \beta_0 + \theta_i * \gamma_i + \theta_i + \beta_1\gamma_i + \beta_2 P_G(X_i) + \beta_3 Y_i + \epsilon_i \tag{14}$$

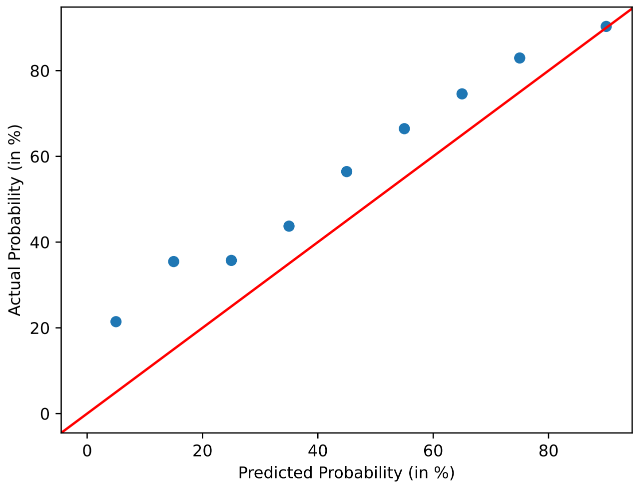
The enrollment specification includes individuals from 2009 until 2020. The graduation specification only contains individuals from 2011 until 2016. The reason is that for individuals before 2011, specific data is missing to obtain $P_G(X_i)$. I only consider people who graduated until 2016, as many individuals who graduated after that are still enrolled in university in 2021.

5.3 Results

I now summarize empirical results on the effect of income subsidies. I first outline the performance of the estimation procedure and treatment effects derived from the reform. After that, I simulate a similar policy with the structural model introduced earlier.

Prediction Performance: The prediction algorithm does an excellent job of predicting people likely to move out. Figure 14 shows the prediction performance of the algorithm. The figure shows the observed proportion of people staying at home for each decile of predictions. The training and test samples only contain individuals who enrolled in university. The dot above the predicted probability

Figure 14: Performance of the Prediction Algorithm

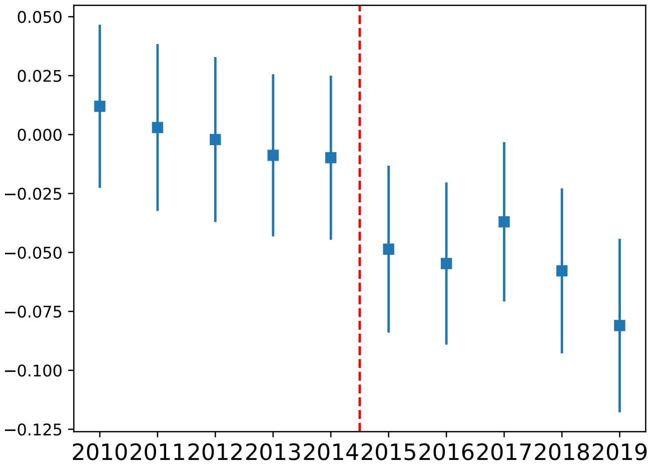


Note: This figure shows the performance of the prediction algorithm. The x-axis shows the predicted probability, and the y-axis shows the actual observed probability in a test sample. To obtain the figure, I have grouped observations in the test sample by their decile of probability predictions. Then, I calculated the probability they would stay home and plotted the data.

of twenty percent, for example, is the proportion of individuals studying and staying at home among all who are predicted to have a probability of staying at home between twenty and thirty percent. The dots are always close to the forty-five degrees line, which shows that the algorithm predicts well.

Changes in Enrollment: Figure 15 shows the evolution of university enrollment of the predicted treatment group relative to the predicted control group. The predicted treatment group has dropped by four percent relative to the predicted control group, which is a substantial reduction considering the size of the income subsidy. Point estimates in section 7.6 of the appendix show that the predicted control

Figure 15: Results University Enrollment

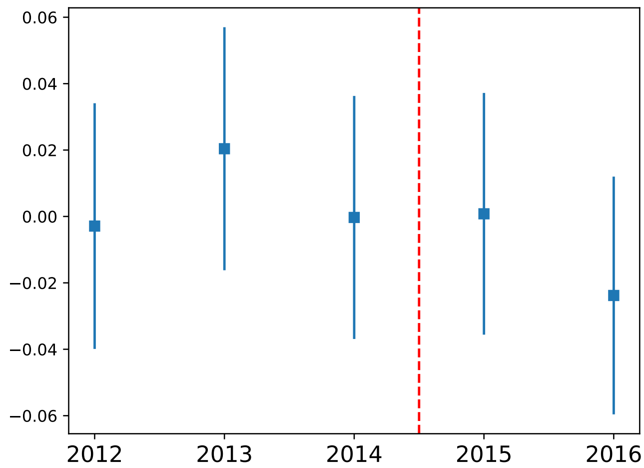


This figure shows coefficients from a two-way fixed effects regression comparing individuals with different propensities to move out. The coefficients depict the evolution of university enrollment of the group that is more than 75% likely to move out relative to the control group that is less than 25% likely to move out. The coefficients are obtained by estimating the linear probability model described in formula 13. Point estimated can be found in section 7.6 of the appendix.

group has also reduced their enrollment by five percent. It is not clear whether they drop because of the reform or whether they respond to other trends. The reform should not affect individuals with a low probability of leaving home. One potential explanation for why the predicted control group drops is that not all individuals are aware that they are entitled to means-tested grants (Konijn et al., 2023). On the other hand, overall labor market conditions improved between 2010 and 2020, which may also impact enrollment decisions. It is thus difficult to pinpoint the exact reason for the enrollment decline of the control group. The four percent decline of the treated group is likely a lower bound for the reform's effect, as the control group may have responded as well.

Graduation: 16 shows the evolution of university graduation. The evolution of graduation looks more noisy. There is no significant drop after the reform has been introduced. One potential issue is that some people take very long to finish their degree and may still be in university six years after the reform has been introduced. If I include people still studying after five years in the definition, the decline is a bit larger, but the overall evolution remains noisy (See 19). The change in university degrees is much less pronounced than the decline in enrollment and more challenging to distinguish from the general trend. The reform has thus pushed people out of university who are either likely to drop out or are likely to need more than five years to graduate. In the appendix, I look at how graduation rates of individuals with low dropout risk react to the reform. 20 show that individuals with low dropout risk show a more significant reaction to the reform that is more distinguishable from

Figure 16: Results University Graduation

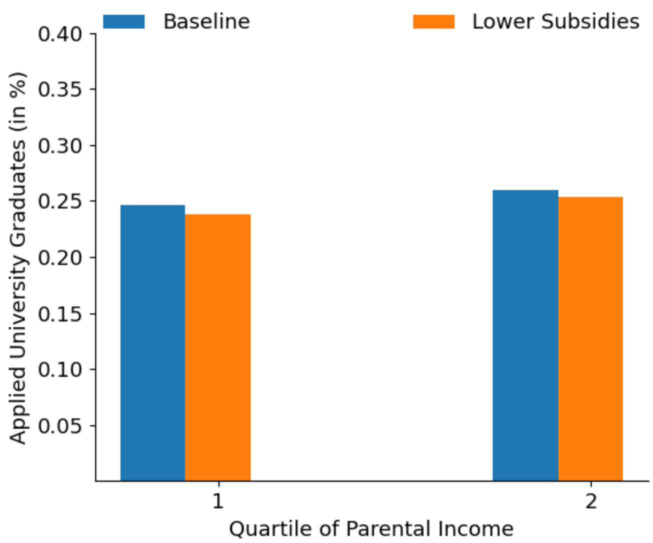


This figure shows coefficients from a two-way fixed effects regression comparing individuals with different propensities to move out. The coefficients depict the evolution of university graduation of the group that is more than 75% likely to move out relative to the control group that is less than 25% likely to move out. The coefficients are obtained by estimating the linear probability model described in formula 14. Point estimated can be found in section 7.6 of the appendix.

the general trend.

Reform Simulation in the model: Reduction of income subsidies is associated with modest declines in enrollment according to the structural model. I simulate an alternative model with lower non-pecuniary returns to university. Figure 18 shows that the model predicts an enrollment decline of

Figure 17: Simulated Effect of the reform.

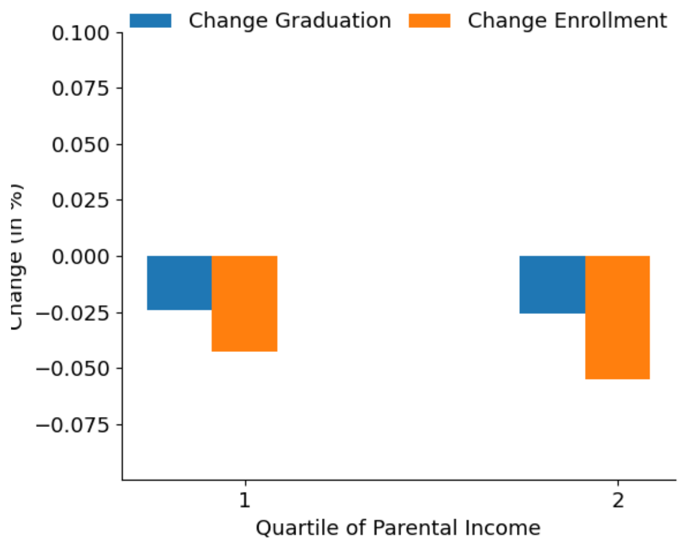


Note: This figure shows the simulated effect of the reform in 2015. To obtain the figure, I simulate an alternative model where the nonpecuniary returns to university are reduced by 2400 annually. I then compare graduation rates between the original model and the counterfactual simulation.

around one percent. Degree completion is predicted to be much lower, particularly for individuals from low-income backgrounds. There are two reasons why the model can potentially not reproduce the reform's effect. The treated group differs from the broad population, and the treatment effect on the treated is potentially larger than that on the broad population. Furthermore, the model is not ideally suited to predict the effect of income subsidies as it includes no consumption component and no risk aversion.

Thus, the reform likely reduces the utility of studying to a larger extent than the monetary value that individuals miss out on. I thus simulate an alternative model where I reduce the utility of the university until the reduction in enrollment is similar to what the reform predicts. 18 shows that complier of the simulated policy have considerable academic risk, and the degree reduction is less than two-thirds of the reduction in enrollment. The model and the reform thus agree on the characteristics of the complier of the reform. While the model cannot exactly reproduce the reform, it gets the selection right, which increases confidence in the other policy simulations.

Figure 18: Simulated Complier



Note: This figure shows the compiler of a simulated reform with the same size as the empirical results.

6 Conclusion

I have investigated the effect of education policy in the presence of early achievement gaps and alternative paths to university. I have found that returns to applied university are substantial for many low income individuals despite early achievement gaps. Increasing flexibility of the tracking system would increase graduation and wages of low income individuals. Alternative paths to university are important for low income individuals as many people only find their interest in academic studies later in life. Thus it is important to design the education system such that individuals that opted out of academic education earlier can still go to university without having to incur large transition costs.

7 Appendix

7.1 Model Parametrization

In this section I show the full model parametrization. Wage equations have been specified in 4 and 5 respectively.

Nonpecuniary Returns Formula 15 shows nonpecuniary utility for working without applied university degree. Utility for working with applied university degree looks the same without the degree term.

$$F_v(Y, A_t, E) = \beta^F_{0,v} + \beta^F_{1,v} * E_t + \beta^F_{2,v} * A_t + \xi^F_{0,v} * Y \tag{15}$$

Formula 16 shows nonpecuniary utility for applied university and both forms of vocational training. Utility returns to high school additionally include grades.

$$F_d(Y, \theta) = \beta^F_{0,d} + \xi^F_{0,d} * \theta + \xi^F_{1,d} * Y \tag{16}$$

Dropout Risk Formula 1 shows the specification that holds for high school. For university I additionally include an indicator whether an individual has entered university after high school or after vocational training. For the higher vocational program I have left out latent types and for the lower vocational program I have left out both latent types and grades.

Duration Risk Formula 2 shows the specification of duration risk for applied university and higher vocational programs. For the lower vocational program I left out grades. High School and higher vocational training after lower vocational training have fixed lengths.

7.2 Parameter Estimates

Table 3: Wage Returns to Academic Work

name	value	SE
Age	0.01	0.0042
Constant	2.1	0.04
Experience	0.11	0.0044
$Experience^2$	-0.24	0.026
G_2	0.014	0.018
G_3	0.018	0.016
G_4	0.032	0.019
θ_2	0.33	0.021
θ_3	-0.16	0.042

Table 4: Wage Returns to Vocational Work

name	value	SE
Age	0.024	0.0056
Constant	2.2	0.03
Experience	0.075	0.0025
$Experience^2$	-0.21	0.013
G_2	0.039	0.0088
G_3	0.012	0.0092
G_4	0.024	0.011
MBO3	0.1	0.026
MBO4	0.12	0.024
θ_2	-0.052	0.035
θ_3	-0.14	0.035
Dropout	0.056	0.027
VMBO	-0.044	0.025

Table 5: Nonpecuniary Returns to Academic Work

name	value	SE
Age	3e+02	85
Constant	9.1e+04	1.1e+02
Y_2	1.1e+04	79
Y_3	1.8e+04	97
Y_4	2.7e+04	96

Table 6: Nonpecuniary Returns to Academic Work

name	value	SE
Age	2.7e+03	87
Constant	2.5e+04	95
MBO3	2.2e+04	69
MBO4	3.5e+04	78
Y_2	7.4e+03	96
Y_3	2.5e+04	87
Y_4	2.6e+04	88
VMBO	-1.2e+04	71

Table 7: Nonpecuniary Returns to Applied University

name	value	SE
Constant	8.7e+04	96
Y_2	2.6e+03	94
Y_3	1.3e+04	93
Y_4	9e+03	1.1e+02
θ_2	3.8e+04	84
θ_3	-5e+04	1e+02

Table 8: Nonpecuniary Returns to High School

name	value	SE
Constant	-1.7e+05	1.1e+02
G_2	2.1e+04	76
G_3	7.5e+04	1e+02
G_4	1.2e+05	1.1e+02
Y_2	2.2e+03	84
Y_3	7.6e+02	93
Y_4	4.5e+03	89
θ_2	8e+03	1.1e+02
θ_3	-2.5e+04	97

Table 9: Nonpecuniary Returns to MBO4

name	value	SE
Constant	6.4e+04	80
Y_2	-3.1e+03	75
Y_3	1.6e+04	93
Y_4	1.4e+04	1e+02
θ_2	-3e+04	83
θ_3	-1.1e+04	90

Table 10: Nonpecuniary Returns to MBO3

name	value	SE
Constant	1e+05	82
Y_2	-2.3e+04	74
Y_3	6.1e+02	1.2e+02
Y_4	-2.7e+04	1.1e+02
θ_2	-4.5e+04	1e+02
θ_3	5e+04	81

Table 11: Degree Risk Applied University

name	value	SE
Constant	0.2	0.034
G_2	0.18	0.036
G_3	0.48	0.045
G_4	0.94	0.049
MBO4	-0.068	0.042
Y_2	0.14	0.039
Y_3	0.17	0.043
Y_4	0.28	0.044
θ_2	0.0081	0.047
θ_3	-0.2	0.035

Table 12: Degree Risk High School

name	value	SE
Constant	0.19	0.042
G_2	0.35	0.046
G_3	0.62	0.049
G_4	0.97	0.04
Y_2	0.023	0.049
Y_3	0.0095	0.041
Y_4	-0.00089	0.045
θ_2	0	0.033
θ_3	0	0.024

Table 13: Degree Risk MBO4

name	value	SE
Constant	1.2	0.039
G_2	0.2	0.045
G_3	0.05	0.041
G_4	0.05	0.037
Y_2	0.19	0.038
Y_3	0.34	0.04
Y_4	0.34	0.046

Table 14: Degree Risk MBO3

name	value	SE
Constant	0.66	0.034
Y_2	0.012	0.045
Y_3	0.21	0.036
Y_4	0.39	0.045

Table 15: Duration Risk Applied University

name	value	SE
Constant	3	0.029
G_2	-0.014	0.044
G_3	0.0048	0.042
G_4	-0.19	0.041
Y_2	-0.11	0.038
Y_3	-0.22	0.042
Y_4	-0.26	0.044

Table 16: Duration Risk MBO4

name	value	SE
Constant	3.1	0.044
G_2	-0.11	0.039
G_3	-0.082	0.053
G_4	-0.26	0.041
Y_2	-0.057	0.058
Y_3	-0.0017	0.043
Y_4	-0.026	0.036

Table 17: Duration Risk MBO3

name	value	SE
Constant	0.94	0.044
Y_2	-0.22	0.048
Y_3	-0.17	0.038
Y_4	-0.061	0.041

Table 18: Probabilities Latent Type 2

name	value	SE
Constant	-0.22	0.045
G_2	0.32	0.041
G_3	0.27	0.04
G_4	0.81	0.042
Y_2	-0.44	0.044
Y_3	0.3	0.043
Y_4	0.4	0.046
U_2	0.25	0.044
U_3	0.088	0.047

Table 19: Probabilities Latent Type 3

name	value	SE
Constant	0.59	0.046
G_2	-0.33	0.043
G_3	-0.9	0.048
G_4	-0.96	0.043
Y_2	-0.15	0.047
Y_3	-0.15	0.038
Y_4	0.038	0.039
U_2	0.22	0.041
U_3	-0.13	0.046

Table 20: Transition Costs High School

name	value	SE
U_2	8.5e+04	1.2e+02
U_3	2.1e+05	94

Table 21: Distribution Taste Shocks

name	value	SE
Scale	1.2e+05	85

7.3 Model Fit

Table 22: Degree Combinations by Grades

Grade Quartile	Degree Combination	Observed	Estimated
0	havo	0.006	0.019
	$havo - bachelor$	0.015	0.024
	mbo3	0.187	0.134
	$mbo3 - mbo4$	0.105	0.109
	$mbo3 - mbo4 - bachelor$	0.028	0.043
	mbo4	0.346	0.362
	$mbo4 - bachelor$	0.159	0.171
	vmbo	0.154	0.138
1	havo	0.019	0.028
	$havo - bachelor$	0.048	0.044
	mbo3	0.135	0.115
	$mbo3 - mbo4$	0.089	0.086
	$mbo3 - mbo4 - bachelor$	0.035	0.043
	mbo4	0.344	0.351
	$mbo4 - bachelor$	0.220	0.220
	vmbo	0.109	0.113
2	havo	0.045	0.050
	$havo - bachelor$	0.113	0.109
	mbo3	0.098	0.104
	$mbo3 - mbo4$	0.071	0.071
	$mbo3 - mbo4 - bachelor$	0.036	0.044
	mbo4	0.314	0.282
	$mbo4 - bachelor$	0.242	0.237
	vmbo	0.079	0.104
3	havo	0.086	0.077
	$havo - bachelor$	0.274	0.266
	mbo3	0.054	0.079
	$mbo3 - mbo4$	0.045	0.046
	$mbo3 - mbo4 - bachelor$	0.029	0.041
	mbo4	0.228	0.187
	$mbo4 - bachelor$	0.236	0.227
	vmbo	0.049	0.078

Table 23: Degree Combinations by Income

Income Quartile	Degree Combination	Observed	Estimated
0	havo	0.040	0.044
	$havo - bachelor$	0.099	0.100
	mbo3	0.126	0.122
	$mbo3 - mbo4$	0.083	0.078
	$mbo3 - mbo4 - bachelor$	0.030	0.042
	mbo4	0.308	0.285
	$mbo4 - bachelor$	0.188	0.204
	vmbo	0.126	0.125
1	havo	0.036	0.046
	$havo - bachelor$	0.104	0.115
	mbo3	0.128	0.098
	$mbo3 - mbo4$	0.082	0.073
	$mbo3 - mbo4 - bachelor$	0.033	0.042
	mbo4	0.315	0.297
	$mbo4 - bachelor$	0.214	0.218
	vmbo	0.089	0.110
2	havo	0.037	0.040
	$havo - bachelor$	0.117	0.104
	mbo3	0.116	0.106
	$mbo3 - mbo4$	0.075	0.084
	$mbo3 - mbo4 - bachelor$	0.035	0.043
	mbo4	0.308	0.310
	$mbo4 - bachelor$	0.233	0.211
	vmbo	0.079	0.102
3	havo	0.042	0.042
	$havo - bachelor$	0.141	0.133
	mbo3	0.095	0.103
	$mbo3 - mbo4$	0.064	0.078
	$mbo3 - mbo4 - bachelor$	0.031	0.045
	mbo4	0.297	0.287
	$mbo4 - bachelor$	0.236	0.233
	vmbo	0.093	0.079

Table 24: Degree Combination by Grade & School Type

School Type	Grade Quartile	Degree Combination	Observed	Estimated
0	0	havo	0.002	0.007
		$havo - bachelor$	0.004	0.010
		mbo3	0.201	0.134

Continued on next page

School Type	Grade Quartile	Degree Combination	Observed	Estimated
		$mbo3 - mbo4$	0.116	0.113
		$mbo3 - mbo4 - bachelor$	0.030	0.046
		mbo4	0.342	0.372
		$mbo4 - bachelor$	0.154	0.177
		vmbo	0.152	0.142
	1	havo	0.008	0.013
		$havo - bachelor$	0.018	0.017
		mbo3	0.152	0.121
		$mbo3 - mbo4$	0.100	0.087
		$mbo3 - mbo4 - bachelor$	0.038	0.044
		mbo4	0.357	0.366
		$mbo4 - bachelor$	0.219	0.233
		vmbo	0.108	0.118
	2	havo	0.023	0.024
		$havo - bachelor$	0.059	0.051
		mbo3	0.112	0.113
		$mbo3 - mbo4$	0.081	0.075
		$mbo3 - mbo4 - bachelor$	0.046	0.050
		mbo4	0.342	0.307
		$mbo4 - bachelor$	0.257	0.264
		vmbo	0.080	0.115
	3	havo	0.055	0.050
		$havo - bachelor$	0.194	0.172
		mbo3	0.062	0.090
		$mbo3 - mbo4$	0.056	0.051
		$mbo3 - mbo4 - bachelor$	0.035	0.050
		mbo4	0.265	0.221
		$mbo4 - bachelor$	0.283	0.275

Continued on next page

School Type	Grade Quartile	Degree Combination	Observed	Estimated
		vmbo	0.050	0.090
1	0	havo	0.003	0.012
		havo − bachelor	0.007	0.017
		mbo3	0.187	0.138
		mbo3 − mbo4	0.105	0.112
		mbo3 − mbo4 − bachelor	0.030	0.043
		mbo4	0.349	0.366
		mbo4 − bachelor	0.161	0.171
		vmbo	0.158	0.142
	1	havo	0.015	0.019
		havo − bachelor	0.038	0.037
		mbo3	0.135	0.116
		mbo3 − mbo4	0.091	0.089
		mbo3 − mbo4 − bachelor	0.036	0.043
		mbo4	0.347	0.361
		mbo4 − bachelor	0.228	0.223
		vmbo	0.111	0.113
	2	havo	0.040	0.044
		havo − bachelor	0.107	0.095
		mbo3	0.098	0.105
		mbo3 − mbo4	0.073	0.076
		mbo3 − mbo4 − bachelor	0.037	0.046
		mbo4	0.313	0.290
		mbo4 − bachelor	0.250	0.240
		vmbo	0.083	0.104
	3	havo	0.085	0.074
		havo − bachelor	0.281	0.256
		mbo3	0.053	0.082

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School Type	Grade Quartile	Degree Combination	Observed	Estimated
		$mbo3 - mbo4$	0.042	0.047
		$mbo3 - mbo4 - bachelor$	0.031	0.041
		mbo4	0.226	0.187
		$mbo4 - bachelor$	0.234	0.231
		vmbo	0.048	0.081
2	0	havo	0.011	0.036
		$havo - bachelor$	0.034	0.044
		mbo3	0.174	0.131
		$mbo3 - mbo4$	0.094	0.104
		$mbo3 - mbo4 - bachelor$	0.026	0.040
		mbo4	0.346	0.351
		$mbo4 - bachelor$	0.162	0.166
		vmbo	0.154	0.129
	1	havo	0.035	0.051
		$havo - bachelor$	0.088	0.076
		mbo3	0.119	0.108
		$mbo3 - mbo4$	0.076	0.082
		$mbo3 - mbo4 - bachelor$	0.032	0.043
		mbo4	0.328	0.326
		$mbo4 - bachelor$	0.213	0.206
		vmbo	0.110	0.108
	2	havo	0.075	0.086
		$havo - bachelor$	0.180	0.188
		mbo3	0.081	0.093
		$mbo3 - mbo4$	0.059	0.063
		$mbo3 - mbo4 - bachelor$	0.026	0.034
		mbo4	0.286	0.244
		$mbo4 - bachelor$	0.218	0.202

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School Type	Grade Quartile	Degree Combination	Observed	Estimated
		vmbo	0.076	0.091
	3	havo	0.120	0.109
		$havo - bachelor$	0.354	0.379
		mbo3	0.045	0.063
		$mbo3 - mbo4$	0.036	0.039
		$mbo3 - mbo4 - bachelor$	0.021	0.031
		mbo4	0.189	0.148
		$mbo4 - bachelor$	0.188	0.169
		vmbo	0.047	0.063

Table 25: Enrollment Proportions by Grade

Programme	Grade Quartile	Observed	Estimated
havo	0	0.051	0.080
	1	0.122	0.112
	2	0.222	0.229
	3	0.406	0.447
hbo	0	0.380	0.430
	1	0.491	0.508
	2	0.575	0.576
	3	0.706	0.690
mbo3	0	0.469	0.423
	1	0.379	0.355
	2	0.302	0.321
	3	0.193	0.242
mbo4	0	0.819	0.833
	1	0.821	0.824
	2	0.768	0.758
	3	0.616	0.596

Table 26: Enrollment Proportions by Income

Programme	Income Quartile	Observed	Estimated
havo	0	0.194	0.205
	1	0.186	0.229
	2	0.201	0.201
	3	0.231	0.246
hbo	0	0.509	0.545
	1	0.522	0.563
	2	0.558	0.526
	3	0.580	0.583
mbo3	0	0.357	0.366
	1	0.351	0.321
	2	0.327	0.333
	3	0.286	0.303
mbo4	0	0.760	0.754
	1	0.764	0.749
	2	0.759	0.758
	3	0.731	0.750

Table 27: Enrollment Proportions by School Type & Grades

Programme	School Type	Grade Quartile	Observed	Estimated
havo	0	0	0.018	0.029
		1	0.048	0.042
		2	0.120	0.110
		3	0.284	0.287
	1	0	0.029	0.055
		1	0.099	0.085
		2	0.208	0.199
		3	0.410	0.435
	2	0	0.102	0.154
		1	0.217	0.203
		2	0.351	0.396
		3	0.535	0.636
hbo	0	0	0.356	0.420
		1	0.458	0.489
		2	0.540	0.543
		3	0.666	0.645
	1	0	0.373	0.416
		1	0.491	0.496
		2	0.573	0.566
		3	0.712	0.686
	2	0	0.408	0.455
		1	0.522	0.539
		2	0.616	0.622
		3	0.743	0.745
mbo3	0	0	0.498	0.433
		1	0.412	0.368
		2	0.335	0.351
		3	0.223	0.280
	1	0	0.480	0.433
		1	0.385	0.359
		2	0.305	0.329
		3	0.189	0.250
	2	0	0.432	0.402
		1	0.342	0.339
		2	0.262	0.279
		3	0.164	0.194
mbo4	0	0	0.822	0.856
		1	0.852	0.863
		2	0.828	0.833
		3	0.714	0.710
	1	0	0.825	0.841
		1	0.828	0.838
		2	0.776	0.776
		3	0.611	0.606
	2	0	0.810	0.805
		1	0.783	0.774
		2	0.694	0.653
		3	0.514	0.461

Table 28: Final Schooling Ages by Grades

Grade Quartile	Age Range	Observed	Estimated
0	0-5	0.595	0.589
	10-15	0.059	0.039
	5-10	0.346	0.372
1	0-5	0.512	0.526
	10-15	0.070	0.047
	5-10	0.418	0.427
2	0-5	0.462	0.474
	10-15	0.069	0.054
	5-10	0.469	0.473
3	0-5	0.385	0.391
	10-15	0.076	0.055
	5-10	0.539	0.554

Table 29: Nonpecuniary Returns to MBO3

Table 30: Final Schooling Ages by Income

Income Quartile	Age Range	Observed	Estimated
0	0-5	0.498	0.499
	10-15	0.084	0.050
	5-10	0.417	0.451
1	0-5	0.499	0.490
	10-15	0.066	0.049
	5-10	0.436	0.461
2	0-5	0.479	0.517
	10-15	0.057	0.045
	5-10	0.464	0.439
3	0-5	0.468	0.461
	10-15	0.059	0.051
	5-10	0.472	0.488

Table 31: Wage Equation No Bachelor Degree

Coefficients	Observed	Estimated
Intercept	2.241	2.183
experience	0.025	0.032
$experience**2$	-0.000	-0.002
Grade Quart. 2	0.011	0.049
Grade Quart. 3	0.016	0.034
Grade Quart. 4	0.029	0.041
Income Quart. 2	0.016	0.001
Income Quart. 3	0.028	0.006
Income Quart. 4	0.044	-0.001
mbo3	0.062	0.012
$mbo3 * experience$	-0.007	0.000
mbo4	0.058	0.045
$mbo4 * experience$	-0.002	-0.000
Period 10	0.297	0.344
Period 11	0.346	0.388
Period 12	0.393	0.432
Period 13	0.443	0.475
Period 14	0.471	0.521
Period 3	0.021	0.044
Period 4	0.032	0.084
Period 5	0.071	0.120
Period 6	0.109	0.168
Period 7	0.161	0.212
Period 8	0.204	0.257
Period 9	0.250	0.301
RSE	0.235	0.209
vmbo	-0.013	-0.097
$vmbo * experience$	-0.007	0.000

Table 32: Wage Equation Bachelor Degree Holder

Coefficients	Observed	Estimated
Intercept	2.403	2.442
experience	0.075	0.065
$experience * *2$	-0.003	-0.002
Grade Quart. 2	-0.008	0.064
Grade Quart. 3	-0.009	0.070
Grade Quart. 4	-0.000	0.109
Income Quart. 2	0.002	-0.036
Income Quart. 3	0.012	0.055
Income Quart. 4	0.019	0.044
$mbo3 - mbo4 - bachelor$	0.002	-0.178
$mbo4 - bachelor$	0.018	-0.130
Period 10	0.169	0.155
Period 11	0.218	0.195
Period 12	0.259	0.238
Period 13	0.305	0.278
Period 14	0.323	0.318
Period 7	0.035	0.039
Period 8	0.075	0.076
Period 9	0.123	0.115
RSE	0.213	0.231
Duration Uni	0.011	-0.030

7.4 Treatment Effects

I now decompose differences in differences between individuals with a high probability of staying at home $P_{T_0}(X) \geq P_H$ and individuals that have a low probability of staying at home $P_{T_0}(X) \leq P_L$. For simplicity I write $E[d_{i,pre}|P_{T_0}(X) \leq P_L] = E[d_{i,pre}|P_L]$ and $E[d_{i,pre}|P_{T_0}(X) \geq P_H] = E[d_{i,pre}|P_H]$. Let $\hat{P}_L$ be $E[P_{T_0}(X)|P_{T_0}(X) \leq P_L]$ and let $\hat{P}_H$ be $E[P_{T_0}(X)|P_{T_0}(X) \geq P_H]$. Let $\Delta Y_i = Y_{i,pre} - Y_{i,post}$. Differences in differences across treatment groups can be decomposed as follows:

$$(E[\delta Y_i|P_L] - E[\delta Y_i|P_H]) =$$

$$(1 - P_L)(E[\Delta Y_i|Y_{t,0} = (0,1), P_L, Z]) + P_L(E[\Delta Y_i|d_{t,0} \neq (0,1), P_L, Z])$$

$$-(1 - P_H)(E[\Delta Y_i|Y_{t,0} = (0,1), P_H, Z) - P_H(E[\Delta Y_i|d_{t,0} \neq (0,1), P_H, Z]$$

Now I rearrange to obtain the following terms:

$$E[\Delta Y_i|d_{t,0} = (0,1), P_L, Z]) - E[\Delta Y_i|d_{t,0} \neq (0,1), P_H, Z])-$$

$$P_L(E[\Delta Y_i|d_{t,0} = (0,1), P_L, Z]) - E[\Delta Y_i|d_{t,0} \neq (0,1), P_L, Z]))-$$

$$(1 - P_H)(E[\Delta Y_i|d_{t,0} = (0,1), P_H, Z]) - E[\Delta Y_i|d_{t,0} \neq (0,1), P_L, Z]))$$

Now I invoke **??** to simplify:

$$(1 - P_L)(E[\Delta Y_i|d_{t,0} = (0,1), P_L, Z]) - E[\Delta Y_i|d_{t,0} \neq (0,1), P_L, Z]))-$$

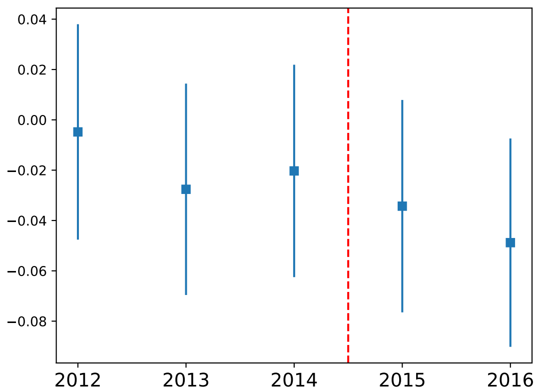
$$(1 - P_H)(E[\Delta Y_i|d_{t,0} = (0,1), P_H, Z]) - E[\Delta Y_i|d_{t,0} \neq (0,1), P_H, Z]))$$

The first term is proportional to the treatment effect on treated individuals with a high probability of being treated. The second term is proportional to the treatment effect on treated individuals with a low probability of being treated. The whole term is thus weakly smaller than the full treatment effect. The discrepancy will grow once $\P_H$ and P_L get larger.

7.5 Robustness Reduced Form

Other Definition of Degree

Figure 19: Results University Enrollment

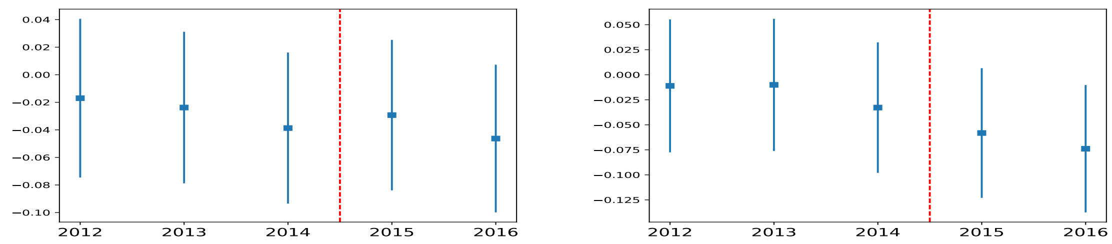


This figure shows coefficients from a two-way fixed effects regression comparing individuals with different propensities to move out. The outcome is an indicator for individuals who have either graduated from university or are still enrolled five years after graduation. The coefficients depict the evolution of the outcome for the group that is more than 75% likely to move out relative to the control group that is less than 25% likely to move out. The coefficients are obtained by estimating the linear probability model described in formula 14. Point estimated can be found in section 7.6 of the appendix.

Differences by initial heterogeneity

?? shows the evolution of enrollment for individuals with and low risk of dropping out. The figures demonstrate that larger dropout risk is associated with substantially bigger responses to the reform.

Figure 20: Effect on Graduation for Individuals with Low and High Dropout Risk



(a) Lowest Dropout Risk

(b) High Dropout Risk

This figure shows coefficie
This figure focuses on a su
the group that is more th
coefficients are obtained by
?? of the appendix.

7.6 Parameter Estimates Reduced Form

I now provide the exact parameter estimates for the main specification.

	Enrolled	Enrolled	Bachelor	Bachelor	*Bachelor∗*	*Bachelor∗*
Index						
2nd Income Quartile	-0.0584***	0.0026	0.0297***	-0.0112***	-0.0167***	-0.0405***
	(0.0023)	(0.0024)	(0.0025)	(0.0027)	(0.0023)	(0.0025)
$Group_1$	-0.0463***	-0.0037	-0.0791***	-0.0494***	-0.0660***	-0.0319***
	(0.0093)	(0.0092)	(0.0094)	(0.0102)	(0.0103)	(0.0112)
$Group_2$	-0.0835***	0.0040	-0.1216***	-0.0574***	-0.1077***	-0.0285*
	(0.0119)	(0.0123)	(0.0113)	(0.0144)	(0.0129)	(0.0165)
2011	-0.0023	-0.0053				
	(0.0107)	(0.0103)				
$2010xGroup_1$	0.0009	-0.0000				
	(0.0130)	(0.0128)				
$2010xGroup_2$	0.0119	0.0120				
	(0.0167)	(0.0173)				
2011	-0.0088	-0.0167				
	(0.0111)	(0.0106)				
$2011xGroup_1$	-0.0024	-0.0040				
	(0.0134)	(0.0131)				

Continued on next page

Index	Enrolled	Enrolled	Bachelor	Bachelor	$Bachelor*$	$Bachelor*$
$2011xGroup_2$	-0.0027	0.0030				
	(0.0172)	(0.0177)				
2012	0.0054	-0.0079	0.0061	0.0022	0.0034	0.0023
	(0.0106)	(0.0103)	(0.0111)	(0.0114)	(0.0120)	(0.0123)
$2012xGroup_1$	-0.0233*	-0.0208	-0.0083	-0.0013	-0.0024	-0.0022
	(0.0129)	(0.0127)	(0.0129)	(0.0136)	(0.0142)	(0.0149)
$2012xGroup_2$	-0.0157	-0.0021	-0.0115	-0.0029	-0.0050	-0.0048
	(0.0169)	(0.0175)	(0.0156)	(0.0185)	(0.0179)	(0.0214)
2013	-0.0079	-0.0170*	-0.0120	-0.0143	0.0017	0.0019
	(0.0105)	(0.0101)	(0.0108)	(0.0111)	(0.0117)	(0.0121)
$2013xGroup_1$	0.0017	0.0003	0.0219*	0.0263**	0.0032	-0.0016
	(0.0127)	(0.0125)	(0.0126)	(0.0133)	(0.0139)	(0.0146)
$2013xGroup_2$	-0.0183	-0.0088	0.0169	0.0204	-0.0144	-0.0276
	(0.0167)	(0.0172)	(0.0153)	(0.0183)	(0.0176)	(0.0210)
2014	-0.0142	-0.0316***	-0.0078	-0.0042	-0.0063	-0.0030
	(0.0107)	(0.0103)	(0.0110)	(0.0114)	(0.0119)	(0.0123)
$2014xGroup_1$	-0.0005	0.0043	0.0113	0.0129	0.0105	0.0046
	(0.0129)	(0.0126)	(0.0128)	(0.0135)	(0.0141)	(0.0149)
$2014xGroup_2$	-0.0278*	-0.0098	0.0137	-0.0003	-0.0033	-0.0203
	(0.0168)	(0.0174)	(0.0154)	(0.0183)	(0.0177)	(0.0211)
2015	-0.0512***	-0.0640***	-0.0350***	-0.0305***	-0.0233*	-0.0236*
	(0.0110)	(0.0106)	(0.0110)	(0.0114)	(0.0120)	(0.0125)
$2015xGroup_1$	-0.0142	-0.0134	0.0146	0.0142	-0.0012	-0.0064
	(0.0132)	(0.0130)	(0.0127)	(0.0135)	(0.0141)	(0.0150)
$2015xGroup_2$	-0.0493***	-0.0486***	0.0119	0.0008	-0.0110	-0.0343
	(0.0171)	(0.0177)	(0.0152)	(0.0182)	(0.0177)	(0.0211)
2016	-0.0259**	-0.0422***	-0.0037	-0.0052	-0.0074	-0.0093
	(0.0104)	(0.0100)	(0.0107)	(0.0111)	(0.0115)	(0.0119)

Continued on next page

Index	Enrolled	Enrolled	Bachelor	Bachelor	*Bachelor∗*	*Bachelor∗*
$2016xGroup_1$	-0.0292**	-0.0249**	0.0051	0.0023	-0.0066	-0.0128
	(0.0125)	(0.0123)	(0.0124)	(0.0131)	(0.0136)	(0.0144)
$2016xGroup_2$	-0.0610***	-0.0547***	-0.0173	-0.0238	-0.0354**	-0.0488**
	(0.0165)	(0.0172)	(0.0149)	(0.0179)	(0.0172)	(0.0207)
2017	-0.0525***	-0.0683***	-0.1471***	-0.1527***	-0.1398***	-0.1473***
	(0.0103)	(0.0100)	(0.0097)	(0.0101)	(0.0111)	(0.0115)
$2017xGroup_1$	-0.0264**	-0.0249**	0.0306***	0.0327***	0.0188	0.0171
	(0.0124)	(0.0122)	(0.0112)	(0.0120)	(0.0130)	(0.0139)
$2017xGroup_2$	-0.0411**	-0.0370**	0.0521***	0.0502***	0.0346**	0.0250
	(0.0163)	(0.0169)	(0.0135)	(0.0166)	(0.0165)	(0.0200)
2018	-0.0286***	-0.0521***			-0.4613***	-0.4770***
	(0.0104)	(0.0101)			(0.0089)	(0.0094)
$2018xGroup_1$	-0.0333***	-0.0265**			0.0665***	0.0714***
	(0.0126)	(0.0125)			(0.0105)	(0.0115)
$2018xGroup_2$	-0.0708***	-0.0578***			0.1122***	0.1090***
	(0.0167)	(0.0175)			(0.0132)	(0.0169)
2019	-0.0275**	-0.0523***			-0.4713***	-0.4835***
	(0.0110)	(0.0108)			(0.0088)	(0.0093)
$2019xGroup_1$	-0.0306**	-0.0288**			0.0659***	0.0657***
	(0.0132)	(0.0132)			(0.0104)	(0.0113)
$2019xGroup_2$	-0.0886***	-0.0810***			0.1089***	0.0994***
	(0.0175)	(0.0184)			(0.0129)	(0.0167)
Intercept	0.7124***	0.0763***	0.2397***	0.0167	0.4365***	0.4058***
	(0.0082)	(0.0143)	(0.0087)	(0.0125)	(0.0093)	(0.0129)
Duration Training		-0.0150***		0.0032*		-0.0311***
		(0.0018)		(0.0019)		(0.0018)
Higher Voc	0.0632***	-0.0105***	0.0451***	0.0132***	0.0539***	0.0102***
	(0.0032)	(0.0033)	(0.0031)	(0.0035)	(0.0031)	(0.0035)

Continued on next page

Index	Enrolled	Enrolled	Bachelor	Bachelor	*Bachelor∗*	*Bachelor∗*
P(Graduate—X)				0.9277***		0.6778***
				(0.0152)		(0.0132)
P(Enroll—X)		1.0092***				
		(0.0098)				
Female	-0.0564***	0.0117***	0.0391***	0.0188***	-0.0070***	-0.0306***
	(0.0024)	(0.0026)	(0.0025)	(0.0027)	(0.0023)	(0.0025)
N	178076	159805	116269	97129	149078	125205
R2	0.019000	0.092000	0.024000	0.063000	0.130000	0.157000

Index	Enrolled	Bachelor	*Bachelor∗*
2nd Income Quartile	-0.0006	-0.0054	-0.0415***
	(0.0038)	(0.0042)	(0.0046)
$Group_1$	0.0106	-0.0598***	-0.0431***
	(0.0165)	(0.0139)	(0.0145)
$Group_2$	0.0166	-0.0505**	0.0011
	(0.0218)	(0.0232)	(0.0248)
2011			
$2010xGroup_1$			
$2010xGroup_2$			
2011			
$2011xGroup_1$			

Continued on next page

Index	Enrolled	Bachelor	$Bachelor*$
$2011xGroup_2$			
2012	0.0225	0.0033	-0.0016
	(0.0186)	(0.0150)	(0.0155)
$2012xGroup_1$	-0.0321	0.0007	0.0223
	(0.0217)	(0.0188)	(0.0196)
$2012xGroup_2$	-0.0116	-0.0032	-0.0111
	(0.0280)	(0.0311)	(0.0332)
2013	-0.0078	-0.0006	0.0094
	(0.0183)	(0.0147)	(0.0152)
$2013xGroup_1$	0.0057	0.0290	0.0145
	(0.0213)	(0.0184)	(0.0192)
$2013xGroup_2$	-0.0109	0.0030	-0.0101
	(0.0270)	(0.0309)	(0.0330)
2014	-0.0040	-0.0114	-0.0160
	(0.0181)	(0.0152)	(0.0156)
$2014xGroup_1$	-0.0036	0.0132	0.0276
	(0.0210)	(0.0189)	(0.0197)
$2014xGroup_2$	-0.0046	-0.0168	-0.0328
	(0.0267)	(0.0304)	(0.0326)
2015	-0.0396**	-0.0387**	-0.0312**
	(0.0185)	(0.0153)	(0.0159)
$2015xGroup_1$	-0.0124	0.0125	0.0029
	(0.0214)	(0.0189)	(0.0199)
$2015xGroup_2$	-0.0321	-0.0361	-0.0582*
	(0.0270)	(0.0298)	(0.0324)
2016	-0.0290	-0.0043	-0.0183

Continued on next page

Index	Enrolled	Bachelor	$Bachelor*$
	(0.0180)	(0.0146)	(0.0150)
$2016xGroup_1$	-0.0144	-0.0124	0.0004
	(0.0209)	(0.0180)	(0.0189)
$2016xGroup_2$	-0.0419	-0.0538*	-0.0739**
	(0.0265)	(0.0295)	(0.0318)
2017	-0.0326*	-0.1749***	-0.1727***
	(0.0181)	(0.0134)	(0.0144)
$2017xGroup_1$	-0.0444**	0.0281*	0.0318*
	(0.0210)	(0.0166)	(0.0182)
$2017xGroup_2$	-0.0521**	0.0076	0.0056
	(0.0264)	(0.0272)	(0.0305)
2018	-0.0267		
	(0.0187)		
$2018xGroup_1$	-0.0235		
	(0.0217)		
$2018xGroup_2$	-0.0656**		
	(0.0272)		
2019	-0.0159		
	(0.0197)		
$2019xGroup_1$	-0.0313		
	(0.0228)		
$2019xGroup_2$	-0.0743***		
	(0.0283)		
Intercept	0.0318	-0.0410**	0.3507***
	(0.0220)	(0.0209)	(0.0226)
Duration Training	-0.0120***	0.0091***	-0.0361***
	(0.0020)	(0.0029)	(0.0033)
Higher Voc	-0.0174***	0.0189***	0.0061

Continued on next page

Index	Enrolled	Bachelor	*Bachelor**
	(0.0042)	(0.0062)	(0.0069)
P(Graduate—X)		1.0358***	0.9554***
		(0.0319)	(0.0332)
P(Enroll—X)	1.0089***		
	(0.0154)		
Female	0.0081**	0.0244***	-0.0274***
	(0.0041)	(0.0044)	(0.0048)
N	74809	48462	48462
R2	0.108000	0.044000	0.038000

References

Arcidiacono, P., Aucejo, E., Maurel, A., and Ransom, T. (2016). College attrition and the dynamics of information revelation. Technical report, National Bureau of Economic Research.

Attanasio, O. P. and Kaufmann, K. M. (2017). Education choices and returns on the labor and marriage markets: Evidence from data on subjective expectations. *Journal of Economic Behavior & Organization*, 140:35–55.

Bertrand, M., Mogstad, M., and Mountjoy, J. (2021). Improving educational pathways to social mobility: evidence from norway's reform 94. *Journal of Labor Economics*, 39(4):965–1010.

Bhuller, M., Eisenhauer, P., and Mendel, M. (2022). Sequential choices, option values, and the returns to education. *arXiv preprint arXiv:2205.05444*.

Birkelund, J. F. and van de Werfhorst, H. G. (2022). Long-term labor market returns to upper secondary school track choice: Leveraging idiosyncratic variation in peers' choices. *Social Science Research*, 102:102629.

Callaway, B., Goodman-Bacon, A., and Sant'Anna, P. H. (2021). Difference-in-differences with a continuous treatment. *arXiv preprint arXiv:2107.02637*.

Castleman, B. L. and Long, B. T. (2016). Looking beyond enrollment: The causal effect of need-based grants on college access, persistence, and graduation. *Journal of Labor Economics*, 34(4):1023–1073.

Cohodes, S. R. and Goodman, J. S. (2014). Merit aid, college quality, and college completion: Massachusetts' adams scholarship as an in-kind subsidy. *American Economic Journal: Applied Economics*, 6(4):251–85.

Deming, D. and Dynarski, S. (2010). College aid. In *Targeting investments in children: Fighting poverty when resources are limited*, pages 283–302. University of Chicago Press.

Eckardt, D. (2019). Are chemists good bankers? returns to the match between training and occupation. Technical report, Mimeo, London School of Economics.

Ehrmantraut, L., Pinger, P., and Stans, R. (2020). The expected (signaling) value of higher education.

Gabler, J. (2022). A python tool for the estimation of large scale scientific models.

Hanushek, E. A., Schwerdt, G., Woessmann, L., and Zhang, L. (2017). General education, vocational education, and labor-market outcomes over the lifecycle. *Journal of human resources*, 52(1):48–87.

Heckman, J. J., Humphries, J. E., and Veramendi, G. (2018). Returns to education: The causal effects of education on earnings, health, and smoking. *Journal of Political Economy*, 126(S1):S197–S246.

Kane, T. J. (2006). Public intervention in post-secondary education. *Handbook of the Economics of Education*, 2:1369–1401.

Keane, M. P. and Wolpin, K. I. (1997). The career decisions of young men. *Journal of political Economy*, 105(3):473–522.

Konijn, S., Visser, D., and Zumbuehl, M. (2023). Quantifying the non-take-up of a need-based student grant in the netherlands. *De Economist*, pages 1–28.

Lee, S. Y. T., Shin, Y., and Lee, D. (2015). The option value of human capital: Higher education and wage inequality. Technical report, National Bureau of Economic Research.

Maralani, V. (2011). From ged to college: Age trajectories of nontraditional educational paths. *American Educational Research Journal*, 48(5):1058–1090.

Matthewes, S. H. and Ventura, G. (2022). On track to success?: Returns to vocational education against different alternatives.

OECD (2012). *Equity and Quality in Education.*

OECD (2019). *PISA 2018 Results (Volume II).*

OECD (2020). *PISA 2018 Results (Volume V).*

Proctor, A. (2022). Did the apple fall far from the tree?

Silliman, M. and Virtanen, H. (2022). Labor market returns to vocational secondary education. *American Economic Journal: Applied Economics*, 14(1):197–224.

Stange, K. M. (2012). An empirical investigation of the option value of college enrollment. *American Economic Journal: Applied Economics*, 4(1):49–84.

Stinebrickner, T. and Stinebrickner, R. (2012). Learning about academic ability and the college dropout decision. *Journal of Labor Economics*, 30(4):707–748.

Trachter, N. (2015). Stepping stone and option value in a model of postsecondary education. *Quantitative Economics*, 6(1):223–256.

Van Esch, W. and J., N. (2010). Van vmbo naar havo: tweestrijd over tweesprong? Technical report.

Wiswall, M. and Zafar, B. (2015). Determinants of college major choice: Identification using an information experiment. *The Review of Economic Studies*, 82(2):791–824.

Zumbuehl, M., Chehber, N., Dillingh, R., et al. (2022). Can skills differences explain the gap in track recommendation by socio-economic status? Technical report, CPB Netherlands Bureau for Economic Policy Analysis.