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 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 countries' education systems. 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 that graduate from vocational training. In the United States, where all students are kept together until high school graduation, low-income individuals are more likely 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 which is consistent with evidence on achievement gaps. Secondly university graduates from low-income backgrounds are twice as likely to have entered university after completing vocational training. Motivated by these observation I analyze educational careers of graduates of vocational school in the Netherlands. More precisely I estimate a dynamic model of educational choices and analyze a recent reform to income subsidies for students.

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 either enroll

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

in 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 substantial effect of the reform shows that graduates of vocational training are particularly sensitive to the costs of higher education. This may be caused by the fact that graduates of vocational are older and from lower income backgrounds than graduates of high school. Policy makers should explicitly take alternative paths to university into account 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, which receives individuals with the lowest assessed academic potential and prepares students for vocational training. 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.

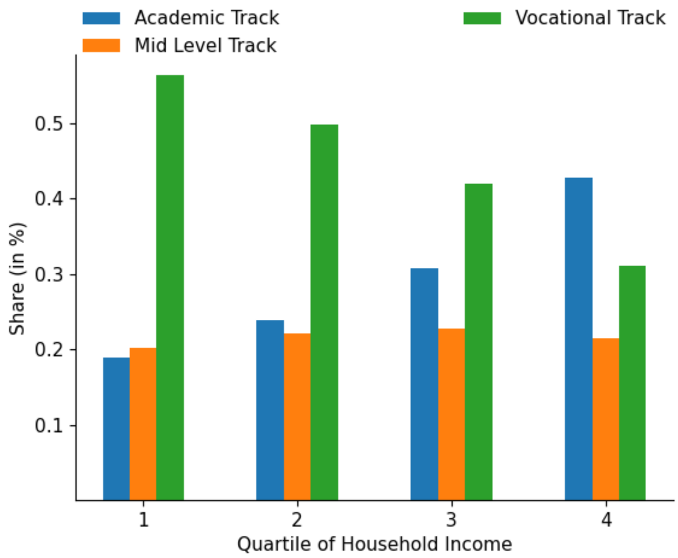
2.2 Data

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 **??** 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 cognitive 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

Figure 1: Track Assignment by Parental Income

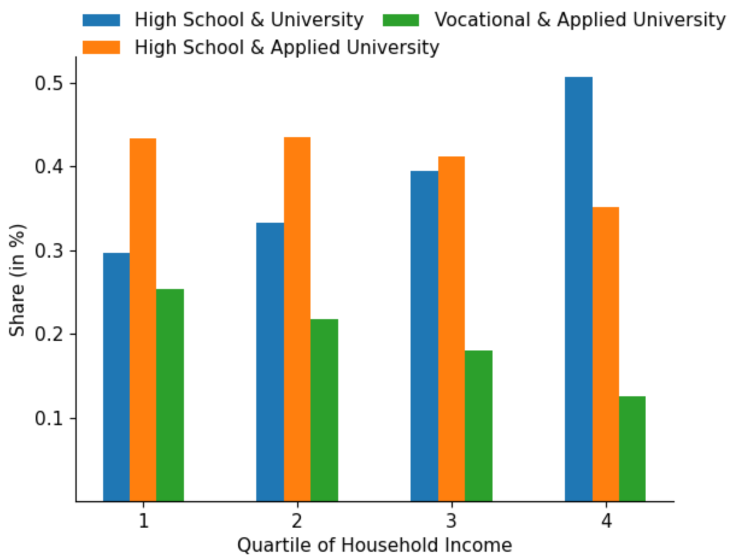


Note: This figure shows track assignment by quartile of parental household income. The vocational track includes all branches of VMBO.

in their life.

Alternative Paths to education are more common among low-income individuals: Figure 2 shows how careers differ by parental income. Conditional on reaching a tertiary degree, individuals from low socioeconomic backgrounds are twice as likely to have entered higher education after vocational education. Entering university after finishing is thus a well-established career in the Netherlands h

Figure 2: Schooling Careers conditional on Graduating from Applied University

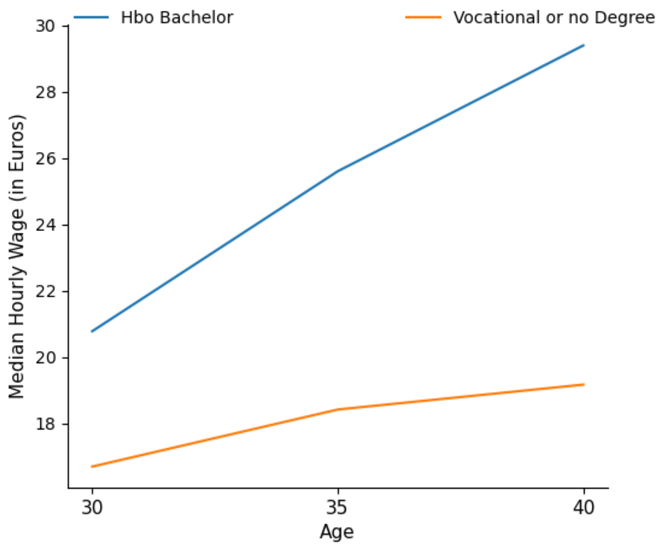


Note: This figure shows schooling careers conditional on holding at least a bachelor's degree.

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. The

Figure 3: Wage Inequality over Time



Note: This figure shows the evolution of 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.

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.

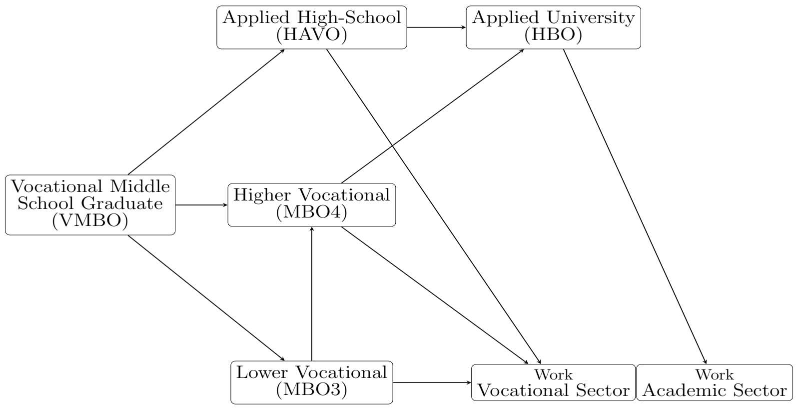
2.4 Pathways to University

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

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

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 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(**?**). 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 S, and lagged choice $d_{\tau-1}$.

One state is a tuple that consists of all fixed characteristics and dynamic states $s_\tau = (a_\tau, S, C^{\tau-1}, G_i, \nu_i, Y_i)$. 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.

$$Logit(d_{i\tau} = 1) = \beta_0 + \beta_1 * Y_i + \beta_2 * age + \beta_3(agexY_i) + \xi_1 * G_i + xi_2 * \theta_i + \nu_i \tag{1}$$

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

$$T_{si}^{pass} \sim Poisson(0, \beta_0 + \beta_1 * Y_i + \xi_1 * G_i + xi_2 * \theta_i) \tag{2}$$

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:

$$T_{si}^{pass} \sim Poisson(0, \beta_0) \tag{3}$$

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. Log wages for the vocational sector look as follows:

$$W_{i,s,t} = \alpha_{0,s} + \alpha_{1,s} * degree_i + \alpha_{2,s} * exp + \alpha_{2,s} * exp^2 + \alpha_{3,s} * age + \xi_{1,s} * G_i + \xi_{2,s} * \theta_i + \xi 3, s * Y_i + \epsilon_{i,s,t} \tag{4}$$

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:

$$W_{i,s,t} = \alpha_{0,s} + \alpha_{1,s} * degree_i + \alpha_{2,s} * exp + \alpha_{2,s} * exp^2 + \alpha_{3,s} * age + \xi_{1,s} * G_i + \xi_{2,s} * \theta_i + \xi 3, s * Y_i + \epsilon_{i,s,t} \quad (5)$$

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

$$U^d(s) = F(s,d) + e^(W(d,s)) + T \quad (6)$$

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

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

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. The agent's problem can thus be formulated as follows:

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

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 **?** for the optimization of the criterion function[6].

$$\hat{\theta} = argmin_{\theta \in \Theta} \, (M_D - M_S(\theta)) W^{-1} (M_D - M_S(\theta))' \tag{8}$$

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

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

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.

$$w_{i,t} = exp_{i,t} + exp_{i,t}^2 + t + h_{i,t} + \epsilon_{i,t}$$

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.

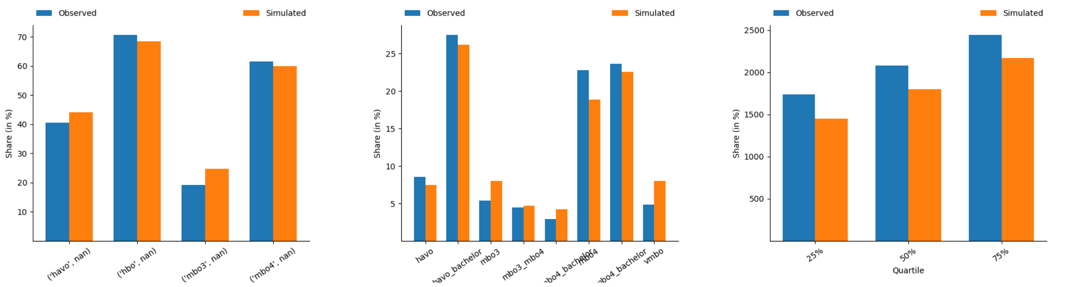
4 Results

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

4.1 Estimation & Model Fit

Figure 5 provides a short summary of 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 first panel shows wage quartiles at age 30 for individuals with 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 contains a summary of the model fit.

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.

Table 2: Distribution of returns to applied university.

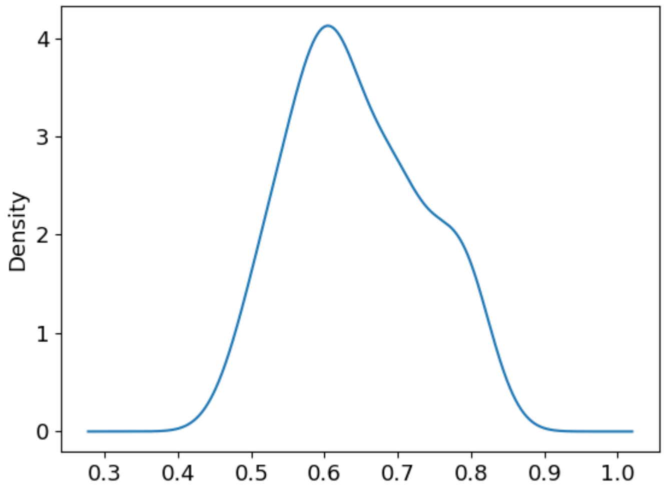
Percentile	**Return Age 30**	**Return Age 40**
25th percentile	-3.5	3.8
50th percentile	-3	4.6
75th percentile	2.9	14.4

Note: This table summarizes the distribution of returns to applied university 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 distribution of wage returns highlights that understanding 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 contributes to narrowing 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 Taking into account that the model suggest that returns to applied university are substantial for most of the population the relevant question is what factors drive substantial 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 large 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 that enter university from vocational education are slightly more likely to dropout than individuals that enter university from high school. During high school individuals are explicitly prepared for university

Figure 6: Distribution of dropout risk

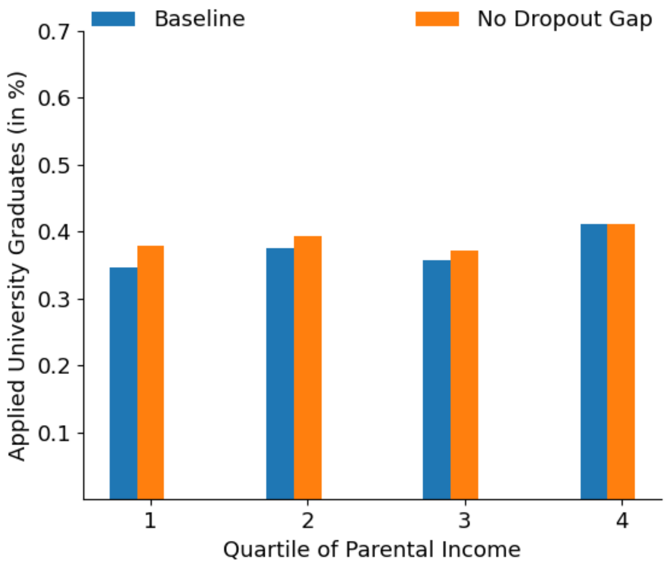


Note: This figure shows a histogram visualizing the distribution of dropout risk. This figure is obtained by calculating the fraction of dropouts out of all individuals that enrolled in university for each combination of observed and unobserved characteristics in the model.

while vocational programs usually set a different focus. The difference in dropout rates is however not particularly large. This finding is remarkable since it shows that pursuing more practical education for some time does not have a large effect on eventual success at applied university. Unobserved factors also matter for dropout risk. Individuals with large returns to applied university also have a larger probability of passing applied university. It is thus even more important to understand which individuals are shifted by a particular policy. If people with modest returns and large risk are marginal for a certain 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 that suits them. It is essential to understand which factors are driving this gap and how policy can address it.

Figure 7: Gradient in dropout risk



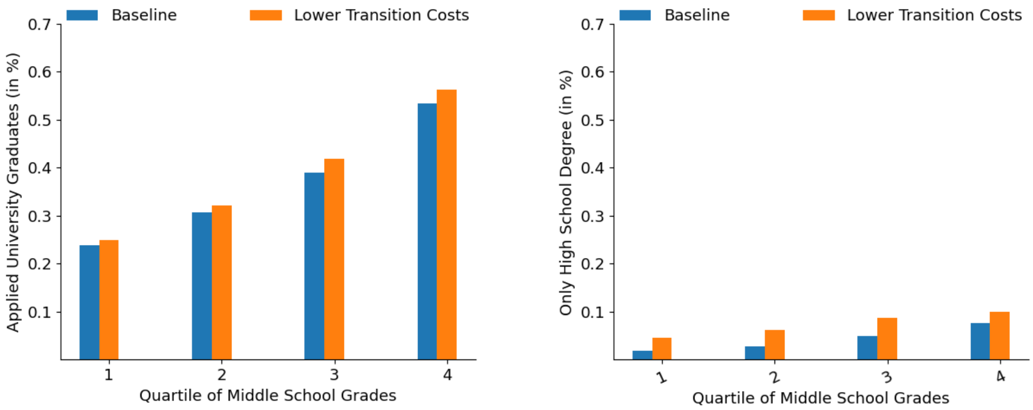
Note: This figure shows how graduation rates would change if there was no dropout gap by parental income. The blue bars show graduation rates for parental income quartiles in the estimated model. The orange bars show graduation rates in an alternative model without a dropout gap by parental income.

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

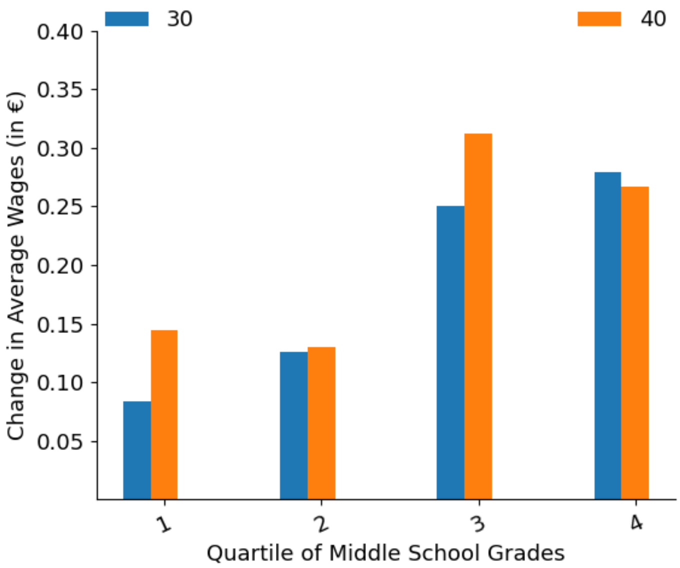


(a) University Graduates (b) HAVO only

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

Figure **??** 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 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.

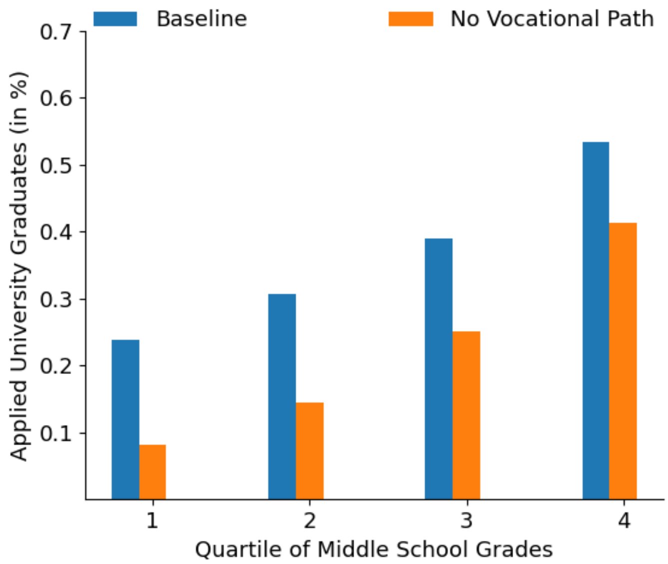
Figure 9: The effect of enforcing higher acceptance rates at high school.



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

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 but with lower transition costs to high school. The figure shows that university graduation would fall quite 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 not much lower than returns to vocational training.

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

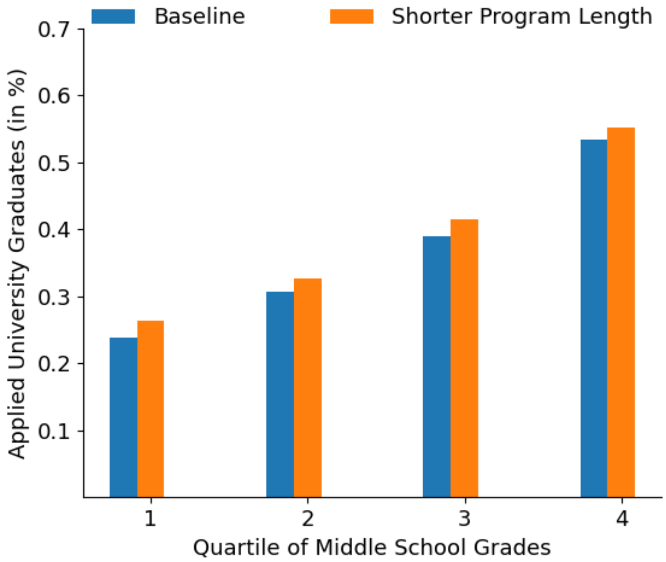


H **Note:** This figure shows how removing the vocational path to applied university would affect applied university graduation. The blue bar shows proportions in the baseline model while the orange bar shows the proportion in counterfactual scenario without vocational path to university.

There could be a lot of motives behind changing your mind about wanting to go to university. Not having a lot 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. Understanding what exact factors are relevant may be an important path for future research.

Changing Program Characteristics To understand the effect of shorter program duration I simulate a model where vocational programs only take 3 years. It is important to mention that many programs already offer the option to get a vocational degree within 3 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 exactly implement this policy. The results however show effects of measures that would decrease time until graduation in vocational education.

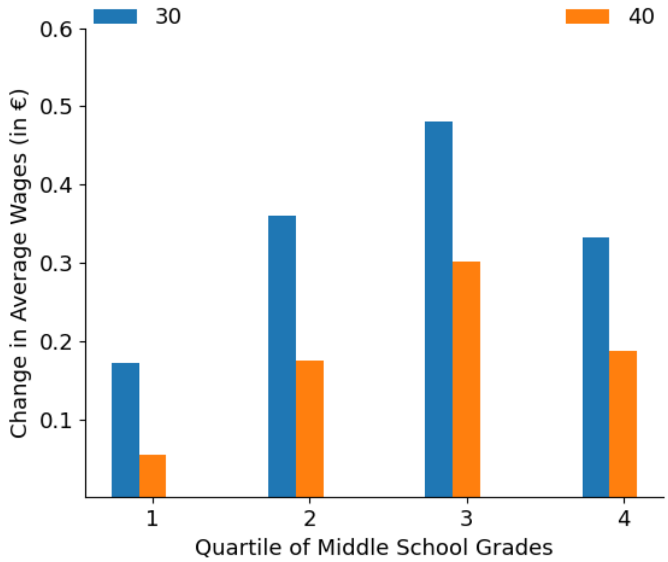
Figure 11: Effect of shorter vocational programs.



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 counterfactual scenario where higher vocational programs only take 3 years.

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 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.

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 counterfactual scenario where higher vocational programs only take 3 years.

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, policy makers should trade off the volume of programs with the fact that people may want to proceed to university afterward.

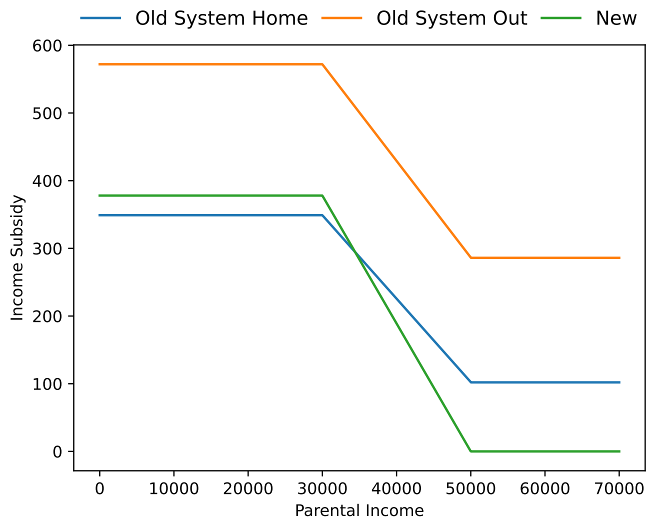
5 The Effect of Income Subsidies

I now discuss the impact of income subsidies. I first introduce a recent reform to student income subsidies.

5.1 A Reform to Student Income Subsidies

A reform to student income subsidies in 2015 raised the costs of studying and moving out while leaving the costs of other options unchanged. 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 siblings that are still dependent on the parents all of the 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 $d_i(T_t)$. According to Figure 13 it holds that $T_{pre}((0, 1)) - T_{post}((0, 1)) > T_{pre}(d) - Tpost1(d)$ for any $d \neq (0, 1)$. For individuals with lower-income parents and a prior intention of studying and staying at home, the expression on the right-hand side is even slightly negative, implying that they should not have been adversely affected by the reform. I will only focus on individuals from lower-income backgrounds since higher-income individuals have lost out in either case. People who would not have been attending university will not change their decision because of the reform since it makes studying less attractive. Formula 9 formally defines the latent control group. Everyone who would not have studied and stayed at home under the old reform scheme will not change their decision under the new scheme.

$$d_i(T_0) = d_i(T_1) \text{ for any } d_i(T_0) \neq (0, 1) \tag{9}$$

If this assumption holds, one can compare enrollment changes across the latent control and treatment groups to identify the reform's effect. Additionally, I assume that treatment assignment is stable over time. Let $d_{i,t}(T)$ be an individual's joint decision at time t under subsidy scheme T. Formula 10 implies that individuals make the same decision when confronted with the same scheme.

$$d_{i,t}(T) = d_{i,t+n}(T) = d_i(T) \tag{10}$$

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 a prediction algorithm and a large set of observable characteristics retrieved from administrative data. Let X_i be a vector of observables. Now 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 predict the probability of staying at home conditional on going to university instead of the probability of staying home and going to university since the former allows one to retrieve a better prediction in practice. I will control for the probability of going to university when comparing individuals with a high and low probability of moving out. This ensures that the number of individuals entering university is the same across groups. I can observe X for all individuals and $d_i(T_0)$ only for individuals who graduated before the reform was introduced. I use data from the pre-reform period to train a prediction algorithm that predicts the probability of latent treatment with observed characteristics X latent treatment status $m(X) = \hat{P}_d(X)$. X includes spatial factors, personal characteristics, data on the family situation, and information on the prior schooling career [7]. I use a gradient boosting algorithm to predict $P_d(X)$ where I use data on university enrollees between 2011 and 2013 as training data and data on individuals who graduated in 2014 as test data.

I need to make a parallel trends assumption to interpret differences across individuals with a high and low probability of being treated causally. In particular, I assume parallel trends between both actual latent treatment and individuals with a high and low probability of treatment. 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. 11 shows the parallel trends assumption. Trends need to be parallel across latent treatment and the probability of receiving the latent treatment. Without the reform, enrollment, and graduation would change similarly for individuals who would study and leave their parental home and everyone else. I need to adapt the usual parallel trends assumption because treatment effects could differ across observables I use to predict treatment.

$$E[Y_{i,post}(T_{pre}) - d_{i,pre}(T_{pre})|d_i(T_{pre}) \neq (0,1), P_H, Z_i] = E[d_{i,t}(T_{post}) - d_{i,t-1}(T_{pre})|d_{i,pre} = (0,1), P_L, Z_i] \tag{11}$$

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.

[7] For more information on the variables, consider appendix A

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 the treatment effect on the treated conditional on controls. A more detailed composition of the effect is provided in the appendix. The differences across groups can be written as the difference between a term proportional to the treatment effect on the treated with a high probability of being treated and a term containing the treatment effect of the treated for individuals with a low probability of being treated. If one increases the windows for treatment and control group, one increases the sample size and the importance of the heterogeneity term. While the increased sample size increases precision of the estimates it also leads to a greater downward-bias in the estimated effect of the reform. In the appendix derivation I use the actual 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 (**?**).

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 stay at home conditional on going to university, 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:

$$E_i = \beta_0 + \theta_i * \gamma_i + \theta_i + \beta_1 \gamma_i + \beta_2 \hat{P}_E(X_i) + \beta_3 Y_i + \epsilon_i \tag{12}$$

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:

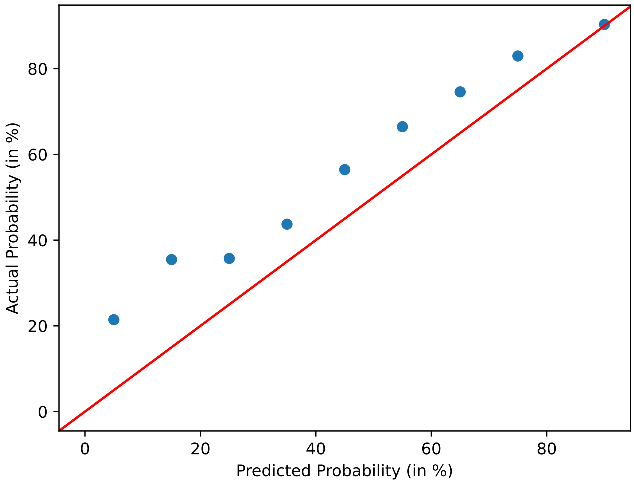
$$G_i = \beta_0 + \theta_i * \gamma_i + \theta_i + \beta_1\gamma_i + \beta_2 P_G(X_i) + \beta_3 Y_i + \epsilon_i \tag{13}$$

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 summarize the performance of the estimation procedure and treatment effects derived from the reform. Thereafter 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. I train a gradient-boosting algorithm on data between 2011 and 2013 and use observations in 2014 as a holdout sample. 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.

Figure 14: Performance of the Prediction Algorithm

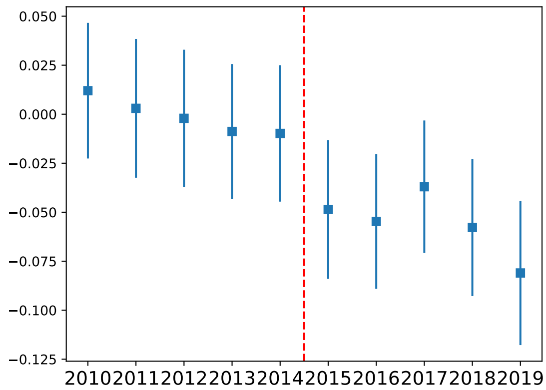


Note: This figure shows the performance of the prediction algorithm. The x axis shows predicted probability and the y axis shows the actual observed probability in a test sample. To obtain the figure I have grouped observations in the test sample by their decile of probability predictions. I then calculated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

The dot above the predicted probability 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 18 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 taking into account the size of the income subsidy.

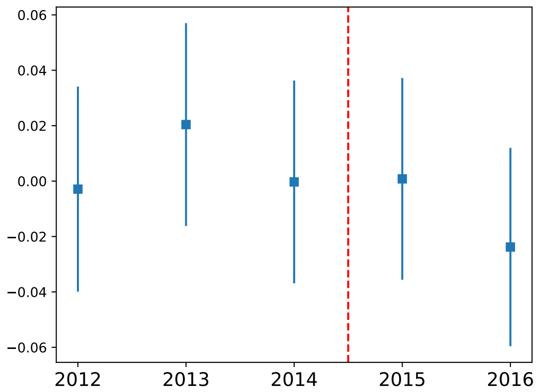
Figure 15: Results University Enrollment



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 most likely to move out relative to the control group that is least likely.

Point estimates in the appendix show that the predicted control 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. Individuals with a low probability of leaving home should not be affected by the reform. One potential explanation for why the predicted control group drops as well is that not all individuals are aware that they entitled to means tested grants (**?**). On the other hand it is important to mention that overall labor market conditions improved between 2010 and 2020 and that this may also have an impact on enrollment decisions. It is thus difficult to pin down 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 effect of the reform as it is possible that the control group has responded as well.

Graduation: **??** 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.

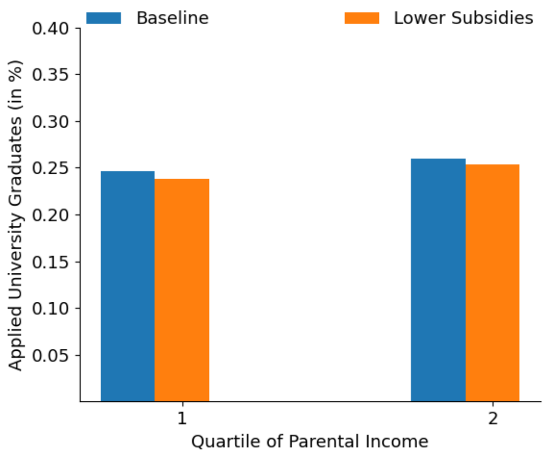


This figure shows coefficients from a two way fixed effects regression comparing individuals with different propensities to move out. The coefficients depict the evolution of university enrollment of the group that is most likely to move out relative to the control group that is least likely.

If I include people still studying after six years in the definition the decline is a bit larger but the overall evolution remains noisy. The change in university degrees is much less pronounced as the decline in enrollment and more difficult 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. 19 show that individuals with low dropout risk show a larger reaction to the reform that is more distinguishable from the general trend.

Reform Simulation in the model: Reduction of income subsidies are associated with modest declines in enrollment according to the structural model. I simulate an alternative model with lower non-pecuniary returns to university.

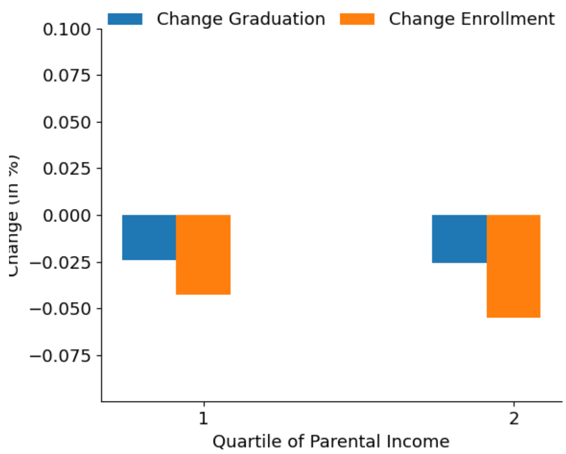
Figure 16: Simulated Effect of the reform.



Note: This figure shows the simulated effect of the reform in 2015.

Figure 17 shows that the model predicts an enrollment decline of 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 effect of the reform. The treated group is different from the broad population and the treatment effect on the treated is potentially larger than the treatment effect on the treated group. Furthermore the model is not perfectly suited to predict the effect of income subsidies as it includes no consumption component and no risk aversion. It is thus likely that the reform reduces utility of studying to a larger extent than the monetary value that individuals miss out on. I thus simulate an alternative model were I reduce utility of university until the reduction in enrollment is similar to what the reform predicts. **??** shows that complier of the simulated policy have large academic risk and the reduction in degrees is less than two thirds of the reduction in enrollment. The model and the reform thus agree on the characteristics of complier to the reform. While the model cannot exactly reproduce the reform it gets selection right which increases confidence in the other policy simulations.

Figure 17: Simulated Complier



Note: This figure shows the complier 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. I have found that returns to applied university are substantial for many low income individuals despite early achievement gaps. I found that increasing flexibility of the tracking system would increase graduation and wages of low income individuals. Furthermore I established that 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. Future research should investigate reasons for large dropout rates among low income individuals.

7 Appendix

7.1 Model Parametrization

In this section I show the full model parametrization. I first show all nonpecuniary utility terms. Then I show the specification of degree risk and degree duration. Wage equations have been specified in 4 and 5.

$$F^a = \beta_0^a + \xi_{1,a}^F * \theta + \xi_{2,a}^F * Y + \tag{14}$$

$$F^v = \beta_0^v + \xi_{1,v}^F * \theta + \xi_{2,v}^F * Y \tag{15}$$

$$F^u = \beta_0^u + \xi_{1,u}^F * \theta + \xi_{2,u}^F * Y \tag{16}$$

$$F^h = \beta_0^h + \xi_{1,h}^F * G + \xi_{2,h}^F * \theta + \xi_{3,h}^F * Y \tag{17}$$

$$F^{m3} = \beta_0^{m3} + \xi_{1,m3}^F * \theta + \xi_{2,m3}^F * Y \tag{18}$$

$$F^{m4} = \beta_0^{m4} + \xi_{1,m4}^F * \theta + \xi_{2,m4}^F * Y \tag{19}$$

$$R^u = \beta_0^u + \xi_{1,u}^R * G + \xi_{2,m4}^R * \theta \tag{20}$$

$$R^h = \beta_{0,h}^R + \xi_{1,h}^R * G + \xi_{2,h}^R * \theta + \xi_{3,h}^R * Y \tag{21}$$

$$R^h = \beta_{0,h}^R + \xi_{1,h}^R * G + \xi_{2,h}^R * \theta + \xi_{3,h}^R * Y \tag{22}$$

$$R^h = \beta_{0,h}^R + \xi_{1,h}^R * G + \xi_{2,h}^R * \theta + \xi_{3,h}^R * Y \tag{23}$$

$$R^h = \beta_{0,h}^R + \xi_{1,h}^R * G + \xi_{2,h}^R * \theta + \xi_{3,h}^R * Y \tag{24}$$

$$D^u = \beta_0^u + \xi_{1,u}^R * G + \xi_{2,m4}^R * \theta \tag{25}$$

$$D^h = \beta_{0,h}^R + \xi_{1,h}^R * G + \xi_{2,h}^R * \theta + \xi_{3,h}^R * Y \tag{26}$$

$$D^h = \beta_{0,h}^R + \xi_{1,h}^R * G + \xi_{2,h}^R * \theta + \xi_{3,h}^R * Y \tag{27}$$

$$D^h = \beta_{0,h}^R + \xi_{1,h}^R * G + \xi_{2,h}^R * \theta + \xi_{3,h}^R * Y \tag{28}$$

$$D^h = \beta_{0,h}^R + \xi_{1,h}^R * G + \xi_{2,h}^R * \theta + \xi_{3,h}^R * Y \tag{29}$$

7.2 Parameter Estimates

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 3: Wage Returns to Academic 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 4: Wage Returns to Vocational 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 5: 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 6: Nonpecuniary Returns to Academic Work

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 7: Nonpecuniary Returns to Applied University

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 8: Nonpecuniary Returns to High School

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 9: Nonpecuniary Returns to MBO4

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 10: Nonpecuniary Returns to MBO3

7.3 Model Fit

Table 11: 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 12: Nonpecuniary Returns to MBO3

Table 13: 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 14: Degree Combinations by School Type & Grades

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
		$mbo3 - mbo4$	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
		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

Table 16: 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 17: 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 18: 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 19: 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 20: Nonpecuniary Returns to MBO3

Table 21: 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 22: 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 23: 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 Additional Policy Simulations

7.5 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:

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

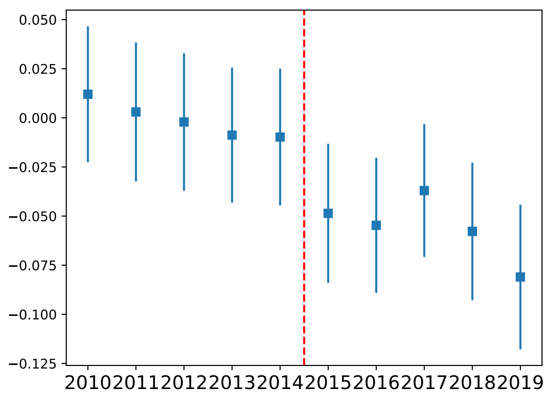
$$(1 - P_H)(E[\Delta Y_i|d_{t,0} = (0,1), P_H, Z]) - E[\Delta Y_i|d_{t,0} \neq (0,1), P_H, Z]))$$

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

7.6 Robustness Reduced Form

Other Definition of Degree

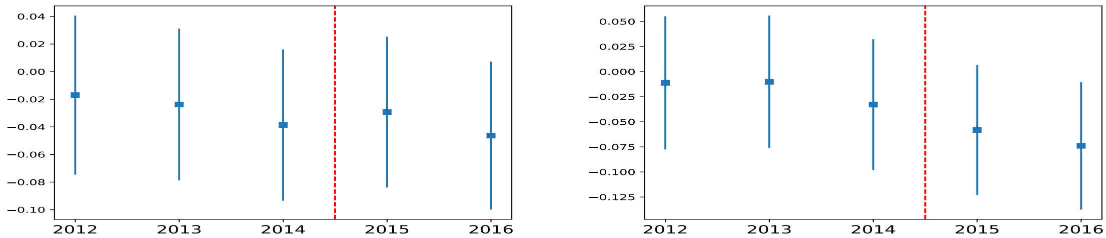
Figure 18: Results University Enrollment



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 most likely to move out relative to the control group that is least likely.

Differences by initial heterogeneity The most plausible explanation for the patterns induced by the reform are individuals selecting based on expected academic risk. Academic risk is substantial among vocational graduates. Dropout rates are high and many individuals require more than 5 years to finish their studies. Taking up debt could be particularly costly if individuals are at risk to study for an extended amount of time. Furthermore wage returns to university differ greatly by vocational subject. While some degrees are associated with substantial wage returns others are not associated with any return right after graduating. To explore the relative importance of these factors I compare individuals with high and low dropout risk and high and low wage expectations respectively. I obtain dropout risk in the same way as I obtain the probability of staying at home. I use observables to train and predict dropout risk of vocational graduates.

Figure 19: Effect on Graduation for Individuals with Low and High Dropout Risk



(a) Lowest Dropout Risk

(b) High Dropout Risk

?? 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.

Debt and Spatial Factors Not enrolling in university is not the only margin of adjustment to the reform. Affected individuals can also stay at home, increase work hours or take up more study debt. All of these factors could itself have important consequences for individual outcomes. There are two major complications with this approach. First and foremost the incentive to truthfully report housing status falls away after the reform ha been introduced. Thus it is difficult to say whether individuals stay at home or left home after the reform. Another important issue is that the population of university entrants changes since many people decide to opt out in response to the reform. This makes comparisons over time difficult and requires to carefully think about selection into higher education.

Figure **??** shows how debt, hours worked while studying and university locations have been affected by the reform. There is no substantial change in any of these dimensions. It is important to note that affected individuals were already likely to have much higher debt levels before the reform which potentially reduces their capacity to take up further debt. Furthermore individuals already worked relatively high hours before the reform and thus there is limited potential to increase work hours while studying. There is also no trend in university location. This could be expected if people are more likely to live at home. However the reform also led many people to enroll at all. The most marginal people are potentially less likely to leave their region all together which would contaminate the comparison.

7.7 Parameter Estimates Reduced Form

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

Index	Enrolled	Enrolled	Bachelor	Bachelor	*Bachelor∗*	*Bachelor∗*
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)				
$2011xGroup_2$	-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)

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Index	Enrolled	Enrolled	Bachelor	Bachelor	*Bachelor∗*	*Bachelor∗*
$2012xGroup_2$	-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)
$2016xGroup_1$	-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)

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	Enrolled	Enrolled	Bachelor	Bachelor	*Bachelor∗*	*Bachelor∗*
Index						
$2017xGroup_1$	-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)
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)

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Index	Enrolled	Enrolled	Bachelor	Bachelor	*Bachelor∗*	*Bachelor∗*
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			
$2011xGroup_1$			
$2011xGroup_2$			
2012	0.0225	0.0033	-0.0016
	(0.0186)	(0.0150)	(0.0155)
$2012xGroup_1$	-0.0321	0.0007	0.0223

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Index	Enrolled	Bachelor	$Bachelor*$
	(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
	(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***

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	Enrolled	Bachelor	$Bachelor*$
Index			
	(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
	(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***

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Index	Enrolled	Bachelor	$Bachelor*$
	(0.0041)	(0.0044)	(0.0048)
N	74809	48462	48462
R2	0.108000	0.044000	0.038000

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