Persistent Inequality & Education Policy during Adolescence.

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This paper evaluates how education policy during adolescence affects long-run outcomes of individuals from low-income backgrounds in the presence of achievement gaps across socioeconomic status. Individuals from low-income backgrounds perform worse than their higher-income peers early in their schooling career. Furthermore they are more likely to enter university after having worked or complete vocational training. I specify a dynamic model of education that explicitly accounts for the situation that most low-income individuals face and allows for different paths to university. 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. Nonstandard 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 has a lasting impact on educational careers and 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 and working 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 aims to extend the literature by evaluating how education policy during adolescence affects long-run outcomes of individuals from low-income backgrounds in the presence of achievement gaps and alternative routes to higher education.

The exact way achievement gaps affect low-income individuals' educational careers varies by the education system a particular country uses. In the United States, where all students are kept together until high school graduation, low-income individuals are more likely to be retained in grade (OECD, 2020) or to drop out of secondary schooling (OECD, 2012). Many low-income individuals enter higher education after dropping out of high school earlier and obtaining a GED certification (see, e.g., (Maralani, 2011)). 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). In the Netherlands, I document that university graduates from low-income backgrounds are twice as likely to have entered university after completing vocational training.

To address the research question, I estimate a dynamic model of education in the Netherlands. Unlike prior literature, I explicitly account for most low-income individuals' situation at school due to early achievement gaps. Furthermore, I allow different paths to university consistent with what can be observed in the data. Additionally, I analyze a recent reform to student income subsidies. I use the reform to validate model predictions and to gather further evidence on the importance of income subsidies.

I use the model to consider two sets of policies in this paper. First, I consider all components of the education system that are relevant for individuals at the bottom of the grade distribution. This includes the presence and organization of tracking and the organization of vocational training and its integration with secondary school and higher education. Secondly, I consider income subsidies during higher education.

In the first part of the paper, I introduce a dynamic discrete choice model of education based on Keane and Wolpin (1997). In particular, I introduce a model of further educational careers of graduates of vocational school in the Netherlands. I focus on graduates of the vocational school because most low-income individuals are tracked into vocational education, which is why the population is well suited to address the research question. After graduating from vocational school, individuals decide between pursuing vocational training or moving up to high school[1]. 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. Individuals can enter applied university[2] 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.

Having estimated the model, I first summarize the estimated parameters and discuss their policy implications. I document 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

[1]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

[2]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.

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 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[3]. 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 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

[3]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 A model of further education.

I now introduce a structural model of education. I will first describe the setting in more detail. Thereafter I will summarize all model components.

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 degrees in this context as most of graduates of vocational school never enroll in either.

2.2 Decision Tree

The model allows agents to choose most of the career options that graduates of vocational school can pursue. Graph 1 shows an illustration of the decision tree that agents face in the model. In the first

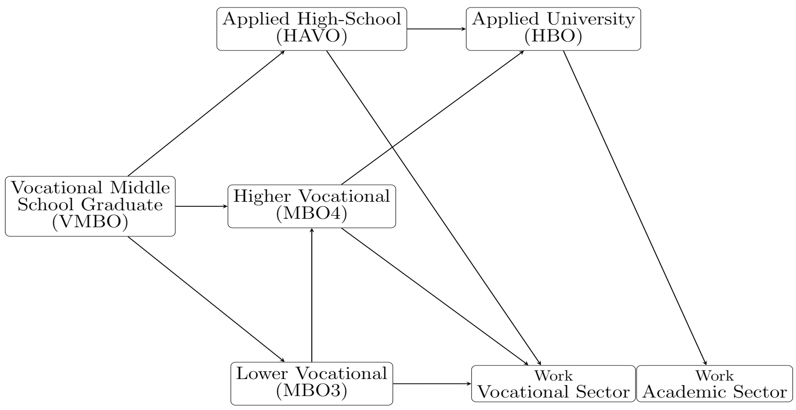


Figure 1: This graph shows the decision tree

period individuals can either enroll in different vocational programs or switch up to the schooling track that prepares for applied university, which I refer to as high school for simplicity. Once individuals graduate from high school or a higher vocational program they can enter university. If they hold a lower vocational degree they can decide to pursue the higher vocational degree to enter university in the third period. At each point in the decision tree individuals can decide to leave education and work which is a terminal decision in this context.

School Types: The transition to high school is not organized in a central way. High Schools have employed their own rules for admitting students from vocational middle school[4]. 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. The model included transfer costs to high school that vary by school type in order to capture this.

2.3 Model Organization & Decision Period

Contrary to prior dynamic discrete choice models of education individuals do not take a new decision each year. 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 that an individual spends in a particular education as a consequence of 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.

I choose this alternative way of specifying the model in order to reduce the computational complexity model. 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.

2.4 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 middle school grades. Y_i denotes the quartile of parental household income of individual i. School Type U denotes the type of transit policy in individual i's school. This variable captures that transition to high school after graduating from vocational middle school is easier at some schools than at 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 $d_{\tau-1}$. school.

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

[4]Make a reference

Individuals start the model with 16 which is the age that most people have when finishing vocational middle

2.5 Choices and Timing

Let $d_{i,\tau}$ denote the choice of individual i at decision period τ. At each decision period an individual takes a choice. Afterwards 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 that 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 repeatedly enroll in the same program. 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 $s_{\tau+1}$. Thereafter the individual receives utility for each of these states and makes a new decision in the arrival state which corresponds to the next decision period. If the transition function for example determines that an individual that has enrolled in a higher vocational program will graduate within 4 years the individual will receive utility for these four years and make a new decision after she graduated from the vocational program.

If an individual decides to leave education and starts working the choice is terminal. Individuals receive the discounted life time income associated with their characteristics and their final education.

2.6 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 coefficient of all these equations are model objects which are estimated jointly with all other parameters.

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

The inclusion of type and academic ability reflects the fact that people with less academic ability are less likely to graduate form a particular program. The inclusion of parental income reflects the fact that children from low income backgrounds are less likely to receive support by their environment or that they are more likely to be subject to shocks that lead to dropout. If individual i completes a degree successfully she faces a poison process that determines the duration of her degree:

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

Type, observed academic ability and parental income are included for the same reasons as in the equation above. 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:

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

This equation contains less variables because there may be a lot of reasons why individuals may take different amounts of time before they dropout. For the sake of this analysis I abstract from these particular reasons and assume that they are orthogonal to the individual characteristics featured in the model. The exact parametrization differs between the particular 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.

2.7 Wages & Nonpecuniary Preferences

Wages are modeled as two separate mincer equations for individuals with higher education diploma 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. Wages are modeled separately for bachelor degree holders and everyone else. Log wages for the vocational sector look as follows:

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

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 looks as follows:

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

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 in the same scale as wages 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. To capture differences across school types I furthermore include transition to high school $T(U)$. If an agent reaches a terminal state she receives discounted life time utility from working which can be written as:

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

2.8 The Agent's Problem & Solution Algorithm

Expected utility is the weighted average over all possible paths that a decision could lead to. One needs to sum over all states that could possibly 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 backwards 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 take decisions in the model. I then follow the following steps for each age that I iterate backwards 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 Data & Implementation

In this section I explain relevant features of the Dutch education system and introduce the data used for estimating the model. This section summarizes relevant features of the Dutch education system presents descriptive statistics about schooling careers of students with lower grades.

3.1 Data

I use Dutch administrative records to follow graduates of vocational middle school. The main sample consists of individuals that graduated from vocational middle school between 2008 and 2010. I focus on this time period because there is less information available for earlier cohorts and I do not observe labor market outcomes for later cohorts. I then combine information on educational careers, grades in middle school, the economic situation of their parents, school characteristics and future labor market outcomes.

3.2 Stylized Facts

I now show some basic facts about tracking and inequality in Dutch education.

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 into vocational school. Track assignment is decided by both teacher evaluations and a

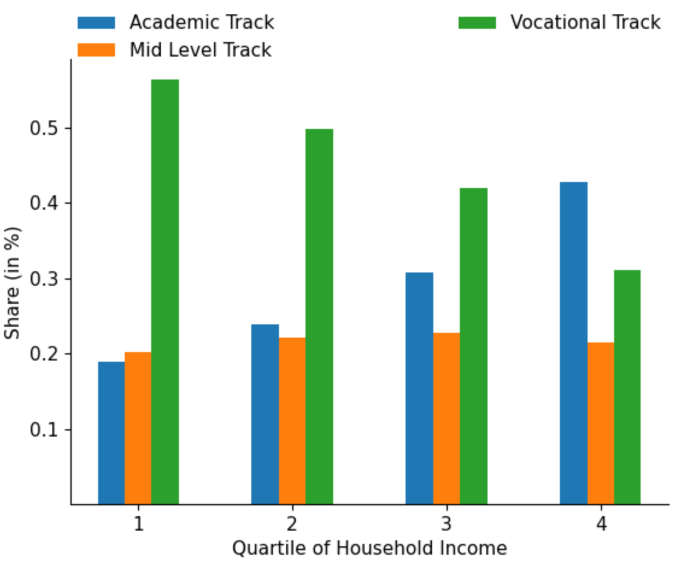
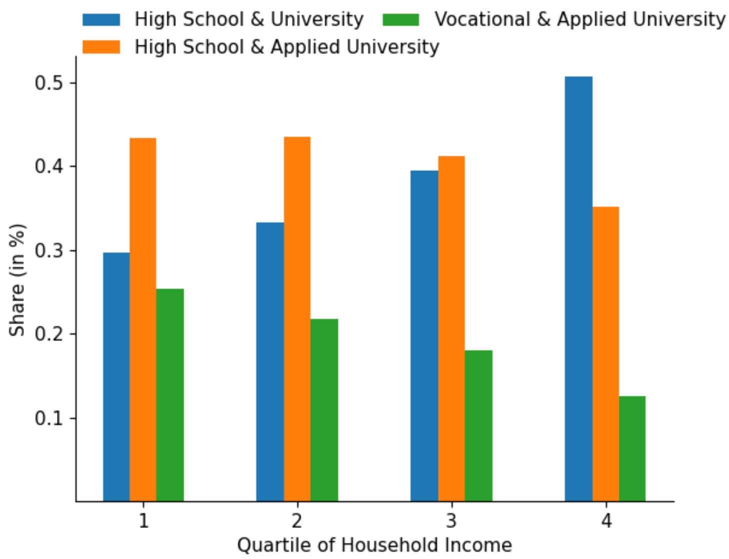


Figure 2: ...

centralized test that individuals take at the end of primary school. A substantial part of the differences in track choice can be explained by grade differences at the end of primary school. 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 as compared to their higher income peers. The picture shows that addressing persistent inequality in education requires that at least some low income individuals in vocational school need to complete higher education later in their life.

Alternative Paths to education are more common among low income individuals: Figure 3 shows how careers differ by parental income. Conditional on reaching a tertiary degree individuals from low socioeconomic background are twice as likely to have entered igher educational after vocational education. Entering university after finishing is thus a well established career in the Netherlands that h



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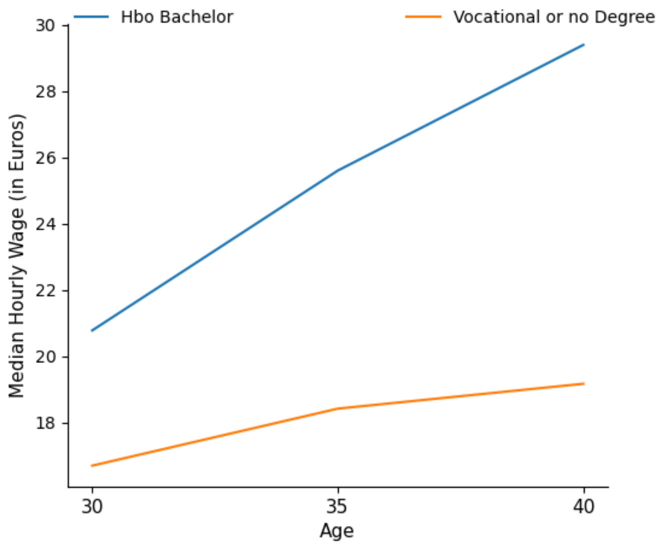
is particularly important for low income individuals. Graduates of vocational education are older and have received less academic education when they consider entering university.

The wage gap between vocational and academic schooling increases over the life cycle: Wage gaps across individuals with bachelor degrees from applied university and individuals without a university degree are growing quickly. Figure 4 shows median wages for individuals with applied university degrees and for individuals without university degrees between age thirty and forty. The wage gap is modest at age thirty but grows quickly thereafter. It is important to understand how much of these differences are driven by selection and actual returns to applied university degrees. Increasing



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applied university graduation among low income individuals would contribute to narrowing the wage gap if substantial returns remain after accounting for selection.

3.3 Identification

Table 1 provides an overview over all 353 statistics that are used in the model estimation. Enrollment percentage for a particular program indicates how many people have been enrolled in that respective program. By income, grade and school type x grade refers to all the subset that this statistic is included for. By grad 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 that the statistic is included for all 12 combinations of school types and grades at the end of vocational school. Final degree combination indicates all post middle school degrees that an individual receives before starting to work. If a person first graduates from a vocational program and then graduates form applied university her degree will be higher-vocational & bachelor. I combined some programs and removed some individuals with very uncommon careers. Furthermore I include last schooling age for all observed ability and income groups. Last schooling age refers to the age where 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 were individuals leave education. In practice I however 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 applied university degree at ages 30, 35 and 40. Finally I match coefficients of three separate wage equations. Two of them are wage regressions for individuals with and without bachelor degree respectively.

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

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

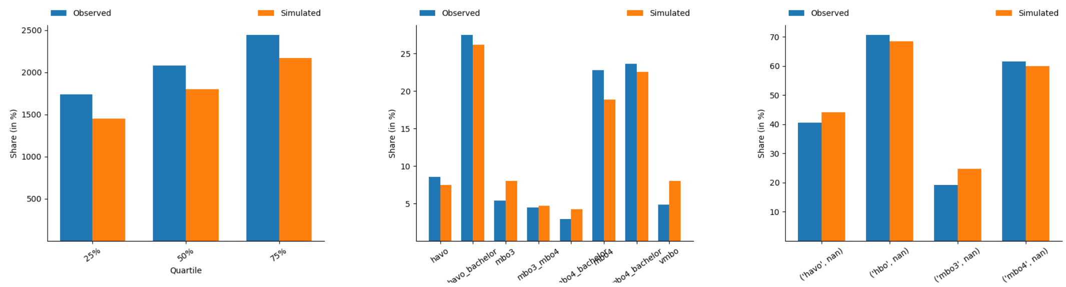
Note: This table summarizes all 353 moment used to estimate the model. The left column indicates a particular category of statistics and the right column indicates the number of moment that the respective category has.

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. Components of the wage equation are pinned down by coefficients of wage equations and wage quartiles. Academic risk is identified by the discrepancy between enrollment and graduation in each program. The distribution of degree duration are pinned down by the distribution of final schooling ages. Non-pecuniary returns to work and education programs are pinned down by residual variation in choices across characteristics that can not be explained by wage returns. The distribution of taste shocks is pinned down by variation in choices holding all characteristics fixed. Transition costs to high school by school types are identified by differences in choices and outcomes of individuals that 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 overt time which minimized residual heterogeneity. Secondly the differences in transition costs across schools leads to a difference 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.

3.4 Estimation & Model Fit

I now asses the in sample model fit of the estimated model. The model is estimated with **?** who provide an excellent toolbox for the estimation of large scale scientific models in python. Figure **??**

provides a short summary of the model fit. A more detailed summary can be found in the appendix. 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.



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

Figure 5: ..

The other two panels show the fit of degree combinations and enrollment proportions for individuals with high grades. Both sets of simulated moments are closely aligned with their observed counterparts.

4 Results

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

4.1 Mechanisms

I summarize estimated parameters and discuss their implications for policy in this section. I first discuss the implied distribution of returns to university. Then I discuss dropout risk and selection. Finally I discuss the role of the vocational path to university.

Wage Returns to Applied University: The model parameters show that wage returns to applied university are substantial. The most important difference between the wage process in the academic and vocational sector are returns to experience. Individuals with a bachelor degree enjoy substantially larger returns to experience than people without. The college wage premium increases particularly strongly between the ages of 30 and 40. 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 percentile of the distribution of wage returns to applied university. Returns to applied university differ substantially across the population. The majority of individuals receive negative at age thirty while some individuals receive positive returns. It is important to point out that individuals without applied university degree have accumulated more experience at this point. This may explain why returns at age thirty are negative for a large amount of individuals. Most individuals receive positive returns at age forty while some people receive large 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 highlight that understanding the long term effect of policy requires to understand what kind of individuals are shifted. Returns to applied university do not substantially differ by parental income. Increasing the amount of low income individuals with an applied university degree would thus contribute towards narrowing the income gap across socioeconomic background.

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 individuals with high school degree only. Individuals may thus choose a vocational degree before the enter university as it is associated with a higher paying outside option if they dropout of university. The gap is however not particularly large 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 **??** shows the distribution of dropout risk in the population. The figure

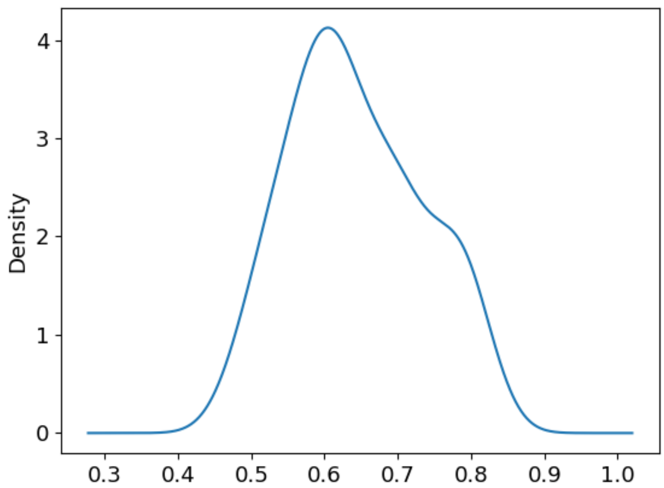
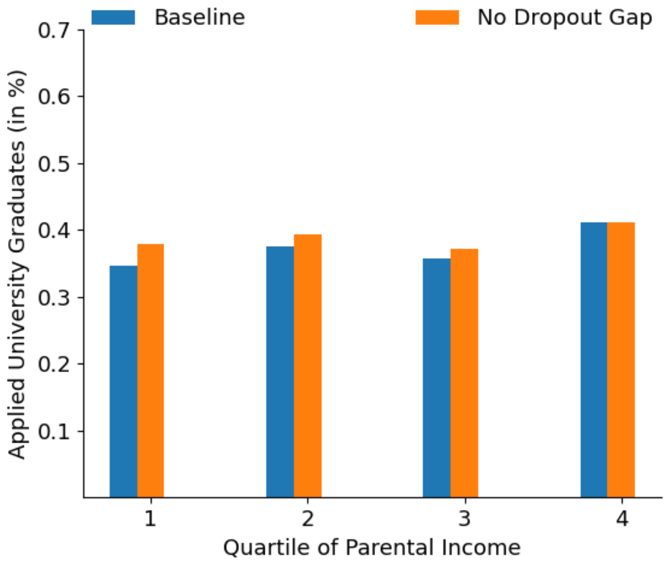


Figure 6: This figure shows a histogram visualizing the distribution of dropout risk. This figure is obtained by calculating the fraction of dropouts out of all individuals that enrolled in university for each combination of observed and unobserved characteristics in the model.

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 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 of the previous factors. Particularly individuals from the lowest income quartile appear to be more likely to dropout of university holding other factors fixed. This is very important as it contributes to overall inequality. Figure **??** shows how applied university graduation

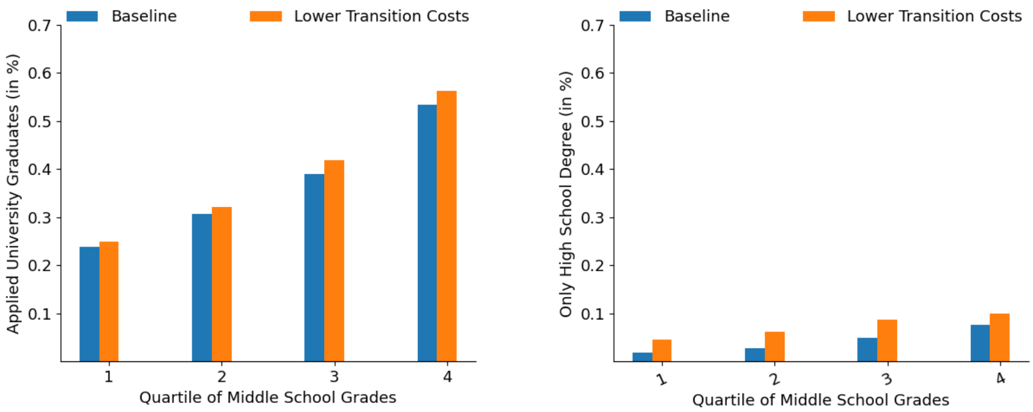


would change if the risk gap between students from different socioeconomic backgrounds was removed. The applied university graduation rate among individuals from low income backgrounds would increase substantially. There could be several reasons for the estimated risk gap. Individuals from low income backgrounds may have to work on the sides or face more economic which makes them more likely to dropout after they have received an initial shock. Another potential reason is that they have less information and have a harder time choosing a university subject that suits them. It is important to understand which factors are driving this gap and how it can be addressed by policy.

4.2 Counterfactuals

I use the estimated model to run several counterfactual policies. I estimate the potential impact of changed tracking policies, of removing the vocational path to university and of changed program characteristics. I will discuss the effect of income subsidies next chapter together with reduced form results on a recent reform to income subsidies for students. I show the effect of policies on individual outcomes for each group of observable ability since the differences there are particularly interesting. Whenever patterns differ substantially between individuals from lower and higher income backgrounds I discuss these differences.

Transition Costs Lower transaction costs would benefit people at the higher end of the grade distribution while it would have an ambiguous effect on individuals at the lower end of the distribution. Transition costs to applied high school are substantial and constitute a barrier to higher education for individuals with high grade. To understand how a more flexible tracking system would shift outcomes I change two aspects of the model. 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 mid level high school. Figure **??**

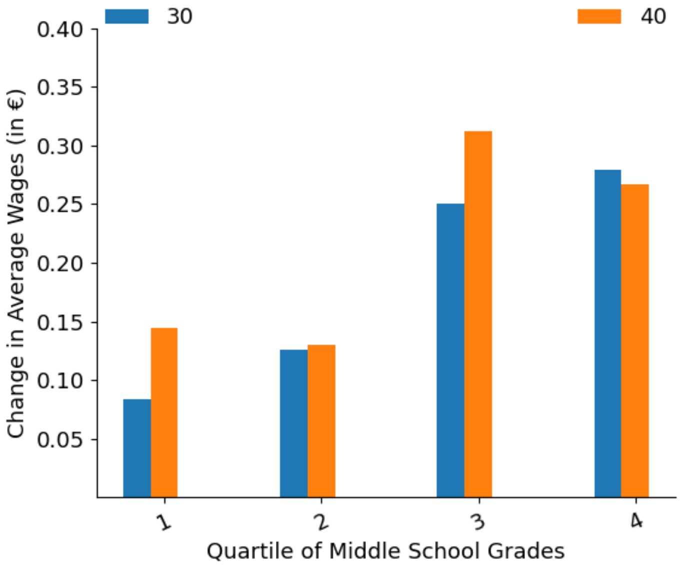


(a) University Graduates

(b) HAVO only

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. There are however also more people who only complete a high school degree. Individuals with low observed ability see a smaller increase in university graduations but a larger 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 **??** shows changes in average hourly wages caused by the reform. The increase in average hourly wages show that the complier have substantial returns from the reform.

The simulated effect of the policy shows that high school is associated with large risks for lower grade groups but may lead to substantial returns if these individuals manage to graduate. It is important to point out that the increases number of individuals with a high school degree may have consequences that are not contained in the model. Holding a mid level high school degree could be associated with lower job security or different job amenities. This information is important to decide whether more



individuals with low grades should attend high school. Increasing flexibility for individuals with higher grades appears to be a good policy since they have lower dropout risk and their long-run returns are positive.

Vocational path to university: The vocational path to university increases university graduation as it allows individuals to hedge risk and to reconsider their initial decision. In the absence of 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. In a world with uncertainty the vocational path however plays two important roles. First of all it allows individuals to manage risk. If they directly proceed to high school and dropout of university later they only have high school degree which is associated with lower labor market returns. Moreover there is also substantial risk to dropout of high school which could also cost 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 afterwards. Another role is that some individuals may only discover their interest in academic education at a later stage. In particular if they are not from an academic background they may not know whether they would like higher education at the age of 16. Model parameters suggest that both motives are important in the model. Figure **??** shows a simulated model without vocational path to university but with lower transition costs to high school. The figure shows that across all grade levels university graduation would fall quite drastically.

There could be a lot of motives behind changing your mind about wanting to go to university. Simply not having a lot of information about university could be a reason. Maturing over time could also be

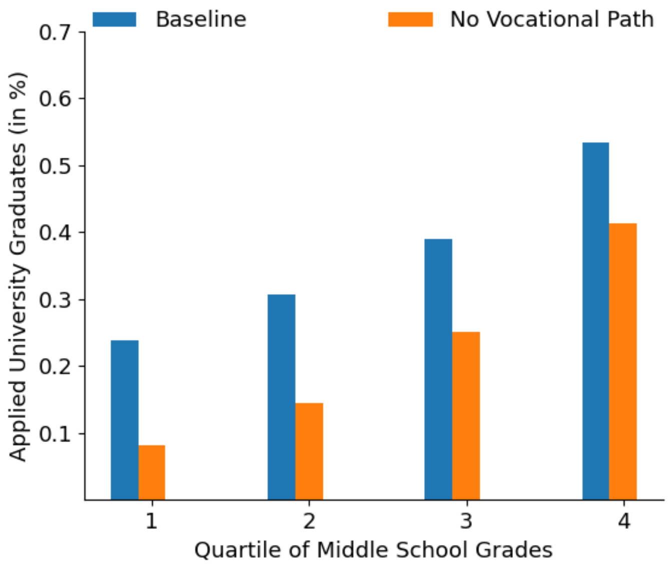


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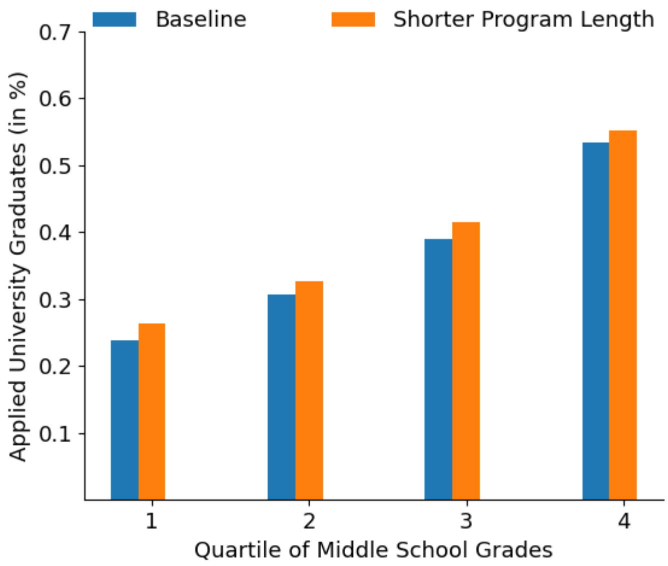
Figure 7: ..

important. In particular as children from academic households are more likely to get pressured into academic education as opposed to non academic households. Yet another reason could be learning about returns or about own ability over time. It is beyond the scope of the model to separate these factors. The results show however that this block of reasons appears to be important for individual decisions. Understanding what exact factors are relevant may be an important path for future research.

Changing Program Characteristics Shorter vocational programs would increase university enrollment as it is easier to forgo earnings at a younger age. 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 **??** shows how shorter programs would change university graduation. Decreasing program length is associated with an increase in university graduation of around 3 percent. The effect is slightly smaller for individuals in the lowest observed ability group but relatively similar for everyone else. Increasing opportunity costs are thus an important factor in individuals decision. Vocational programs should thus encourage quicker programs to the extent that this is possible. Figure **??** shows the change in wages that the simulated reform would trigger. The effect is larger at age 35 because individuals in the simulated data also graduate earlier which leads to more experience at any given point in time. The



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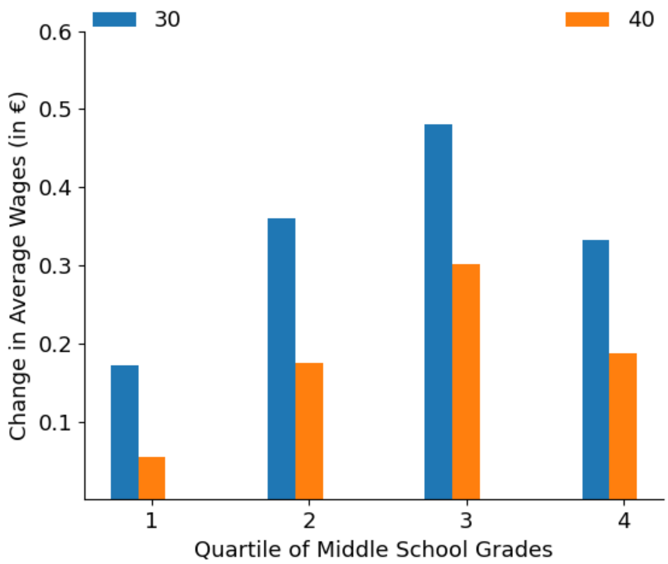

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Figure 9: ..

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 afterwards.

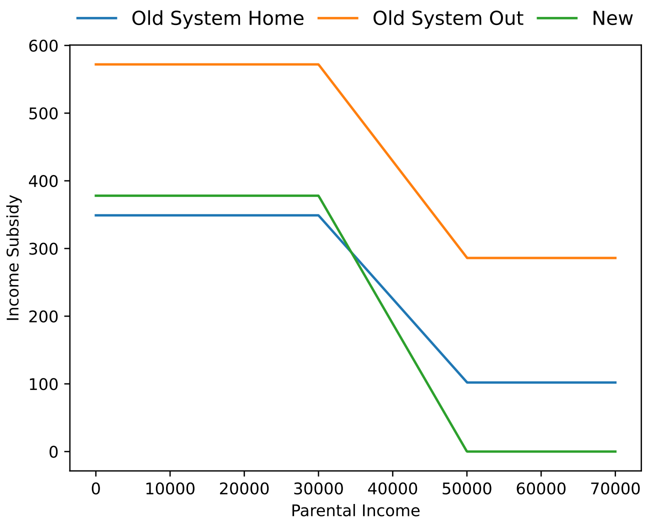
5 The Effect of Income Subsidies

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 gives 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 loan scheme. Figure **??** summarizes the changes that have been introduced. Subsidies for individuals from

Figure 10: Out of sample performance of the algorithm



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higher-income households have been removed. For lower-income households, privileges for individuals wanting to move out have been removed. Low-income individuals who want to move out have lost 200 euros after the reform.

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 less affected and can thus be used as a control group. Figure

3 shows that the reform has mainly changed subsidies for people who would have moved out and entered university. Let $d_i = (h_i, w_i)$ be the joint housing and education decision of an individual, where $h_i \in \{0,1\}$ denotes the decision to remain at home and $w_i \in \{0,1\}$ 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_0 refer to the old subsidy scheme and T_1 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 **??** it holds that $T_0((0,1)) - T_1((0,1)) > T_0(d) - T_1(d)$ 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. People who would not have been attending university will not change their decision because of the reform since it makes studying less attractive. I will only focus on individual from lower income backgrounds since higher income individuals have lost out in either case. Thus, I assume that $d_i(T_0) = d_i(T_1)$ for any $d \neq (0,1)$, which implies that the reform should only change decisions for people to study and move out. If this assumption holds, one can compare enrollment changes across the latent control and treatment groups to identify how the reform has changed choices. If there are parallel trends between treatment and control group effects, one can recover the impact of the reform with a difference in difference strategy.

Empirical approximation of latent treatment: Identifying the treatment and control group requires predicting latent choices with pre-reform data. 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 treatment and control group. Instead I predict latent treatment status with a prediction algorithm and a large set of observable characteristics retrieved form administrative data. Each individual i can be characterized by a vector of observable variables X_i. Now let $P_{T_0}(X) = P(d_i(T_0) = (1,1)|h_i(T_0) = 1, X_i = X)$ be the probability that an individual with characteristics X would stay at home if she would attend university. I can observe X for all individuals and $d_i(T_0)$ only for individuals that graduated before the reform has been introduced. Thus I use data from the pre-reform period to train a prediction algorithm that associates X with latent treatment status $m(X) = d(T_0)$. X includes spatial factors, personal characteristics, data on the family situation and information on the prior schooling career [5]. I use a gradient boosting algorithm to predict $P_{T_0}(X)$ where I use data on university enrollees between 2011 and 2013 as training data and data on individuals that graduated in 2014 as test data. 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 latter

[5]For more information on the variables consider appendix A

one allows one to retrieve a better prediction in practice. I additionally use similar data to predict the probability of going to university which I will use as a control variable in the analysis.

Estimation Strategy If one assumes that treated and untreated individuals would have been would have been subject to parallel trends absent the reform one can retrieve lower bounds of the effect by comparing individuals with high and low probability of being treated. Since we can not directly observe latent treatment status we can only compare how the reform changed choices across individuals with different probabilities of being treated. Comparing individuals with a high probability of staying at home $P_{T_0}(X) = P_H$ with individuals that have a low probability of staying at home $P_{T_0}(X) = P_L$ leads to a treatment effect on the people with high probability and a term that captures treatment heterogeneity across probability scores. If the group with the high probability

Parallel Trends across propensity scores. The main assumption underlying the empirical strategy is that individuals with high and low treatment propensity exhibit parallel trends in the absence of the reform:

$$E[d_{i,t}(T_{pre}) - d_{i,t-1}(T_{pre})|d_{i,pre} = (0,1), Z_i] = E[d_{i,t}(T_{pre}) - d_{i,t-1}(T_{pre})|Z_i] \textbf{ for } m \in [0,1]$$

. Where Z_i denotes some individual controls I condition on. Z_i cannot include too many variables since otherwise most of the variation in the propensity score is controlled away. I compare individuals that graduated in the same year. The issue that arises in practice is that some individuals that graduated earlier could also have been affected because many people take one or two gap years before they enter university. Thus it is well possible that the effect is gradually building up rather than appearing only after the reform has been introduced.

Treatment Effects There are different ways of comparing people with low and high probability and they have different interpretation. Comparing a group with low and high propensity score can then be written as follows.

$$E[d_{i,t} - d_{i,t-1}|m(X_i) = m, Z_i] - E[d_{i,t} - d_{i,t-1}|m(X_i) = m', Z_i]$$

$$= (m - m')E[d_{i,t}(1) - d_{i,t}(0)|m(X_i) = m] - (m - m')(m - m')E[d_{i,t}(0) - d_{i,t}(0)|m(X_i) = m] + (m)$$

As the propensity score gets bigger the group of treated people increases. The composition of the treated group however also changes. Treated people can differ across different propensity scores. Thus the comparison across different propensity scores has two elements. A more detailed composition of the effect is provided in the appendix. One way to derive effects of the reform is to run a continuous two way fixed effects regression where the coefficient of interest is the interaction between time and propensity score. This allows one to use the full range of people. The estimate is however sensitive to treatment effect heterogeneity across propensity scores. This is because the change in choices as the propensity score increases could be both due to effect heterogeneity and the effect of more people being treated. Another approach is to use a group with sufficiently small scores as control group and comparing different groups with higher propensity scores to this group. In this case the base group does not contain too many treated individuals. I will compare individuals who are less likely to be treated than twenty five percent with individuals who are more likely to be treated than seventy five percent in this application.

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.

5.4 Prediction Performance

The prediction algorithm does a good in job in predicting people with a high likelihood of moving out. Figure **??** shows the prediction performance of the algorithm. The prediction is trained on data between 2011 and 2013. The year 2014 is used as a holdout sample. The figure shows the actual proportion of people staying at home for each decile of predictions. The dot above the predicted prob-

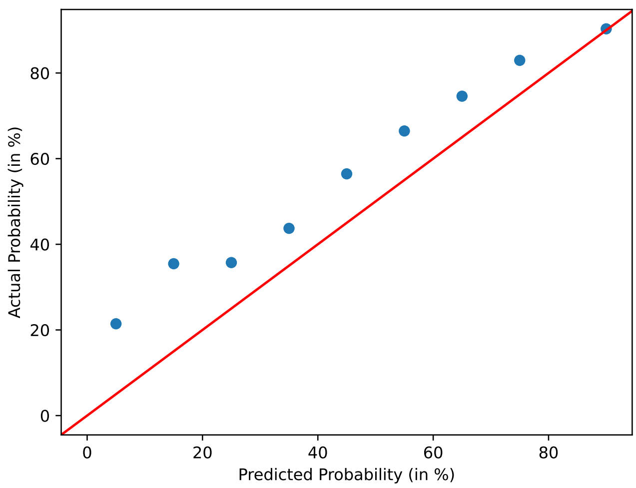


Figure 11: ...

ability of twenty percent is the actual proportion of individuals staying at home among all individuals that are predicted to have a probability of staying at home between twenty and thirty percent. The dots are always close to the forty five degree which shows that the algorithm predicts well.

Changes in Enrollment: The predicted treatment group reduces enrollment by four percent after the reform has been introduced. Figure **??** shows the evolution of university enrollment for the group that is most likely to leave home relative to the group that is least likely to leave home. The results are based on the population of individuals with low income parents. The most affected group has dropped by four percent relative to the least affected group which is a substantial reduction taking into account the size of the income subsidy.

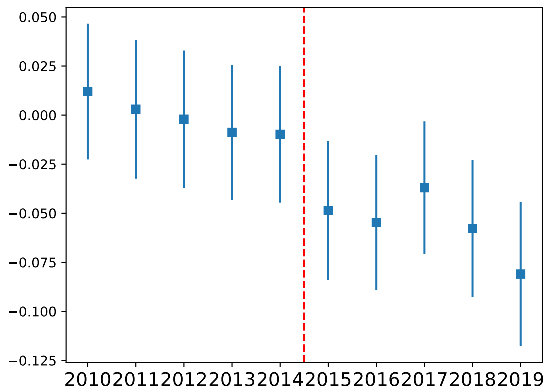
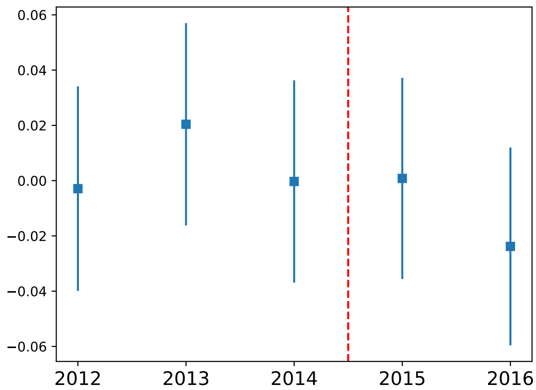


Figure 12:
This figure shows coefficients from a two way fixed effects regression comparing individuals with different propensities to move out. The coefficients depict the evolution of university enrollment of the group that is most likely to move out relative to the control group that is least likely.

The estimates however show that the control group also reduces their enrollment by five percent. It is not clear whether they also 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. Some individuals may however not be informed about the reform and others may not know about means tested grants that they are entitled to receive. 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. The four percent decline is thus very likely a lower bound for the effect of the reform. **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. If I include people still studying after six years in the definition the decline is a bit larger but the overall evolution remains noisy. It is important The change



in university degrees is however much less pronounced as the decline in enrollment and more difficult to distinguish from the general trend. The reform has thus pushed people with relatively large degree risk out of higher education.

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 **??** shows that the model predicts an enrollment decline

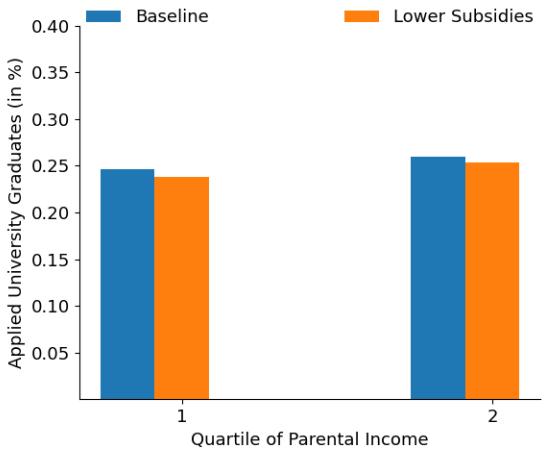


Figure 13:

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. Complier of the simulated

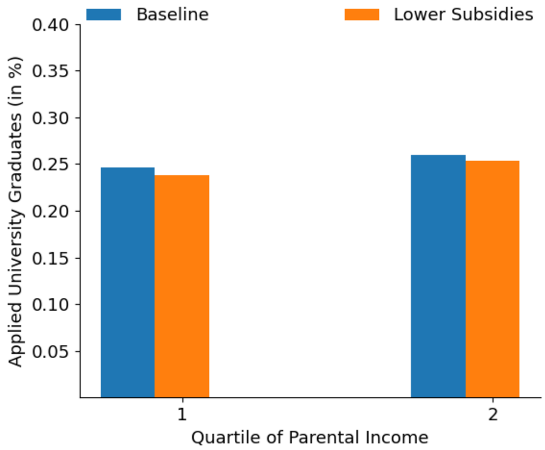


Figure 14: This figure shows coefficients from a two way fixed effects regression comparing individuals with different propensities to move out. The coefficients depict the evolution of university enrollment of the group that is most likely to move out relative to the control group that is least likely.

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.

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 Parameter Estimates

name	value	SE
Age	0.01	1.2e-09
Constant	2.1	4e-08
Experience	0.11	2e-09
$Experience^2$	-0.24	5e-09
G_2	0.014	2.3e-09
G_3	0.018	1.9e-09
G_4	0.032	1.6e-09
θ_2	0.33	5.4e-09
θ_3	-0.16	3.1e-09

Table 3: Wage Returns to Academic Work

name	value	SE
Age	0.024	1.8e-09
Constant	2.2	4.3e-08
Experience	0.075	1.9e-09
$Experience^2$	-0.21	4.1e-09
G_2	0.039	1.7e-09
G_3	0.012	1.6e-09
G_4	0.024	1.9e-09
MBO3	0.1	2.1e-09
MBO4	0.12	1.7e-09
θ_2	-0.052	1.7e-09
θ_3	-0.14	2.4e-09
Dropout	0.056	1.9e-09
VMBO	-0.044	1.9e-09

Table 4: Wage Returns to Vocational Work

name	value	SE
Age	3e+02	4.9e-06
Constant	9.1e+04	0.0016
Y_2	1.1e+04	0.00022
Y_3	1.8e+04	0.00038
Y_4	2.7e+04	0.00053

Table 5: Nonpecuniary Returns to Academic Work

name	value	SE
Age	2.7e+03	5e-05
Constant	2.5e+04	0.00046
MBO3	2.2e+04	0.00042
MBO4	3.5e+04	0.0006
Y_2	7.4e+03	0.00013
Y_3	2.5e+04	0.00052
Y_4	2.6e+04	0.00047
VMBO	-1.2e+04	0.0002

Table 6: Nonpecuniary Returns to Academic Work

name	value	SE
Constant	8.7e+04	0.0014
Y_2	2.6e+03	4.8e-05
Y_3	1.3e+04	0.00027
Y_4	9e+03	0.00017
θ_2	3.8e+04	0.00068
θ_3	-5e+04	0.00099

Table 7: Nonpecuniary Returns to Applied University

name	value	SE
Constant	-1.7e+05	0.0028
G_2	2.1e+04	0.00043
G_3	7.5e+04	0.0012
G_4	1.2e+05	0.0021
Y_2	2.2e+03	4.1e-05
Y_3	7.6e+02	1.6e-05
Y_4	4.5e+03	9e-05
θ_2	8e+03	0.00015
θ_3	-2.5e+04	0.00052

Table 8: Nonpecuniary Returns to High School

name	value	SE
Constant	6.4e+04	0.0012
Y_2	-3.1e+03	6e-05
Y_3	1.6e+04	0.00029
Y_4	1.4e+04	0.00024
θ_2	-3e+04	0.00057
θ_3	-1.1e+04	0.00021

Table 9: Nonpecuniary Returns to MBO4

name	value	SE
Constant	1e+05	0.0018
Y_2	-2.3e+04	0.00037
Y_3	6.1e+02	1.1e-05
Y_4	-2.7e+04	0.00046
θ_2	-4.5e+04	0.00083
θ_3	5e+04	0.00082

Table 10: Nonpecuniary Returns to MBO3

7.2 Model Fit

7.3 Additional Policy Simulations

7.4 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)

Continued on next page

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

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Index	Enrolled	Enrolled	Bachelor	Bachelor	*Bachelor∗*	*Bachelor∗*
$2014xGroup_2$	-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)
$2017xGroup_1$	-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)

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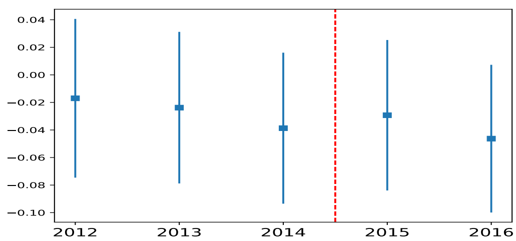
Index	Enrolled	Enrolled	Bachelor	Bachelor	*Bachelor∗*	*Bachelor∗*
$2019xGroup_1$	-0.0306**	-0.0288**			0.0659***	0.0657***
	(0.0132)	(0.0132)			(0.0104)	(0.0113)
$2019xGroup_2$	-0.0886***	-0.0810***			0.1089***	0.0994***
	(0.0175)	(0.0184)			(0.0129)	(0.0167)
Intercept	0.7124***	0.0763***	0.2397***	0.0167	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)
N	178076	159805	116269	97129	149078	125205
R2	0.019000	0.092000	0.024000	0.063000	0.130000	0.157000

7.5 Robustness Reduced Form

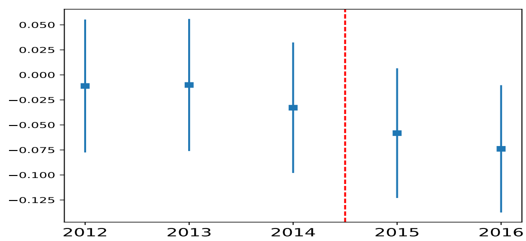
Debt and Spatial Factors Not enrolling in university is not the only margin of adjustment to the reform. Affected individuals can also stay at home, increase work hours or take up more study debt. All of these factors could itself have important consequences for individual outcomes. There are two major 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.

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.



(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.

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