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Introduction

Uncertainty is an essential feature of most economic decisions. When young people decide about the educational career they want to pursue, they need to consider many factors that are not known for sure at that time, such as whether they will pass the program they choose, their future preference for different occupations and job amenities, or future labor demand. Similarly, when people decide to invest their money, they must consider how the stock market and the economy will develop. The same holds for many other choices, such as job-switching, retirement, or moving. The nature of this uncertainty and how people perceive and adapt their choices to it has profound implications for individual outcomes and the design of effective policies. This dissertation analyzes two critical aspects of economic uncertainty: the impact of economic policy in the presence of uncertainty and the formation of household beliefs. The first two chapters of this dissertation analyze the effect of education policy on outcomes and economic inequality, considering the uncertainty young people face when making choices about their future. The third chapter analyzes how households form expectations about the macroeconomy during times of increased economic uncertainty.

Chapter 1 consists of my job market paper. The paper asks whether alternative paths to university promote social mobility. I refer to trajectories that involve vocational training or high school dropout before entering university as alternative paths to university. My analysis is motivated by two stylized facts. Individuals from low-income backgrounds perform worse in school than their peers from higher-income backgrounds. Furthermore, if individuals from low-income backgrounds enter university, they are more likely to take an alternative path to university. I use a dynamic model of education choices and a recent reform to student income subsidies to understand how the presence of alternative paths to university affects individuals from low-income backgrounds.

The model follows individuals from low-income backgrounds in the Netherlands during adolescence and early adulthood. I exploit differences in rules across schools to account for selection on unobservable characteristics.

Returns to applied university differ across the population but are substantial for many low-income individuals despite early achievement gaps. Many individuals face substantial dropout risk at applied university. Alternative paths to university

substantially increase university graduation rates and wages among individuals from low-income backgrounds. The main explanation for this result is that many individuals from low-income backgrounds face substantial uncertainty when deciding about their future education at sixteen. Imposing flexibility between different educational careers consequently improves outcomes significantly.
In the second part of the paper, I analyze a reform to student income subsidies. I use the results to validate features of the structural model and to understand better how income subsidies affect individuals who take alternative paths to university. The reform has affected the cost of studying and moving out but not the cost of studying and staying home.
I use machine learning techniques to identify the control group and run a difference in difference specification with the results. The reform has decreased applied university enrollment among vocational training graduates by four percent. Degree completion has also decreased but much less strongly, which implies that compliers had a relatively large dropout risk on average. The reform's substantial effect shows that vocational training graduates are particularly sensitive to the costs of higher education. This may be caused by the fact that graduates of vocational training are older and from lower-income backgrounds than graduates of high school. Policymakers should explicitly consider alternative paths to university when designing income subsidies in higher education.
The model reproduces the characteristics of compliers if I simulate an alternative model with a similar effect on enrollment as the reform.

In Chapter 2 (joint work with Manudeep Bhuller and Phillip Eisenhauer), we derive returns to education that account for uncertainty and the sequential nature of education choices. We estimate a dynamic structural model of schooling and work decisions with administrative data in Norway. We validate the model against variation in schooling choices induced by a compulsory schooling reform. Our approach allows us to estimate the ex-ante returns to different schooling tracks at different stages of the life-cycle and quantify the contribution of option values. We find substantial heterogeneity in returns and establish crucial roles for option values and re-enrollment in determining schooling choices and the impact of schooling policies.

In Chapter 3 (joint with Hans-Martin von Gaudecker), we document how households update their expectations in times of increased economic uncertainty. We use a k-means clustering algorithm to track how people jointly form expectations about different economic aggregates during the COVID-19 pandemic and after the surge in inflation in early 2022. This allows us to get a more detailed picture of what drives changes in average expectations, as most people are unlikely to think about different macroeconomic aggregates in isolation. We first summarize the most important economic scenarios, which we define as combinations of economic expectations in different domains that people expect at each point in time. Then, we associate scenario choice with various background characteristics. Finally, we consider how individuals update their economic scenarios and associate scenario patterns with background characteristics. We find that a wide range of different economic scenarios drives disagreement in response to economic uncertainty. Scenario choice is associated with various characteristics shown to matter for subjective macroeconomic expectations in the prior literature. Most importantly, we document that different background characteristics are associated with distinct updating behavior. A large part of the disagreement in economic scenarios in times of uncertainty can be traced to disagreement about how current events will affect the economy and what factors are relevant to consider. Some people, however, are generally pessimistic and change their expectations much less in response to news. Finally, there is a significant amount of people with very volatile expectations, often in stark contrast to the current economic situation.

Chapter 1

Nonstandard Educational Careers and Inequality[*]

1.1 Introduction

Children from lower-income backgrounds perform worse than their higher-income peers in school (OECD, 2019). This achievement gap persists in future educational careers and has a lasting impact on future outcomes of individuals from low-income households. Individuals from low-income backgrounds are more likely to drop out of high school to work or pursue vocational training. Later in life, many individuals from low-income backgrounds enter higher education despite earlier achievement gaps. However, they are more likely to do so after finishing vocational training or dropping out of high school. Prior literature has treated nonacademic degrees or high school dropouts as terminal states and abstracted from alternative routes to higher education, even though individuals from low-income backgrounds are particularly likely to choose them.

Alternative paths to university may be particularly important for individuals from low-income backgrounds as they provide a route to higher education for individuals who lack the grades or interest to commit to university early in life. On the other hand, promoting alternative paths to university may have adverse consequences, as leaving academic education for some years may negatively affect success at university. This paper asks whether alternative paths to university can mitigate the impact of early achievement gaps across socioeconomic status. I use a structural

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model and a recent reform to student income subsidies to understand how individuals from low-income backgrounds decide about enrollment in different education options and how these choices shape their final education and future wages. I then use these insights to evaluate whether alternative paths to university promote social mobility. Furthermore, I predict how education policies, such as the organization of vocational training or income subsidies during higher education, affect individuals from low-income backgrounds when alternative paths to university are available.

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

I begin by documenting two stylized facts about education in the Netherlands. First, most individuals from low-income backgrounds are enrolled in vocational school, consistent with achievement gaps across socioeconomic status in school. Secondly, university graduates from low-income backgrounds are twice as likely to have entered university after completing vocational training. Motivated by this observation, I analyze the educational careers of graduates of vocational schools in the Netherlands.

I first introduce a dynamic discrete choice model in the spirit of Keane and Wolpin (1997) that follows graduates of vocational school[1]. Individuals are sixteen when they graduate from vocational school. After graduating from vocational school, individuals can enroll in different vocational training programs or enter high school. Whether individuals can enter high school depends on their grades and the vocational school they graduate from, 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 higher vocational program takes longer than high school 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.

1. In particular, I focus on graduates of the technical branch of vocational school (VMBO-T) in this application.

2. The Netherlands has two types of higher education institutions: academic and applied universities.

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. If individuals select education programs based on unobserved characteristics affecting wages and graduation probabilities, model predictions will be flawed. I exploit the fact that the transition from vocational school to high school is more difficult from some vocational schools than from others. Individuals who enter high school from a vocational school where transition is more challenging have a higher unobserved propensity to enter high school as they incur higher costs on average. The extent to which their outcomes differ from individuals who entered high school from a school where transition is easier identifies how selection on unobserved characteristics drives observed patterns. My approach is robust to selection into different vocational schools as I allow the distribution of unobserved characteristics to differ across schools.

Having estimated the model, I first summarize the estimated parameters and discuss their policy implications. The estimated parameters show that lifetime earnings returns to applied university differ substantially across the population. Some people receive negative returns to receiving an applied university degree since increased earnings later in life are insufficient to offset earnings losses associated with attending applied university earlier. More than 50% of the population, however, receive significantly higher lifetime income if they hold an applied university degree. 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 dropout risk at applied university.

Next, I simulate an alternative model where I remove the option to enter applied university after finishing vocational training. I compare the alternative model to the current policy environment to understand how alternative paths to university affect individuals from low-income backgrounds. Removing the option to enter applied university after finishing vocational training significantly reduces university graduation rates and wages of individuals from low-income backgrounds. The main explanation for this effect is that many individuals from low-income backgrounds face substantial uncertainty when deciding between vocational programs and high school at sixteen. Allowing them to reconsider their initial choice later in life improves outcomes significantly.

The results of the structural model yield two crucial insights. Allowing individuals to pursue vocational training at age sixteen instead of continuing high school improves outcomes for individuals who face considerable dropout risk and have only modest returns to applied university. At the same time, it diverts some individuals who would 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.

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. Individuals from low-income backgrounds 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 the reform decreased applied university enrollment among graduates of vocational training by four percent. Degree completion also decreased but much less strongly, which implies that compliers had a relatively large dropout risk on average. The reform's substantial effect shows that vocational training graduates are particularly sensitive to the costs of higher education. This may be caused by the fact that graduates of vocational training are older and from lower-income backgrounds than graduates of high school. Policymakers should explicitly consider alternative paths to university when designing income subsidies in higher education.

The model predicts a smaller decline in enrollment. This is because the treated group differs from the broad population and because the model includes no consumption component and no risk aversion. If I simulate an alternative model with a similar effect on enrollment as the reform has, the model reproduces the characteristics of reform compliers. 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, Eisenhauer, and Mendel (2022), Lee, Shin, and Lee (2015), Trachter (2015), Stange (2012) and Heckman, Humphries, and Veramendi (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. They find that uncertainty about one's ability drives common phenomena such as dropout or re-enrollment. Wiswall and Zafar (2015), Attanasio and Kaufmann (2017) and Ehrmantraut, Pinger, and Stans (2020) document uncertainty about returns to higher education. Zhu (2021) estimates a dynamic model of education choices where individuals decide between community colleges and regular colleges and evaluates how free community college would promote social mobility. He finds that reducing the tuition in community colleges and regular colleges would be more effective in promoting social mobility than free community college. In contrast to earlier models, my model explicitly accounts for nonacademic education and alternative routes to university. This allows me to show that alternative paths to university promote social mobility and to predict how the effect of education policy changes when alternative paths to university are available.

The second branch I contribute to is a growing literature investigating returns to various education programs different from academic universities and high schools. Hanushek et al. (2017), Birkelund and Werfhorst (2022), Bertrand, Mogstad, and Mountjoy (2021) and Silliman and Virtanen (2022) analyze returns to vocational training against different fixed alternatives. Matthewes and Ventura (2022) consider returns to vocational training against the next best alternative and find that returns vary by the second-best option individuals have. Dustmann, Puhani, and Schönberg (2017) analyze the effects of early track choice in Germany and find that flexibility in the education system limits the impact of choosing a lower track early in life. Adda and Dustmann (2023) analyze how vocational training shapes future wage growth relative to not holding a post-secondary degree. They find that workers with vocational training accumulate cognitive-abstract skills faster which has important consequences for their future job tasks and wages. Eckardt (2019) investigates the consequences of uncertainty in vocational program choice and derives returns to combinations of vocational training programs and occupations. Belfield and Bailey (2017) survey the literature on returns to community colleges in the US. Mountjoy (2022) analyzes returns to community colleges against different next-best alternatives and finds that returns depend on whether the alternative is a regular college or no tertiary education degree. Heckman, Humphries, and Mader (2011) survey prior work documenting returns to GED certificates in the US. They generally find that the GED is associated with lower wage returns than high school degrees. I extend this literature in two ways. I estimate a fully structural model, which requires more assumptions but sheds light on the mechanisms driving choices and outcomes. This allows me to document how returns to vocational training differ across the population and how the expected returns to vocational training relative to university depend on academic risk and ex-post wage returns. Furthermore, I consider further education choices after individuals have completed vocational training. My analysis highlights how the returns to vocational training 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) document 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.

The rest of the paper is organized as follows. Section 2 provides stylized facts and institutional details about the Dutch education system. Section 3 introduces a dynamic model of education choices. Section 4 discusses the main model results. Section 5 contains the analysis of the income subsidy reform. Finally, I conclude in Section 6.

1.2 Setting and Stylized Facts

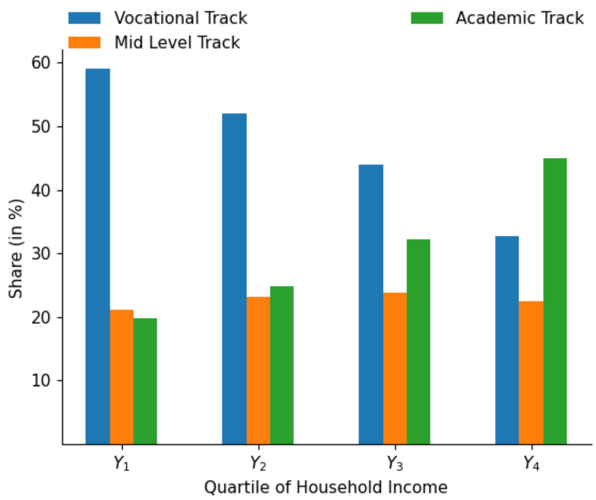
In this section, I explain relevant features of the Dutch education system, show stylized facts motivating the subsequent analysis, and summarize all the options that graduates of vocational school have.

1.2.1 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. The vocational schooling track (VMBO) receives individuals with the lowest assessed academic potential, takes three years, and prepares students for vocational training. This paper will refer to the vocational schooling track as vocational school. Vocational training prepares individuals for particular occupations and takes two to five years. The mid-level track (HAVO) prepares individuals for applied university and takes five years. Higher education in the Netherlands differentiates between applied universities, which are more practical and academic universities. A bachelor's degree at an applied university takes four years. The academic track (VWO) prepares individuals for academic university and takes six years. A bachelor's degree at an applied university takes three years. I will refer to the mid-level track as high school in this application as graduates of vocational school are very unlikely to ever enroll in the academic track. I will describe different career options for graduates of vocational school in section 1.2.4. I will abstract from academic university and master programs in this context as most of the graduates of vocational school never enroll in either.

1.2.2 Data

I use Dutch administrative records to follow graduates of vocational schools. I combine information on educational careers, grades, the economic situation of their par-



Note: This figure shows track assignment by quartile of parental household income. The vocational track includes all branches of VMBO. The figure is based on the dataset described in 1.2.2 and contains data from 2008-2010.

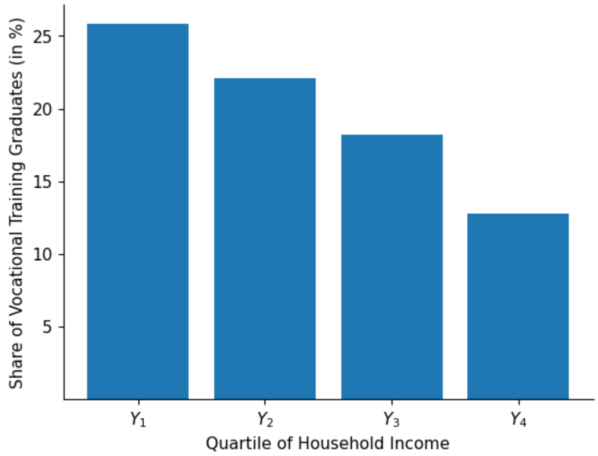
Figure 1.1. Track assignment by parental income

ents, 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 model. The reform evaluation will focus on graduates of vocational training who are mostly between 18 and 23.

1.2.3 Stylized facts

Individuals from low-income backgrounds are most likely to be in the vocational track: Figure 1.1 summarizes the gradient in track choice after primary school. Individuals from low-income backgrounds 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, Chehber, Dillingh, et al. (2022) show that individuals from low-income backgrounds, however, receive lower track recommendations even after controlling for grades and cognitive skills. The misallocation is thus potentially worse among individuals from low-income backgrounds than among their higher-income peers.

Alternative paths to higher education are more common among individuals from low-income backgrounds: I now consider all individuals who at least hold an applied university degree. Figure 1.2 shows the proportion of university graduates that have completed vocational training before. Conditional on reaching a ter-



Note: This figure shows the fraction of university graduates who have completed vocational training before entering university. University graduates include everyone with at least an applied university bachelor's degree. Individuals with an academic university bachelor's degree or any master's degree are also included. Note that these proportions are not synchronized with Figure 1.1, where I show individuals enrolled in different schooling tracks. This figure shows how many individuals graduated from vocational training and went to university afterward. Vocational training comes after vocational school, and some vocational school graduates also choose to enroll in high school, as I explain in section 1.2.4. The figure is based on the dataset described in 1.2.2 and contains data from 2008-2010.

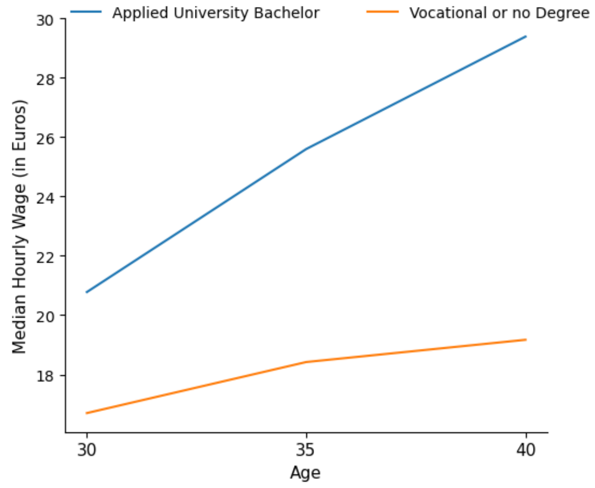
Figure 1.2. Fraction of university graduates who finished vocational training

tiary degree, individuals from low socioeconomic backgrounds are twice as likely to have entered higher education after vocational training. Entering university after finishing vocational training is a well-established career in the Netherlands that is particularly important for individuals from low-income backgrounds. 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 1.3 shows median wages for individuals with applied university degrees and those without university degrees between the ages of thirty and forty. The wage gap is modest at age thirty but grows quickly after that. Understanding how much of these differences are driven by selection and actual returns to applied university degrees is important. Increasing applied university graduation among individuals from low-income backgrounds would contribute to decreasing persistent income inequality if substantial returns remain after accounting for selection.

1.2.4 Pathways to university

Having demonstrated that individuals from low-income backgrounds are most likely to be in vocational school, I now present all possible future pathways for graduates

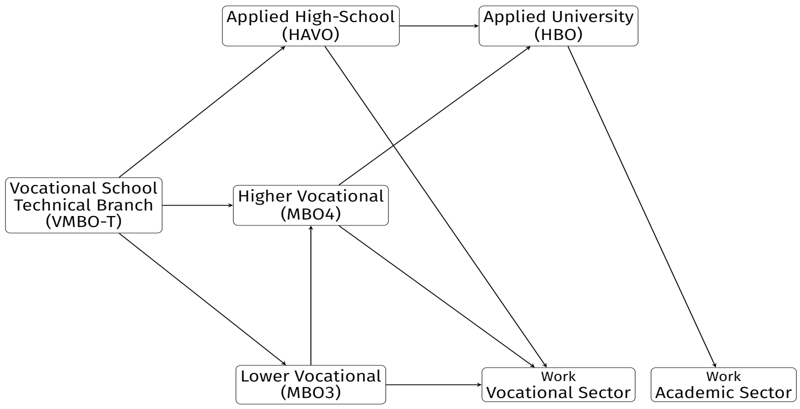


Note: This figure shows the evolution of average hourly wages for individuals with and without applied university degrees. I only include individuals who work full-time. The applied university category only includes individuals with bachelor's degrees. The data is obtained from a cross section of hourly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

Figure 1.3. Wage inequality over time

of vocational school. From now on, I focus on graduates of the technical branch of vocational school[3]. I focus on this branch because it is the largest and because graduates of this branch have the widest choice options. Hence, there is more variation in choices among technical graduates, allowing me to explore the effect of different educational options. The effect of policy on the other branches is likely similar to that of policy at the bottom of the grade distribution in the technical branch, as the technical branch receives individuals with the highest grades. Figure 1.4 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 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 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. Naturally, Figure 1.4 includes some simplifications. In particular, I leave out possibilities that are negligible empirically. While lower vocational programs contain options beyond MBO3, most graduates of the technical branch choose the latter. There are also different options to receive a high school degree, but none of the alternative options plays an important role. Individuals could switch to an academic high school (VWO) after finishing high school (HAVO), and

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



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

Figure 1.4. Pathways for graduates of vocational school

they could change to an academic university during their studies at an applied university. I abstract from both of these options as they are chosen infrequently. Finally, individuals can enroll in a master's degree after finishing applied university. I also abstract from this choice and treat individuals with applied university master's and bachelor's degrees equally.

School types: The transition to high school is not organized centrally. High Schools have employed their own rules for admitting students from vocational school (Van Esch and J., 2010). The number of individuals that transfer to high school from a particular vocational 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.

1.3 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.

1.3.1 Sample and decision tree

The model is based on the summary of pathways introduced in Figure 1.4 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.

1.3.2 Model organization and 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. 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 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 $t \in \{0, 1, 2, 3..., 13\}$ denotes the number of years that have passed since the onset of the model. A decision period $\tau \in \{0, 1, ..\}$ represents the number of choices that the individual has already taken. 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.

1.3.3 States and fixed hetereogeneity

Each individual is characterized by fixed characteristics and dynamic states. Fixed characteristics include observable ability G, latent type θ, parental income Y, and school type U. Observable ability G denotes the quartile of vocational school grades. Y denotes the quartile of parental household income. School Type U denotes the type of transit policy in the individual's school. This variable captures that transitioning to high school after graduating from vocational school is easier from some vocational schools than others. I identify school types by grouping school fixed effects from a regression of vocational schools and individual characteristics on high school attendance. Latent type θ is a latent factor that captures dependence between choices and outcomes not accounted for by observed characteristics. All fixed characteristics are assigned at the beginning of the model. The joint distribution of Y, U, and G is assigned exogenously as observed in the data. The distribution of θ depends on all the other fixed states and is estimated with all other parameters. Dynamic states include age A, current level of schooling E, and lagged choice $d_{\tau-1}$. One state is a tuple that consists of all fixed characteristics and dynamic states as described in Equation 1.1. Individuals start the model at age 16.

$$s_\tau = (A_\tau, E_\tau, C^{\tau-1}, G, \theta, Y, U) \tag{1.1}$$

1.3.4 Choices and timing

Let d_τ denote an individual's choice 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, higher vocational training, and lower vocational training in the first stage. After that, the set of choices depends on their state.

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.

1.3.5 Transitions and uncertainty

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

Equation 1.2 shows the specification of dropout risk. $P(E_{\tau+1} = d_\tau)$ is the probability that an individual successfully graduates from the education program she enrolled in. The equations' coefficients are model objects estimated jointly with all other parameters.

$$Logit(P(E_{\tau+1} = d_\tau))(G, \theta, Y) = \beta^R_{0,d} + \xi^R_{1,d} G + \xi^R_{2,d} \theta + \xi^R_{3,d} Y \tag{1.2}$$

Let min_d be the minimum years required to finish a degree. If an individual i completes a degree successfully, she faces a poison process that determines the duration of her degree:

$$T_d^{E_{\tau+1}=d_\tau}(G,\theta,Y) \sim Poisson(min_d, \beta_{0,d}^D + \xi_{1,d}^D G + \xi_{1,d}^D \theta + \xi_{3,d}^D Y). \tag{1.3}$$

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

$$T_d^{E_{\tau+1}\neq d_\tau} \sim Poisson(min_d, \beta_0). \tag{1.4}$$

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.

1.3.6 Wages and nonpecuniary preferences

Wages are modeled as two separate 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 assume that everyone works full-time after they leave school. Let k_t be work experience at time t and let E^C be an individual's combination of degrees. Log wages for the vocational sector are specified in equation 1.5. Log wages in the vocational sector depend on experience, age, parental income, ability, type, highest degree completed, and highest degree completed interacted with experience.

$$\begin{aligned} w_v(E,A_t,k_{t,v},G,\theta,Y) = \; & \beta_{0,v}^W + \beta_{1,v}^W E + \beta_{2,v}^W k_{t,v} + \beta_{3,v}^W k_{t,v}^2 + \beta_{4,v}^W A_t + \beta_{5,v}^W k_{t,v} E \\ & + \xi_{1,v}^W G + \xi_{2,v}^W \theta + \xi_{3,v}^W Y + \epsilon_{v,t} \end{aligned} \tag{1.5}$$

Log wages in the academic sector are modeled separately in equation 1.6. I use a different specification for academic wages to allow for a flexible form of the applied university wage premium. They depend on experience, age, parental income, ability, type, and educational career.

$$\begin{aligned} w_a(E^C,A_t,k_{t,v},G,\theta,Y) = \; & \beta_{0,a}^W + \beta_{1,a}^W E^C + \beta_{2,a}^W k_t + \beta_{3,a}^W k_t^2 + \beta_{3,a}^W A_t + \xi_{1,a}^W G + \xi_{2,a}^W \theta \\ & + \xi_{3,a}^W Y + \epsilon_{a,t} \end{aligned} \tag{1.6}$$

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 $F(s,d_t)$ 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. Additionally, I include transition costs to high school $T(U)$ to capture differences in transitions across school types. Equation 1.7 shows the utility 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. The coefficients of wage equations, nonpecuniary returns to choices, and transition costs are all model objects that are estimated.

$$U_d(s) \;=\; F_d(s) + e^{w_d(s)} + T \tag{1.7}$$

Equation 1.8 denotes the discounted lifetime utility from working if an agent reaches a terminal state. The term β is the discount factor fixed to 0.95 in the model.

$$\sum_{t\in\{s,..T\}} \beta^t U^w(s) \tag{1.8}$$

1.3.7 The agent's problem and 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. Equation 1.9 shows the optimization problem of an individual in the model at state s_τ.

$$\max_{d\in C(s_\tau)} \sum_{s_{\tau+1}\in R(s_\tau,d)} P_{s_\tau,d}(s_{\tau+1}) \sum_{s\in N(s_\tau,s_{\tau+1})} (\beta^{n(s_\tau,s)}U(s)) + \beta^t V(s_{\tau+1}) + \nu_{i,\tau}(d) \tag{1.9}$$

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 $\hat{s}$:

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

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.

1.3.8 Estimation and identification

Estimation: I use indirect inference to estimate 117 parameters $\hat{\theta}$. Equation 1.10 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 (Altonji and Segal, 1996). I use a package for the estimation of scientific models by Gabler (2022) for the optimization of the criterion function[4].

$$\hat{\theta} \;=\; \arg\min_{\theta \in \Theta} (M_D - M_S(\theta)) W^{-1} (M_D - M_S(\theta))' \tag{1.10}$$

Identification: Table 1.1 provides an overview of all 335 statistics used in the model estimation. The enrollment percentage for a particular program indicates how many people have been enrolled in that respective program. Enrollment percentages are included for each quartile of parental income, each quartile of grades in vocational school, and each combination of school type and vocational school grade quartile. The final degree combination indicates all 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. Final degree combinations are included for the same subsets as enrollment percentages. Furthermore, I include the last schooling age for all grade and income quartiles. The last schooling age is when an individual is done with education and starts to work. 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

4. I use a global version of the BOBYQA algorithm within the package(Powell et al., 2009).

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. Let T^u denote the years someone needs to finish applied university. Let γ be year fixed effects. Equation 1.A.3 is estimated on a panel that includes all full-time individuals who left school without a bachelor's degree from the third period onward. Equation 1.A.4 is estimated on a panel that includes all full-time individuals who left school with a bachelor's degree from the sixth period onward. Both equations capture how wages depend on observable states featured in the model. Both include work experience k_t, grades G, and parental income Y. Equation 1.A.3 additionally includes the non-university degree of an individual and an interaction between the nonacademic degree and work experience. This is either a higher vocational degree (MBO4), a lower vocational degree (MBO3), a high school degree (HAVO), or no degree after vocational school (VMBO-T). Equation 1.A.4 additionally includes a fixed effect for all non-university degrees individuals have completed before entering university. Furthermore, it includes the years an individual took to finish her bachelor's degree. Both of these equations suffer from selection bias. Since the model explicitly models the selection process, they are still helpful for identifying wage components.

$$W_{v,t} = \alpha_{v,0} + \alpha_{v,1}E + \alpha_{v,2}k_t + \alpha_{v,3}k_t^2 + \alpha_{v,4}k_tE + \delta_{v,0}G + \delta_{v,1}Y + \gamma + \omega_{v,t} \quad (1.11)$$

$$W_{a,t} = \alpha_0 + \alpha_1 E^C + \alpha_2 T^u + \alpha_{v,2}k_t + \alpha_{v,3}k_t^2 + \delta_{v,0}G + \delta_{a,1}Y + \gamma + \omega_{a,t} \quad (1.12)$$

Equation 1.A.5 is estimated on a cross-section of all full-time individuals in period thirteen. This equation only contains school type as an independent variable. This equation only adds information about the unconditional dependence of school types.

$$W_h = \alpha_{h,0} + \alpha_{h,0}U + \omega_h \quad (1.13)$$

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.

Table 1.1. Summary of moments used in the estimation

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

Note: This table summarizes all 335 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. Grades always refer to grades at the end of vocational school.

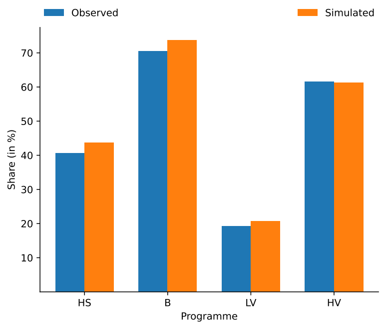
Secondly, the differences in transition costs across schools lead to differences in the joint distribution of unobserved characteristics and choices across schools. This is because individuals who enter high school from a vocational school where transition is more challenging have a higher unobserved propensity to enter high school as they incur higher costs on average. The degree to which outcomes differ across schools holding observed characteristics and the degree of selection fixed helps to identify latent types. The approach is robust to selection into vocational schools as I allow the distribution of the latent type to differ across school types. Selection and differences in rules across schools imply different observed patterns. If differences in rules across school types cause differences in transitions to high school, individuals who do not transfer to high school should be different across school types. Individuals in schools with high transition costs should be more likely to enter university after vocational training, as this path to university is less costly. Thus, I can pin down how much of the differences in observed patterns across schools are due to selection and how much is due to differences in rules.

1.4 Results

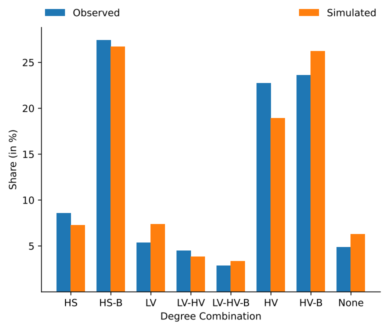
I now present the empirical findings of the structural model. First, I present the model fit of the simulated moments, and then I discuss estimated parameters and their implication for education policy. After that, I simulate three explicit policies and discuss the resulting predictions.

1.4.1 Estimation and model fit

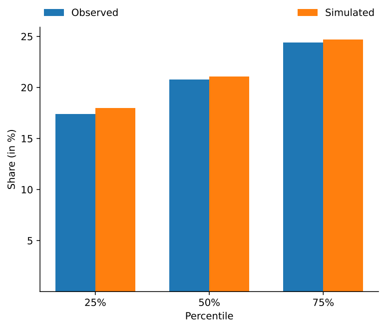
Figure 1.5 briefly summarizes the model fit. A more detailed summary can be found in Section 1.A.5 in the appendix. The first two panels show the fit of enrollment proportions and degree combinations for individuals with high grades. Both sets of simulated moments are closely aligned with their observed counterparts. The third



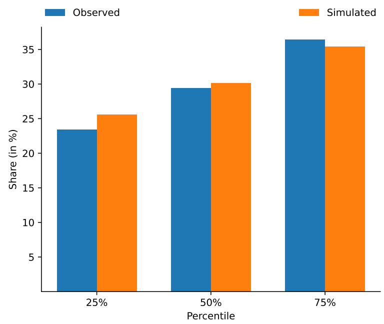
(a) Enrollment Proportion



(b) Degree Combination



(c) Wage Quantiles Bachelor's Degree Holder Age 30



(d) Wage Quantiles Bachelor's Degree Holder Age 40

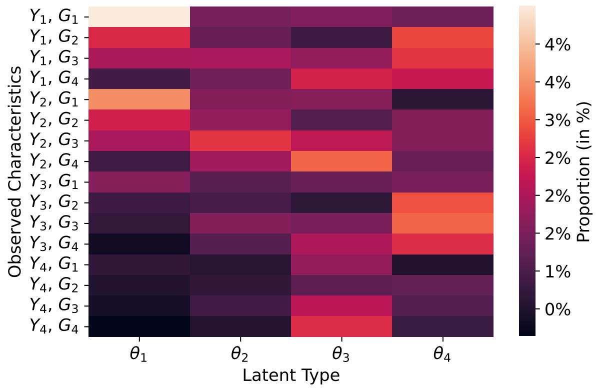
Note: This figure summarizes the model fit. The figures compare observed moments based on the dataset described in 1.2.2 and simulated moments from a model with the estimated parameters. The blue bars show the observed moments, and the orange bars show simulated moments. The x-axis labels for the figures in the first row correspond to education programs specified in Figure 1.4. Labels in the second figure represent paths through the decision tree specified in Figure 1.4. HS-B, for example, indicates that an individual graduates from high school first and from an applied university after that. The figures in the second row depict wage percentiles for individuals who hold a bachelor's degree at age thirty and forty. In particular, they show the 25th, 50th, and 75th percentile of wages among all individuals who work full-time and hold an applied university bachelor's degree.

Figure 1.5. Summary of model fit

and fourth panels show wage quartiles for individuals with an applied university degree at ages thirty and forty. The model slightly underestimates wage 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.

1.4.2 Mechanisms

Estimated parameters contain information about the distribution of wage returns to applied university and the distribution of dropout risk at applied university. A detailed list of parameter estimates and standard errors can be found in the appendix in Section 1.A.4.



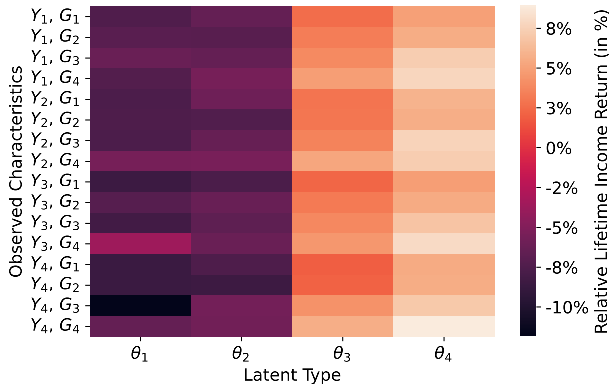
Note: This figure shows a heatmap visualizing the distribution of fixed characteristics in the model. The vertical axis represents one combination of grades and parental income each while the horizontal axis represents one latent type each. Both grades and parental income are exogenously given to the model. The distribution of the latent type given parental income and grades is estimated by the model.

Figure 1.6. Distribution of fixed characteristics in the model

Distribution of observed and unobserved characteristics: Individuals are characterized by parental income, ability and a latent type. The joint distribution of parental income and ability is observed in the data. The distribution of latent types conditional on parental income and ability is estimated along with the other model parameters. Figure 1.6 shows the joint distribution of fixed characteristics in the model. Consistent with achievement gaps across socioeconomic status there are substantially more individuals from low income households as compared to individuals from higher income households. Latent types are correlated with observed characteristics. Individuals in the lowest grade group are more likely to have type θ_1 whereas individuals in the highest grade group are more likely to have type θ_3. Differences in outcomes across individuals with the same parental income, ability and latent type are only due to different realizations of random shocks and not systematic[5]. Wage returns conditional on all fixed characteristics are thus average returns to university for all individuals in the respective subgroup. I can thus assign an average wage return and an average dropout risk to each individual in the sample.

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

5. The model features school type as an additional fixed characteristic but since it only affects the utility associated with choices in the first period it does not directly affect life time outcomes.



Note: This heatmap summarizes the distributions of returns to applied universities. The vertical axis represents one combination of grades and parental income, while the horizontal axis represents one latent type. The returns are expressed in Euros per hour worked. The returns are obtained by calculating the difference in discounted lifetime income of individuals with and without bachelor's degrees for each combination of observed characteristics and latent type. Observed characteristics are parental income and grades at the end of vocational school. School type is not included since it has no direct effect on wages. Discounted lifetime income differentials within a group of observed characteristics and latent type are average returns to applied university for all individuals in that group since wages don't systematically differ conditional on these variables. The value of the respective group is then assigned to each simulated individual to obtain a distribution.

Figure 1.7. Distribution of life-time earnings returns to applied university.

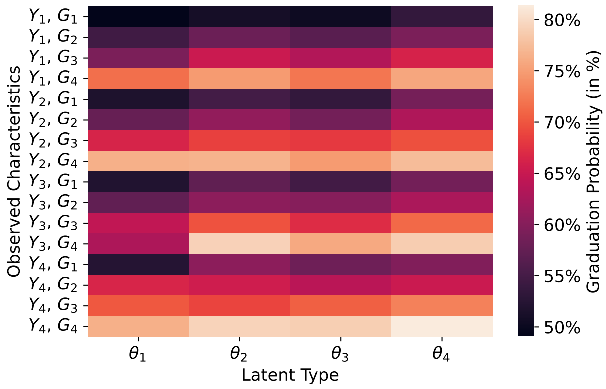
between the ages of thirty and forty. To understand how expected returns to university are distributed, I calculate the average difference in discounted lifetime income between individuals with and without an applied university bachelor's degree for each combination of observed characteristics and latent type in the model. Figure 1.7 shows the distribution of discounted lifetime earnings returns to applied university by combinations of observed characteristics and latent type. Returns to applied university differ substantially across the population. While the first two latent types receive negative lifetime earnings returns to applied university the other two latent types receive positive ones. It is essential to note that individuals without applied university degrees enter the labor market earlier and thus have more years to earn income in the model. This explains why the return to applied university is significantly negative for some people. In fact, if we consider earnings at age 40 instead of discounted lifetime income, returns to holding an applied university degree are positive across the population (see Figure 1.A.1). Returns to applied university do not substantially differ by parental income but by middle-school grades. It is important to point out that the model does not account for several job and university program characteristics such as subject, occupation, or part-time arrangements. The lack of these factors could potentially explain the large role of the latent type in determining discounted lifetime incomes across final schooling levels. The distribution of wage returns highlights that understanding the long-term effect of policy requires understanding what kind of individuals are shifted by particular policies. Increasing the number of individuals from low-income backgrounds with an applied university degree thus narrows the income gap across socioeconomic backgrounds. Wages also differ by the non-academic degree an individual pursues. Quitting school after graduating from vocational school is associated with substantially lower wages than holding a high school or vocational degree. Graduates from a vocational program tend to earn more than those with a high school degree. Individuals may choose a vocational degree before they enter university as it is associated with a higher-paying outside option if they dropout of university. The gap is, however, small and declines over time.

Dropout risk: Heterogenous dropout risk across people is the most dominant factor generating heterogeneity in outcomes across individuals in the model. Considering that the model suggests that returns to applied university are substantial for many individuals, the relevant question is what factors inhibit applied university graduation among individuals without an applied bachelor's degree. Parameter estimates suggest that differences in dropout risk at applied university[6], as opposed to differences in other unexplained preferences, are particularly important.

To understand how dropout risk at applied university is distributed, I calculate the dropout rate at applied university for each combination of observed characteristics and latent type in the model. Figure 1.8 shows the distribution of dropout risk at applied university by combinations of observed characteristics and latent type. Individuals with lower observed grades face substantial dropout risk and only graduate from applied university with a probability of around fifty percent, while individuals in the highest grade group graduate with a probability of around 80%. The differences in dropout risk across grade groups are consistent with significant differences in observed dropout rates across grade quartiles. Large dropout probabilities for lower-grade individuals underline the importance of providing a good non-academic outside option.

In practice, it is relevant to understand what causes these dropout rates and to what extent individuals are aware of the high likelihood of not graduating. Other factors could drive this than failure to comply with grade requirements, such as individuals realizing that they are not interested in an applied university program or prefer a more practical occupation. Substantial dropout rates are not necessarily bad if enrolling in an applied university helps individuals decide whether an applied university suits them. The fact that many dropouts already leave applied university after one year implies that the adverse effect of dropouts may be limited for many

6. The other education programs outlined in Figure 1.4 are also associated with dropout risk. I will focus on applied university in this section as it is the most relevant program for the long-run outcomes of vocational school graduates. See Section 1.A.4 for dropout risk in other programs.



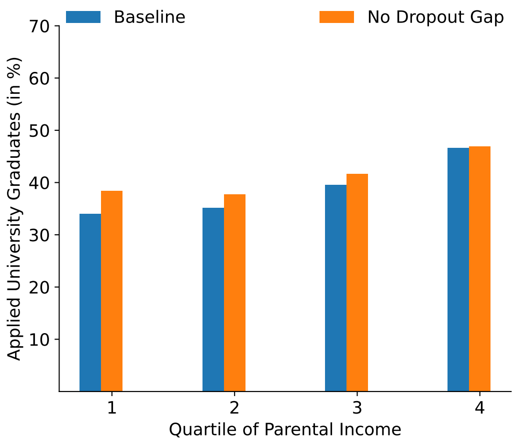
Note: This figure shows a heatmap visualizing the probability of graduation at applied university. The vertical axis represents one combination of grades and parental income, while the horizontal axis represents one latent type. This figure is obtained by calculating the number of applied university students who drop out for each combination of observed characteristics and latent type in the model. Observed characteristics are parental income and grades at the end of vocational school. School type is not included since it has no direct effect on wages. Observed dropout rates within a group of observed characteristics and latent type represent academic risk for all individuals in that group since academic risk does not systematically differ conditional on observed characteristics and latent type. The value of the respective group is then assigned to each simulated individual.

Figure 1.8. Distribution of graduation probability at applied university

individuals. It is beyond the model's scope to differentiate between the exact patterns driving dropout risk in this context. Still, it is an interesting question for future research to understand the underlying causes of ex-ante graduation risk.

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

Dropout gap by parental income: Parental income is associated with a 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 1.9 shows how applied university graduation would change if the risk gap between students from different socioeconomic backgrounds



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

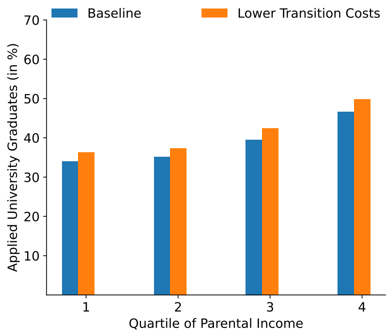
Figure 1.9. Gradient in dropout risk

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. Carrell and Kurlaender (2023) show that faculty engagement can increase graduation rates of individuals from underrepresented groups. Understanding which factors are driving this gap and what measures can address the gradient in dropout risk is essential.

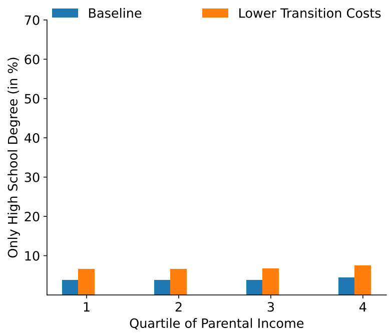
1.4.3 Counterfactuals

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.

Transition costs: Many individuals do not have the option to enroll in high school after vocational school as transition costs are substantial. 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 1.10 shows how the simulated policy would change educational attainment. I plot the fraction of individuals who complete applied university and the fraction



(a) University Graduates

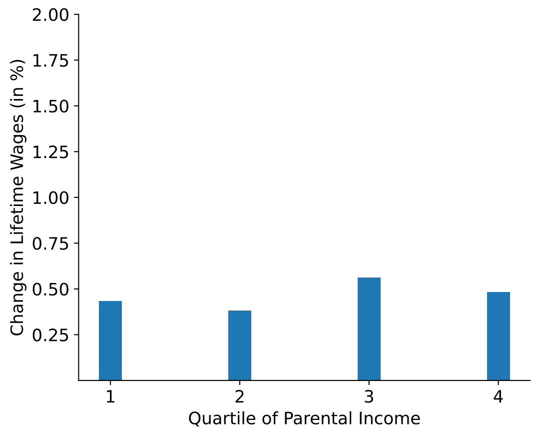


(b) High School only

Note: This figure shows how enforcing higher acceptance rates at high school would affect the number of university graduates and individuals who only hold a high school degree. Blue bars show the baseline model's proportions of applied university and high school-only graduates. The orange bars show the proportions in the counterfactual scenario where all schools behave like the most lenient schools and individuals with low grades face lower barriers. The proportions are shown for each quartile of parental income. Notably, most individuals graduating from vocational school are from households in the lower-income quartiles.

Figure 1.10. The effect of enforcing higher acceptance rates at high school

of individuals who only complete high school for each group of parental income for both the counterfactual and baseline scenarios. Both of these fractions could increase as the policy shifts individuals from vocational training into high school. Applied university graduation increases by around two percent in the counterfactual scenario. The counterfactual scenario is, however, also associated with a higher fraction of individuals who only hold a high school degree. The policy uniformly changes graduation rates across different quartiles of parental income. Figure 1.A.3 shows that the policy has heterogeneous impacts across grade levels. Individuals in the lowest grade quartile see a smaller increase in university graduations but a more significant increase in the fraction of individuals who only hold a high school degree. Many of them dropout of university or do not enroll in university after graduating from high school. Figure 1.11 shows average hourly wages in the counterfactual and baseline scenarios. Wages of individuals shifted to a bachelor's degree by the reform would increase by around one-third. Reform compliers from higher income backgrounds have higher returns to applied university than compliers from lower income backgrounds on average. It is essential to point out that individuals graduating from vocational school are most likely to come from a household in the lowest income quartile. In particular, there are twice as many vocational school graduates from a household in the lowest income quartile as the highest. The policy would thus still contribute to narrowing the wage gap between individuals from different socioeconomic backgrounds. Figure 1.A.8 shows that 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



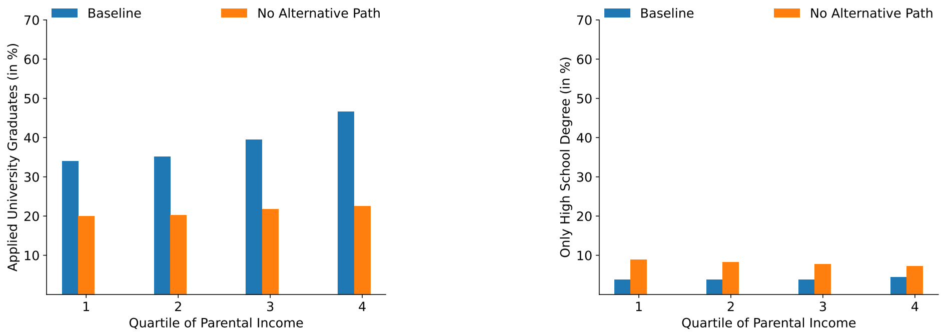
Note: This figure shows how enforcing higher acceptance rates at applied universities would affect average wages. The blue bar shows wage changes at age thirty, and the orange bar shows wage changes at age forty. The differences are obtained by comparing average wages in the baseline model and a counterfactual simulation where all schools behave like the most lenient schools and individuals with low grades face lower barriers. The changes are shown for each quartile of parental income. Notably, most individuals graduating from vocational school are from households in the lower-income quartiles.

Figure 1.11. Wage effect of enforcing higher acceptance rates at high school

enter high school but fail to finish college.

Vocational path to university: Without any uncertainty, there would be no value to the vocational path to university. Entering university after finishing a higher vocational program 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 dropping 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. If that is the case, individuals will value the vocational path to university as it allows them to correct a decision that is suboptimal ex-post. Figure 1.12 compares a simulated model where individuals cannot enter university after graduating from a higher vocational program to the baseline simulation.

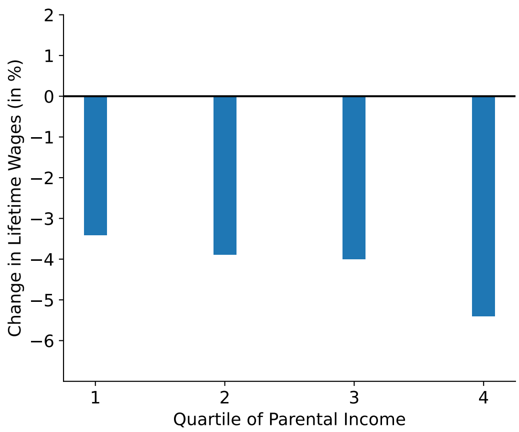
I additionally decrease transition costs to high school in the counterfactual scenario. Otherwise, the policy may mechanically lead to a decrease in university graduation as some individuals cannot switch to high school, which is the only path to university now, after finishing vocational school. The figure shows that university



(a) University Graduates **(b)** High School only

Note: This figure shows how removing the vocational path to applied university would affect the number of university and high school-only graduates. Blue bars show the baseline model's proportions of applied university and high school-only graduates. The orange bars show the proportions in the counterfactual scenario where graduates of a higher vocational program cannot enter an applied university. The proportions are shown for each quartile of parental income. Notably, most individuals graduating from vocational school are from households in the lower-income quartiles.

Figure 1.12. Effect of having no vocational path to applied university



Note: This figure shows how removing the vocational path to university would change average hourly wages. The blue bar shows wage changes at age thirty, and the orange bar shows wage changes at age forty. The differences are obtained by comparing average wages in the baseline model and a counterfactual simulation where individuals are not allowed to enter applied university after graduating from a higher vocational program. The changes are shown for each quartile of parental income. Notably, most individuals graduating from vocational school are from households in the lower-income quartiles.

Figure 1.13. Wage effect of removing vocational path to applied university

graduation would fall drastically across all parental income levels. Furthermore, many individuals who are induced to enroll in high school due to the absence of a vocational path to university would get stuck at the high school level. Figure 1.13 shows that removing the option to enter an applied university after finishing a higher vocational program would decrease average hourly wages by 1.50 €. This implies that the policy would shift many individuals with substantial returns to holding an applied bachelor's degree out of university.

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 Figure 1.12 as wage returns to high school are only slightly lower than wage returns to vocational training. Different motives could explain why individuals reconsider their initial decision at a later point. Once individuals get older, more uncertainty resolves. Individuals learn about their abilities, opportunities and wage returns associated with different educational paths, and subjects they find interesting. Moreover, individuals mature over time and may become more interested in academic education. This may be particularly important for children from non-academic households since they are potentially less likely to get pressured into academic education by their parents. It is beyond the scope of the model to separate these factors. The results show, however, that many individuals do not have sufficient information to decide about their final education at age sixteen and that alternative paths to university significantly improve outcomes for many individuals from low-income backgrounds.

1.5 The Effect of Income Subsidies

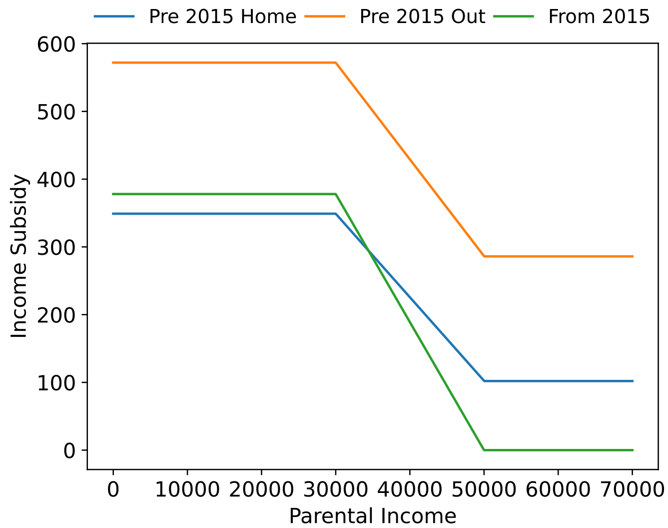
I now discuss the impact of income subsidies. I first introduce a recent reform to student income subsidies. Then, I present the empirical strategy and, finally, the results.

1.5.1 A reform to student income subsidies

The Dutch government pays monthly loans to university students converted to grants upon graduation. Initially, individuals who moved out of their parental homes received higher payments. In 2015, the Dutch government introduced a reform to the subsidy scheme. Figure 1.14 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. Individuals from low-income backgrounds who would have studied and moved out under the initial subsidy scheme have lost 200 euros, while individuals from low-income backgrounds who would have stayed home have lost nothing. Individuals who entered university before 2015 could keep the old subsidy scheme until graduation.

1.5.2 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



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. Note that this shows the amount of subsidies for individuals without siblings. If an individual has one more sibling still dependent on the parents, all lines are shifted to the right by varying amounts.

Figure 1.14. Incidence of the reform

will introduce a method to identify this latent group, and finally, I will show how I use this information to obtain the effect of the reform.

Characterization of a latent control group: Individuals who would not have moved out and entered university before the reform are not affected and can thus be used as a control group. Figure 3 shows that the reform has only changed subsidies for people who would have moved out and entered university. Let $d_i = (h_i, e_i)$ be the joint housing and education decision of an individual, where $h_i \in \{0, 1\}$ denotes the decision to remain at home and $e_i \in \{0, 1\}$ indicates the decision to attend university. Let $T(d)$ be a function that maps a joint decision d into a monthly subsidy amount. Let T_{pre} refer to the old subsidy scheme and T_{post} to the reformed scheme since 2015. Individual i picks the combination of housing and education that maximizes her utility depending on the subsidy scheme she faces $d_i(T_t)$. Figure 1.14 shows that individuals from low-income backgrounds who would have studied and stayed at home before the reform receive slightly higher subsidies after the reform. People who would not have been attending university will not change their decision since the reform made studying less attractive. I will only focus on individuals from lower-income backgrounds since higher-income individuals have lost out in either case. Equation 1.14 formally defines the latent control group. One who would not have studied and moved under the old reform scheme will keep their decision under the new scheme.

$$d_i(T_0) = d_i(T_1) \text{ for any } d_i(T_0) \neq (0, 1) \tag{1.14}$$

Additionally, I assume that treatment assignment is stable over time in Equation1.15.

$$d_{i,t}(T) = d_{i,t+n}(T) = d_i(T) \tag{1.15}$$

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

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

Parallel trends: I need to make a parallel trends assumption to derive treatment effects from differences across individuals with a high and low probability of being treated. Let Z_i be a vector of individual level controls and let Y_i be an individual level outcome such as university enrollment or graduation. Let $Y_{i,pre}$ denote the value of Y_i before the introduction and $Y_{i,post}$ denote the value after the introduction. Figure 1.16 shows my parallel trends assumption. Trends need to be parallel between latent treatment groups and between individuals with different probabilities of receiving the latent treatment. I need to adapt the usual parallel trends assumption because I only approximate the treatment status of individuals. The identification thus comes from comparing individuals who have been treated and have a high probability of being treated and individuals who have not been treated and have a low probability of being treated.

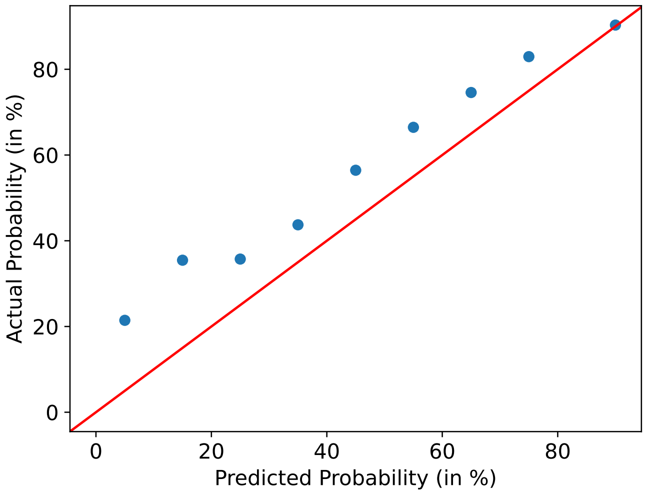
$$\begin{aligned} &E[Y_{i,post}(T_{pre}) - d_{i,pre}(T_{pre})|d_i(T_{pre}) \neq (0,1), P_H, Z_i] = \\ &E[d_{i,t}(T_{post}) - d_{i,t-1}(T_{pre})|d_{i,pre} = (0,1), P_L, Z_i] \end{aligned} \tag{1.16}$$

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 are not treated and have a high probability of being treated will not be significant. Observed trends across predicted probabilities will thus be close to trends across latent treatment groups with different treatment probabilities.

Comparing individuals with high and low probability: The parallel trends assumption allows me to express differences across individuals with a high and low probability of being treated in terms of treatment effect on the treated conditional on controls and treatment probabilities. A more detailed composition of the effect is provided in section 1.A.6 of the appendix. Differences in differences across groups can be written as the difference between two terms. The first term is proportional to the treatment effect on treated individuals with a high probability of being treated. The second term is proportional to the treatment effect on treated individuals with a low probability of being treated. As long as the probability of treatment is high in the predicted treatment group and low in the predicted control group, the whole term is close to the treatment effect on treated individuals with a high probability of being treated. In the appendix derivation, I use the probability of being treated given someone's observables. However, the same decomposition also works if I plug in an estimate of this probability instead. In the estimation, I will use the predicted $\hat{P}_d(X)$ that I described last section. An alternative way to derive the effects of the reform would be to run a continuous two-way fixed effects regression where the coefficient of interest is the interaction between time and the continuous predicted probability. However, using a continuous treatment indicator requires strong assumptions (Callaway, Goodman-Bacon, and Sant'Anna, 2021). If the effect varies across individuals with different treatment probabilities, the estimated coefficient will contain a weighted sum of treatment effects where weights are not necessarily positive.

Empirical strategy: I now present the specification I estimate to derive the reform's effect on enrollment and university graduation. I consider individuals treated if their predicted probability of staying at home conditional on going to university is below twenty-five percent: $\hat{P}_{T_0}(X_i) \leq 25$. Individuals belong to the control group if their expected probability of staying at home conditional on going to university is above seventy-five percent: $\hat{P}_{T_0}(X_i) \geq 75\%$.

I chose these cutoffs as they leave me with a sufficiently large sample and still only contain people with a high probability of being in the control or treatment groups. Let γ_i be a treatment fixed effect. First, I consider the effect of the reform on university enrollment. To account for different enrollment rates across people with high and low propensities to be treated, I control for an individual's probability of entering university $P_E(X_i)$. I predict $\hat{P}_E(X_i)$ the same way as I get the probability of treatment. Furthermore, θ denotes year fixed effects, and W_i denotes a vector of



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

Figure 1.15. Performance of the prediction algorithm

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:

$$E_{i,t} = \beta_{E,0} + \theta_t \gamma_i + \theta_t + \gamma_i + \beta_{E,1} \hat{P}_E(X_i) + \beta_{E,2} W_i + \epsilon_i \tag{1.17}$$

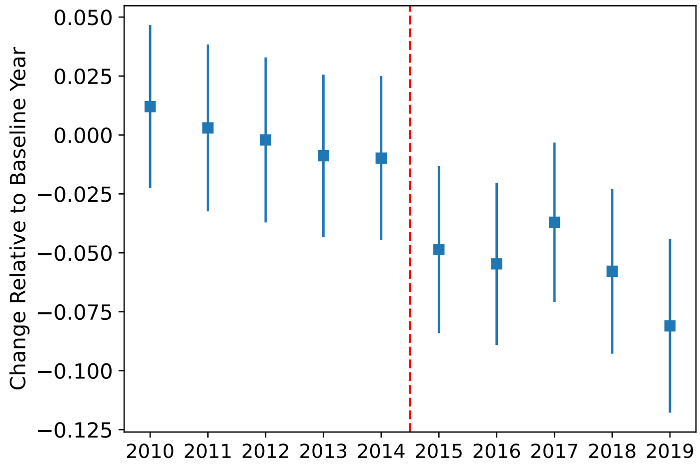
To derive the reform's effect on graduation, I include the probability of graduating from university $P_G(X_i)$ instead of the probability of enrolling in university. I again obtain $\hat{P}_G(X_i)$ by training a gradient boosting algorithm on pre-reform data. The final specification for graduation looks as follows:

$$G_{i,t} = \beta_{G,0} + \theta_t \gamma_i + \theta_t + \gamma_i + \beta_{E,1} P_G(X_i) + \beta_{E,2} W_i + \epsilon_i \tag{1.18}$$

The enrollment specification is estimated with a sample of individuals who graduated between 2009 and 2020. The graduation specification is estimated with a sample of individuals who graduated 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.

1.5.3 Results

I now summarize empirical results on the effect of income subsidies. I first outline the performance of the estimation procedure and treatment effects derived from



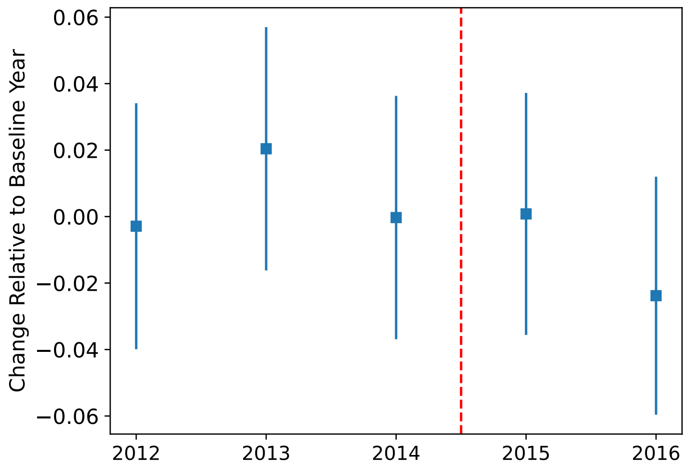
This figure shows coefficients from a two-way fixed effects regression comparing individuals with different propensities to move out. The coefficients depict the evolution of university enrollment of the group that is more than 75% likely to move out relative to the control group that is less than 25% likely to move out. The coefficients are obtained by estimating the linear probability model described in Equation1.17. Point estimated can be found in section 1.A.8 of the appendix.

Figure 1.16. Results university enrollment

the reform. After that, I simulate a similar policy with the structural model introduced earlier.

Prediction performance: The prediction algorithm does an excellent job of predicting people likely to stay at home. Figure 1.15 shows the prediction performance of the algorithm. The figure shows the observed proportion of people staying at home for each decile of predictions. The training and test samples only contain individuals who enrolled in university. The dot above the predicted probability 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 1.16 shows the evolution of university enrollment of the predicted treatment group relative to the predicted control group. The predicted treatment group has dropped by four percent relative to the predicted control group, which is a substantial reduction considering the size of the income subsidy. This may be caused by the fact that graduates of vocational training are older and from lower-income backgrounds than other individuals considering entering university. Point estimates in section 1.A.8 of 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

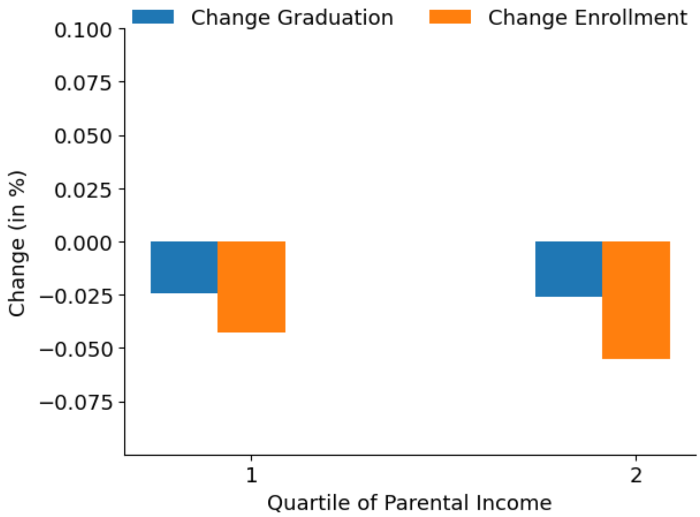


This figure shows coefficients from a two-way fixed effects regression comparing individuals with different propensities to move out. The coefficients depict the evolution of university graduation of the group that is more than 75% likely to move out relative to the control group that is less than 25% likely to move out. The coefficients are obtained by estimating the linear probability model described in Equation1.18. Point estimated can be found in section 1.A.8 of the appendix.

Figure 1.17. Results university graduation

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

Graduation: Figure 1.17 shows the evolution of university graduation. Graduation only significantly drops a year 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 account for people still studying after five years, the decline is a bit larger, but the overall evolution remains noisy (See figure 1.A.11). The change in university degrees is much less pronounced than the decline in enrollment and more challenging to distinguish from the general trend. The reform appears to have pushed people out of university who are likely to drop out or need more than five years to graduate. I examine how individuals with low dropout risk react to the reform in the appendix. 1.A.12 show that individuals with low dropout risk show a more significant reaction to the reform that is more distinguishable from the general trend.



Note: This figure shows the compliers of a simulated reform with the same size as the empirical results. To obtain the figure, I simulate a counterfactual model where the nonpecuniary utility associated with applied university is reduced by an amount that leads to a reduction in enrollment in the alternative simulated model that is equal to the observed reduction in enrollment in response to the reform in 2015. I then show how enrollment and graduation change between the baseline model and the counterfactual model. The orange bars show the difference in applied university graduation between the baseline model and the counterfactual model, where enrollment is reduced. The blue bars show the change in applied university graduation between the baseline model and the counterfactual model, where enrollment is reduced.

Figure 1.18. Simulated compliers

Reform simulation in the model: I simulate the reform I have just analyzed with the structural model by decreasing non-pecuniary returns to university. If I decrease utility by the amount of money that individuals lost after the reform, the model predicts a decline in enrollment by one percent (see Figure 1.A.2). There are two reasons why the model cannot reproduce the reform's effect. The treated group differs from the broad population, and the treatment effect on the treated is potentially larger than that on the broad population. Furthermore, the model is not ideally suited to predict the effect of income subsidies as it includes no consumption component and no risk aversion.

The reform likely reduces the utility of studying to a larger extent than the monetary value that individuals miss out on. I thus simulate an alternative model where I reduce the utility of the university until the reduction in enrollment is similar to what the reform predicts. Figure 1.18 shows that compliers of the simulated policy have considerable academic risk, and the degree reduction is less than two-thirds of the reduction in enrollment. The model and the reform thus agree on the characteristics of the compliers of the reform. While the model cannot precisely reproduce the reform, it gets the selection right, which increases confidence in the other policy simulations.

1.6 Conclusion

In this paper, I have investigated whether alternative paths to university promote social mobility. I have estimated a dynamic model of education that follows individuals from low-income backgrounds after graduating from vocational school in the Netherlands. Returns to applied university differ across the population but are substantial for many low-income individuals despite early achievement gaps. Many individuals face substantial dropout risk at applied university. The presence of alternative paths to university increases university graduation rates and future wages of individuals from low-income backgrounds. I also show that increasing the tracking system's flexibility for individuals with high grades and decreasing the length of vocational programs would improve outcomes for individuals from low-income backgrounds. Furthermore, I document a substantial decrease in enrollment in response to a reduction of monthly income subsidies. The result suggests that many individuals considering entering university after vocational education face a double burden. 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. Policymakers should take this into account when designing income subsidies and scholarships.

Appendix 1.A Appendix

1.A.1 Model parametrization

In this section I show the full model parametrization. Wage equations have been specified in 1.5 and 1.6 respectively.

Nonpecuniary returns Formula 1.A.1 shows nonpecuniary utility for working without applied university degree. Utility for working with applied university degree looks the same without the degree term.

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

Formula 1.A.2 shows nonpecuniary utility for applied university and both forms of vocational training. Utility returns to high school additionally include grades.

$$F_d(Y, \theta) \;=\; \beta^F_{0,d} + \xi^F_{0,d}\theta + \xi^F_{1,d} Y \tag{1.A.2}$$

Dropout Risk Formula 1.2 shows the specification that holds for high school. For university I additionally include an indicator whether an individual has entered university after high school or after vocational training. For the higher vocational program I have left out latent types and for the lower vocational program I have left out both latent types and grades.

Duration Risk Formula 1.3 shows the specification of duration risk for applied university and higher vocational programs. For the lower vocational program I left out grades. High School and higher vocational training after lower vocational training have fixed lengths.

1.A.2 Targeted wage equations

In this section, I present the three wage equations targeted during the model estimation. Let T^u denote the years someone needs to finish applied university. Let γ be year fixed effects. Equation 1.A.3 is estimated on a panel that includes all full-time individuals who left school without a bachelor's degree from the third period onward.

$$W_{v,t} = \alpha_{v,0} + \alpha_{v,1}E + \alpha_{v,2}k_t + \alpha_{v,3} * k_t^2 + \alpha_{v,4}k_tE + \delta_{v,0} * G + \delta v, 1Y + \gamma + \omega_{v,t} \tag{1.A.3}$$

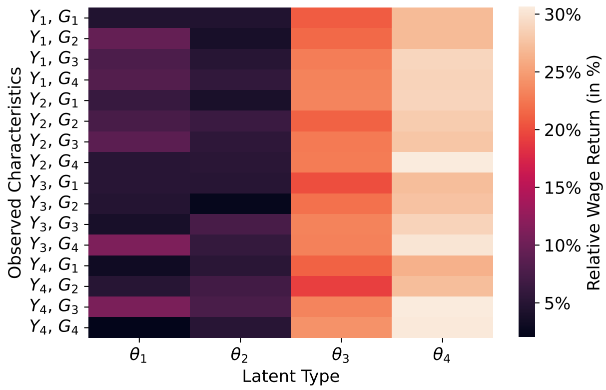
Equation 1.A.4 is estimated on a panel that includes all full-time individuals who left school with a bachelor's degree from the sixth period onward.

$$W_{a,t} = \alpha_0 + \alpha_1 E^C + \alpha_2 T^u + \alpha_{v,2}k_t + \alpha_{v,3}k_t^2 + \delta_{v,0}G + \delta a, 1Y + \gamma + \omega_{a,t} \tag{1.A.4}$$

Equation 1.A.5 is estimated on a cross-section of all full-time individuals in period thirteen.

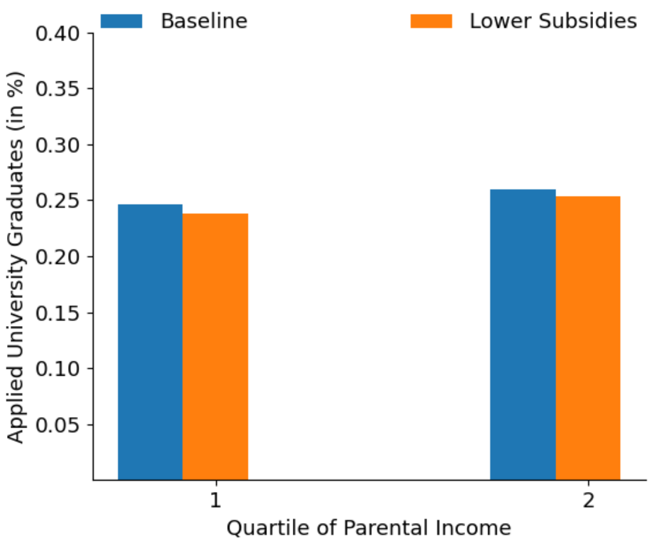
$$W_h = \alpha_{h,0} + \alpha_{h,0}U + \omega_h \tag{1.A.5}$$

1.A.3 Additional figures



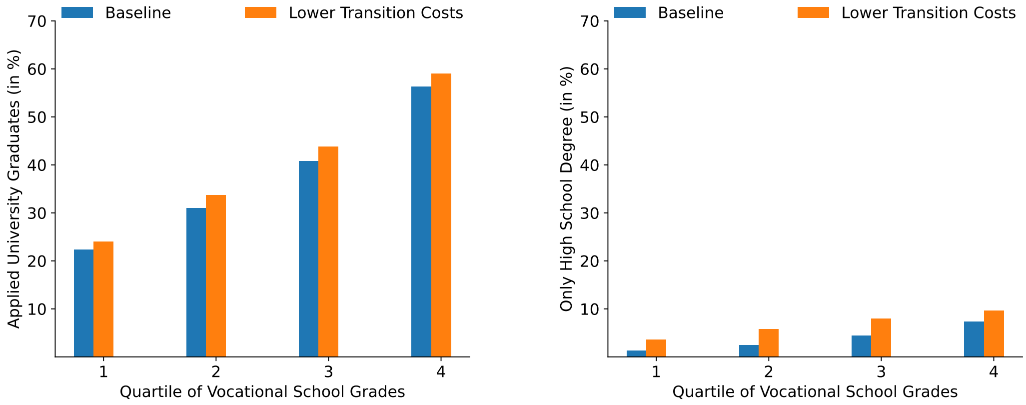
Note: This heatmap summarizes the distributions of returns to applied universities. The vertical axis represents one combination of grades and parental income each while the horizontal axis represents one latent type each. The returns are expressed in Euros per hour worked. The returns are obtained by calculating the difference in average wages of individuals with and without bachelor's degrees for each combination of observed characteristics and latent type. Observed characteristics are parental income and grades at the end of vocational school. School type is not included since it has no direct effect on wages. Wage differentials within a group of observed characteristics and latent type are average returns to applied university for all individuals in that group since wages don't systematically differ conditional on these variables. The value of the respective group is then assigned to each simulated individual to obtain a distribution.

Figure 1.A.1. Distribution of earnings returns to applied university at age 40.



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

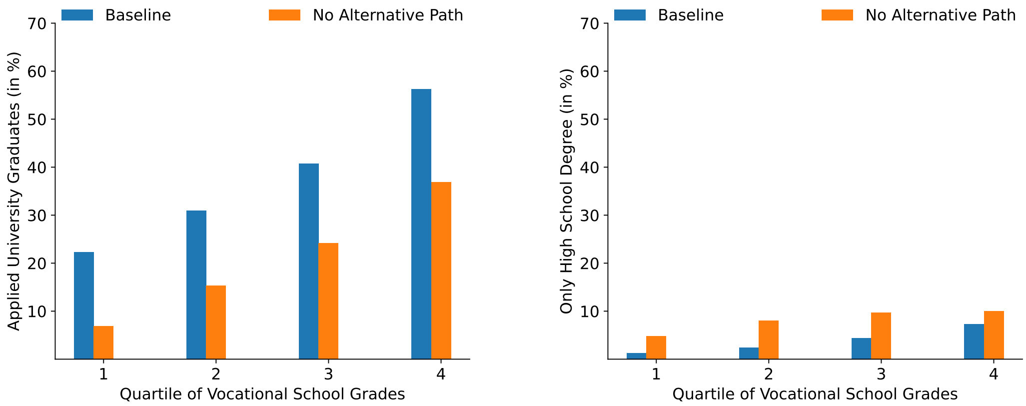
Figure 1.A.2. Simulated effect of the reform



(a) University Graduates **(b)** High School only

Note: This figure shows how enforcing higher acceptance rates at high school would affect the number of university graduates and individuals who only hold a high school degree. Blue bars show the baseline model's proportions of applied university and high school-only graduates. The orange bars show the proportions in the counterfactual scenario where all schools behave like the most lenient schools and individuals with low grades face lower barriers. The proportions are shown for each quartile of grades at the end of vocational school, which is the beginning of the structural model.

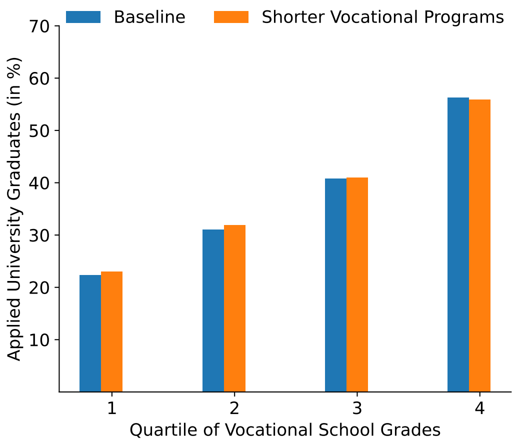
Figure 1.A.3. The effect of enforcing higher acceptance rates at high school



(a) University Graduates **(b)** High School only

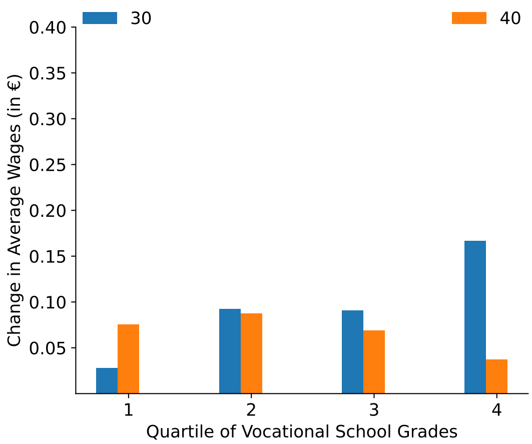
Note: This figure shows how removing the vocational path to applied university would affect the number of university graduates and high school-only graduates. Blue bars show the baseline model's proportions of applied university and high school-only graduates. The orange bars show the proportions in the counterfactual scenario where graduates of a higher vocational program cannot enter applied university. The proportions are shown for each quartile of grades at the end of vocational school, which is the beginning of the structural model. The proportions are shown for each quartile of grades at the end of vocational school, which is the beginning of the structural model.

Figure 1.A.5. Effect of having no vocational path to applied university



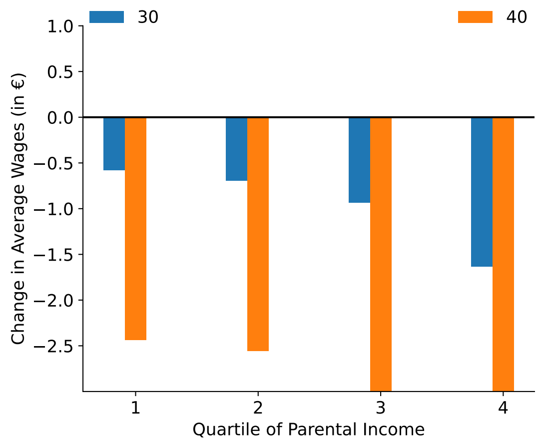
Note: This figure shows how decreasing the duration of vocational programs would affect applied university graduation. Blue bars show the baseline model's proportions of applied university graduates. The orange bars show the proportions in the counterfactual scenario where higher vocational programs only take three years. The proportions are shown for each quartile of grades at the end of vocational school, which is the beginning of the structural model.

Figure 1.A.7. Effect of shorter vocational programs



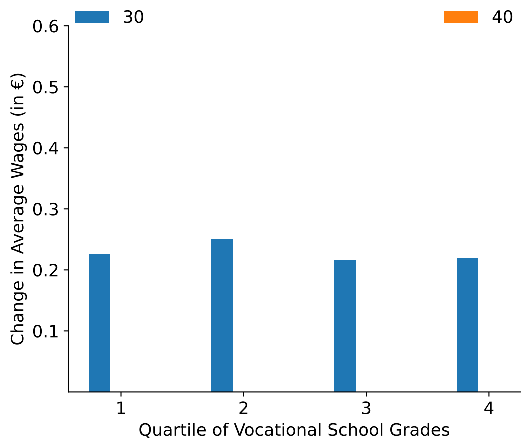
Note: This figure shows how enforcing higher acceptance rates at applied universities would affect average wages. The blue bar shows wage changes at age thirty, and the orange bar shows wage changes at age forty. The differences are obtained by comparing average wages in the baseline model and a counterfactual simulation where all schools behave like the most lenient schools and individuals with low grades face lower barriers. The changes are shown for each quartile of grades at the end of vocational school, which is the beginning of the structural model.

Figure 1.A.8. Wage effect of enforcing higher acceptance rates at high school



Note: This figure shows how removing the vocational path to university would change average hourly wages. The blue bar shows wage changes at age thirty, and the orange bar shows wage changes at age forty. The differences are obtained by comparing average wages in the baseline model and a counterfactual simulation where individuals are not allowed to enter applied university after graduating from a higher vocational program. The changes are shown for each quartile of grades at the end of vocational school, which is the beginning of the structural model.

Figure 1.A.9. Wage effect of removing vocational path to applied university



Note: This figure shows how decreasing the duration of vocational programs would affect average hourly wages. The blue bar shows wage changes at age thirty, and the orange bar shows wage changes at age forty. The differences are obtained by comparing average wages in the baseline model and a counterfactual simulation where vocational programs only take three years. The changes are shown for each quartile of grades at the end of vocational school, which is the beginning of the structural model.

Figure 1.A.10. Wage effect of shorter vocational programs

1.A.4 Parameter estimates

Table 1.A.1. Wage returns to academic work

name	value	SE
Age	0.010	0.004
Constant	2.100	0.040
Experience	0.105	0.004
Experience^2	−0.238	0.026
G_2	0.014	0.018
G_3	0.018	0.016
G_4	0.032	0.019
θ_2	0.326	0.021
θ_3	−0.157	0.042

Table 1.A.2. Wage returns to vocational work

name	value	SE
Age	0.024	0.006
Constant	2.178	0.030
Experience	0.075	0.003
Experience^2	−0.215	0.013
G_2	0.039	0.009
G_3	0.012	0.009
G_4	0.024	0.011
MBO3	0.103	0.026
MBO4	0.119	0.024
θ_2	−0.052	0.035
θ_3	−0.139	0.035
Dropout	0.056	0.027
VMBO	−0.044	0.025

Table 1.A.3. Nonpecuniary returns to academic work

name	value	SE
Age	303	85
Constant	91 284	112
Y_2	10 630	79
Y_3	17 667	97
Y_4	26 821	96

Table 1.A.4. Nonpecuniary returns to academic work

name	value	SE
Age	2748	87
Constant	24 877	95
MBO3	22 418	69
MBO4	35 448	78
Y_2	7359	96
Y_3	25 413	87
Y_4	25 698	88
VMBO	−11 548	71

Table 1.A.5. Nonpecuniary returns to applied university

name	value	SE
Constant	87 116	96
Y_2	2558	94
Y_3	12 712	93
Y_4	9005	113
θ_2	37 942	84
θ_3	−50 000	103

Table 1.A.6. Nonpecuniary returns to high school

name	value	SE
Constant	−166 578	106
G_2	20 846	76
G_3	75 133	100
G_4	123 306	106
Y_2	2243	84
Y_3	757	93
Y_4	4546	89
θ_2	8000	107
θ_3	−25 000	97

Table 1.A.7. Nonpecuniary returns to MBO4

name	value	SE
Constant	64 123	80
Y_2	−3068	75
Y_3	16 054	93
Y_4	14 192	101
θ_2	−29 896	83
θ_3	−11 019	90

Table 1.A.8. Nonpecuniary returns to MBO3

name	value	SE
Constant	100 000	82
Y_2	−23 329	74
Y_3	611	115
Y_4	−26 939	109
θ_2	−45 159	104
θ_3	50 000	81

Table 1.A.9. Degree risk applied university

name	value	SE
Constant	0.199	0.034
G_2	0.179	0.036
G_3	0.481	0.045
G_4	0.943	0.049
MBO4	−0.068	0.042
Y_2	0.137	0.039
Y_3	0.173	0.043
Y_4	0.277	0.044
θ_2	0.008	0.047
θ_3	−0.204	0.035

Table 1.A.10. Degree risk high school

name	value	SE
Constant	0.187	0.042
G_2	0.354	0.046
G_3	0.624	0.049
G_4	0.974	0.040
Y_2	0.023	0.049
Y_3	0.009	0.041
Y_4	−0.001	0.045
θ_2	0.000	0.033
θ_3	0.000	0.024

Table 1.A.11. Degree risk MBO4

name	value	SE
Constant	1.156	0.039
G_2	0.200	0.045
G_3	0.050	0.041
G_4	0.050	0.037
Y_2	0.193	0.038
Y_3	0.341	0.040
Y_4	0.335	0.046

Table 1.A.12. Degree risk MBO3

name	value	SE
Constant	0.657	0.034
Y_2	0.012	0.045
Y_3	0.212	0.036
Y_4	0.393	0.045

Table 1.A.13. Duration risk applied university

name	value	SE
Constant	3.000	0.029
G_2	−0.014	0.044
G_3	0.005	0.042
G_4	−0.186	0.041
Y_2	−0.112	0.038
Y_3	−0.224	0.042
Y_4	−0.257	0.044

Table 1.A.14. Duration risk MBO4

name	value	SE
Constant	3.120	0.044
G_2	−0.111	0.039
G_3	−0.082	0.053
G_4	−0.262	0.041
Y_2	−0.057	0.058
Y_3	−0.002	0.043
Y_4	−0.026	0.036

Table 1.A.15. Duration risk MBO3

name	value	SE
Constant	0.941	0.044
Y_2	−0.219	0.048
Y_3	−0.167	0.038
Y_4	−0.061	0.041

Table 1.A.16. Probabilities latent type 2

name	value	SE
Constant	−0.219	0.045
G_2	0.322	0.041
G_3	0.266	0.040
G_4	0.812	0.042
Y_2	−0.436	0.044
Y_3	0.298	0.043
Y_4	0.397	0.046
U_2	0.246	0.044
U_3	0.088	0.047

Table 1.A.17. Probabilities latent type 3

name	value	SE
Constant	0.588	0.046
G_2	−0.332	0.043
G_3	−0.896	0.048
G_4	−0.963	0.043
Y_2	−0.152	0.047
Y_3	−0.150	0.038
Y_4	0.038	0.039
U_2	0.217	0.041
U_3	−0.127	0.046

Table 1.A.18. Transition costs high school

name	value	SE
U_2	85 220.983	120.473
U_3	210 000.000	94.030

Table 1.A.19. Distribution taste shocks

name	value	SE
Scale	115 801	85

1.A.5 Model fit

Table 1.A.20. 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 1.A.21. 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

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

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

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School Type	Grade Quartile	Degree Combination	Observed	Estimated
		mbo4	0.347	0.361
		mbo4 – bachelor	0.228	0.223
		vmbo	0.111	0.113
	2	havo	0.040	0.044
		havo – bachelor	0.107	0.095
		mbo3	0.098	0.105
		mbo3 – mbo4	0.073	0.076
		mbo3 – mbo4 – bachelor	0.037	0.046
		mbo4	0.313	0.290
		mbo4 – bachelor	0.250	0.240
		vmbo	0.083	0.104
	3	havo	0.085	0.074
		havo – bachelor	0.281	0.256
		mbo3	0.053	0.082
		mbo3 – mbo4	0.042	0.047
		mbo3 – mbo4 – bachelor	0.031	0.041
		mbo4	0.226	0.187
		mbo4 – bachelor	0.234	0.231
		vmbo	0.048	0.081
2	0	havo	0.011	0.036
		havo – bachelor	0.034	0.044
		mbo3	0.174	0.131
		mbo3 – mbo4	0.094	0.104
		mbo3 – mbo4 – bachelor	0.026	0.040
		mbo4	0.346	0.351
		mbo4 – bachelor	0.162	0.166
		vmbo	0.154	0.129
	1	havo	0.035	0.051
		havo – bachelor	0.088	0.076
		mbo3	0.119	0.108
		mbo3 – mbo4	0.076	0.082
		mbo3 – mbo4 – bachelor	0.032	0.043
		mbo4	0.328	0.326
		mbo4 – bachelor	0.213	0.206
		vmbo	0.110	0.108
	2	havo	0.075	0.086
		havo – bachelor	0.180	0.188
		mbo3	0.081	0.093
		mbo3 – mbo4	0.059	0.063
		mbo3 – mbo4 – bachelor	0.026	0.034
		mbo4	0.286	0.244
		mbo4 – bachelor	0.218	0.202

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School Type	Grade Quartile	Degree Combination	Observed	Estimated
		vmbo	0.076	0.091
	3	havo	0.120	0.109
		havo − bachelor	0.354	0.379
		mbo3	0.045	0.063
		*mbo*3 − *mbo*4	0.036	0.039
		*mbo*3 − *mbo*4 − *bachelor*	0.021	0.031
		mbo4	0.189	0.148
		*mbo*4 − *bachelor*	0.188	0.169
		vmbo	0.047	0.063

Table 1.A.22. 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 1.A.23. 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 1.A.24. Enrollment proportions by school type and 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 1.A.25. 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 1.A.26. 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 1.A.27. Wage equation no bachelor's 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
Experience × mbo3	-0.007	0.000
mbo4	0.058	0.045
Experience × mbo4	-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
Experience × vmbo	-0.007	0.000

Table 1.A.28. Wage equation bachelor's 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

1.A.6 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 1.16 to simplify:

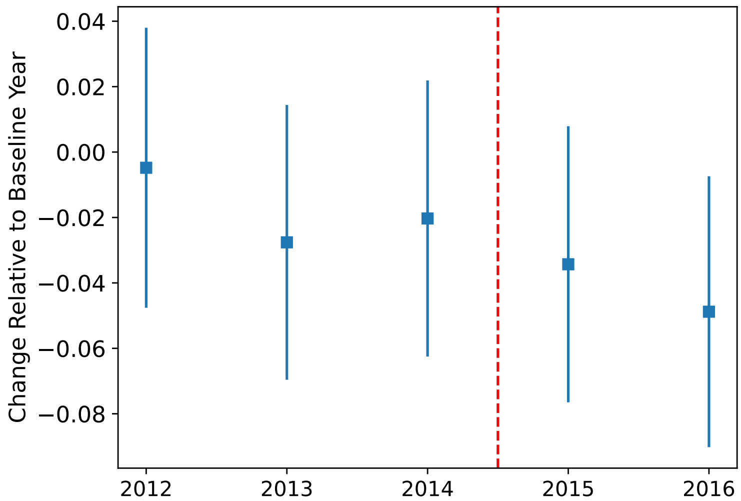
$$(1-P_L)(E[\Delta Y_i|d_{t,0}=(0,1),P_L,Z])-E[\Delta Y_i|d_{t,0}\neq(0,1),P_L,Z]))-$$

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

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

1.A.7 Robustness reduced form

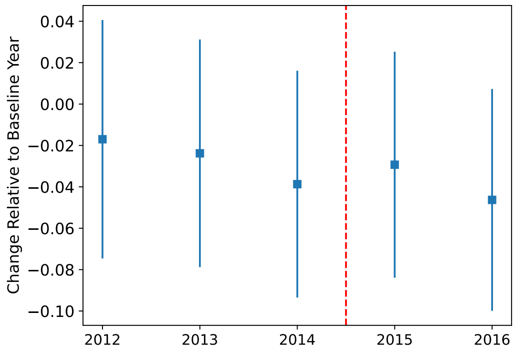
Other definition of degree completion: Figure 1.A.11 shows the fraction of individuals who either graduated after five years or are still enrolled after five years.



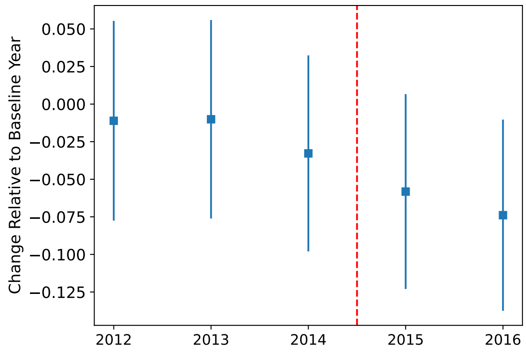
Note: This figure shows coefficients from a two-way fixed effects regression comparing individuals with different propensities to move out. The outcome is an indicator for individuals who have either graduated from university or are still enrolled five years after graduation. The coefficients depict the evolution of the outcome for the group that is more than 75% likely to move out relative to the control group that is less than 25% likely to move out. The coefficients are obtained by estimating the linear probability model described in formula 1.18. Point estimated can be found in section 1.A.8 of the appendix.

Figure 1.A.11. Effect on graduation

Differences by initial heterogeneity: Figure 1.A.12 shows the evolution of graduation rates 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.



(a) Lowest Dropout Risk



(b) High Dropout Risk

Note: This figure shows coefficients from a two-way fixed effects regression comparing individuals with different propensities to move out. This figure focuses on a subset of people with high dropout risk. The coefficients depict the evolution of university graduation of the group that is more than 75% likely to move out relative to the control group that is less than 25% likely to move out. The coefficients are obtained by estimating the linear probability model described in formula 1.18. Point estimated can be found in section 1.A.8 of the appendix.

Figure 1.A.12. Effect on graduation for individuals with low and high dropout risk

1.A.8 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)				
2010 × $Group_1$	0.0009	-0.0000				
	(0.0130)	(0.0128)				
2010 × $Group_2$	0.0119	0.0120				
	(0.0167)	(0.0173)				
2011	-0.0088	-0.0167				
	(0.0111)	(0.0106)				
2011 × $Group_1$	-0.0024	-0.0040				
	(0.0134)	(0.0131)				
2011 × $Group_2$	-0.0027	0.0030				
	(0.0172)	(0.0177)				

Continued on next page

Index	Enrolled	Enrolled	Bachelor	Bachelor	*Bachelor∗*	*Bachelor∗*
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)
2012 × $Group_1$	-0.0233*	-0.0208	-0.0083	-0.0013	-0.0024	-0.0022
	(0.0129)	(0.0127)	(0.0129)	(0.0136)	(0.0142)	(0.0149)
2012 × $Group_2$	-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)
2013 × $Group_1$	0.0017	0.0003	0.0219*	0.0263**	0.0032	-0.0016
	(0.0127)	(0.0125)	(0.0126)	(0.0133)	(0.0139)	(0.0146)
2013 × $Group_2$	-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)
2014 × $Group_1$	-0.0005	0.0043	0.0113	0.0129	0.0105	0.0046
	(0.0129)	(0.0126)	(0.0128)	(0.0135)	(0.0141)	(0.0149)
2014 × $Group_2$	-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)
2015 × $Group_1$	-0.0142	-0.0134	0.0146	0.0142	-0.0012	-0.0064
	(0.0132)	(0.0130)	(0.0127)	(0.0135)	(0.0141)	(0.0150)
2015 × $Group_2$	-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)
2016 × $Group_1$	-0.0292**	-0.0249**	0.0051	0.0023	-0.0066	-0.0128
	(0.0125)	(0.0123)	(0.0124)	(0.0131)	(0.0136)	(0.0144)
2016 × $Group_2$	-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)
2017 × $Group_1$	-0.0264**	-0.0249**	0.0306***	0.0327***	0.0188	0.0171
	(0.0124)	(0.0122)	(0.0112)	(0.0120)	(0.0130)	(0.0139)
2017 × $Group_2$	-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)
2018 × $Group_1$	-0.0333***	-0.0265**			0.0665***	0.0714***
	(0.0126)	(0.0125)			(0.0105)	(0.0115)
2018 × $Group_2$	-0.0708***	-0.0578***			0.1122***	0.1090***
	(0.0167)	(0.0175)			(0.0132)	(0.0169)

Continued on next page

Index	Enrolled	Enrolled	Bachelor	Bachelor	*Bachelor**	*Bachelor**
2019	-0.0275**	-0.0523***			-0.4713***	-0.4835***
	(0.0110)	(0.0108)			(0.0088)	(0.0093)
2019 × $Group_1$	-0.0306**	-0.0288**			0.0659***	0.0657***
	(0.0132)	(0.0132)			(0.0104)	(0.0113)
2019 × $Group_2$	-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

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			
2010 × $Group_1$			
2010 × $Group_2$			
2011			
2011 × $Group_1$			

Continued on next page

Index	Enrolled	Bachelor	*Bachelor∗*
2011 × $Group_2$			
2012	0.0225	0.0033	-0.0016
	(0.0186)	(0.0150)	(0.0155)
2012 × $Group_1$	-0.0321	0.0007	0.0223
	(0.0217)	(0.0188)	(0.0196)
2012 × $Group_2$	-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)
2013 × $Group_1$	0.0057	0.0290	0.0145
	(0.0213)	(0.0184)	(0.0192)
2013 × $Group_2$	-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)
2014 × $Group_1$	-0.0036	0.0132	0.0276
	(0.0210)	(0.0189)	(0.0197)
2014 × $Group_2$	-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)
2015 × $Group_1$	-0.0124	0.0125	0.0029
	(0.0214)	(0.0189)	(0.0199)
2015 × $Group_2$	-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)
2016 × $Group_1$	-0.0144	-0.0124	0.0004
	(0.0209)	(0.0180)	(0.0189)
2016 × $Group_2$	-0.0419	-0.0538*	-0.0739**
	(0.0265)	(0.0295)	(0.0318)
2017	-0.0326*	-0.1749***	-0.1727***
	(0.0181)	(0.0134)	(0.0144)
2017 × $Group_1$	-0.0444**	0.0281*	0.0318*
	(0.0210)	(0.0166)	(0.0182)
2017 × $Group_2$	-0.0521**	0.0076	0.0056
	(0.0264)	(0.0272)	(0.0305)
2018	-0.0267		
	(0.0187)		
2018 × $Group_1$	-0.0235		

Continued on next page

Index	Enrolled	Bachelor	*Bachelor∗*
	(0.0217)		
2018 × $Group_2$	-0.0656**		
	(0.0272)		
2019	-0.0159		
	(0.0197)		
2019 × $Group_1$	-0.0313		
	(0.0228)		
2019 × $Group_2$	-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***
	(0.0041)	(0.0044)	(0.0048)
N	74809	48462	48462
R2	0.108000	0.044000	0.038000

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Chapter 2

Sequential Choices, Option Values, and the Returns to Education*

Joint with Mandueep Bhuller and Phillip Eisenhauer

2.1 Introduction

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

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* Heckman, Lochner, and Todd (2006) and Card (1999) provide extensive reviews of this literature on returns to schooling based on the Becker-Mincer models of human capital investments.

Wiswall and Zafar (2021)).

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

In this paper, we develop and estimate a dynamic structural model of educational choices in a life-cycle context that can accommodate and explain both of the above-mentioned features of educational careers. Agents in our model are forward-looking and make sequential decisions every period from age 15 to 58 on whether to attend school, and if so, the type of educational track to attend, to work, or to stay at home, while they face uncertainty in terms of their work productivity and tastes for schooling tracks, work and leisure, and also differ in terms of their ability and a vector of latent types. Our model is able to generate a rich set of educational and work histories that feature (i) interruptions and re-enrollment in educational careers, (ii) persistence in choices across the life-cycle, (iii) costly switching between tracks, and (iv) heterogeneity across ability and latent types. The model is also able to re-produce "inframarginal" responses to actual and hypothetical compulsory schooling reforms, provide evidence on who is affected and inform about the potential economic mechanisms driving these patterns.

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

[‡] For the U.S., Acemoglu and Angrist (2000) provide further evidence on how the compulsory attendance laws affected the distribution of schooling, while Bedard (2001) provides evidence on how better university access increased high school drop-out rates. Relatedly, Meghir and Palme (2005) found evidence on "inframarginal" responses to a compulsory schooling reform in Sweden, while similar evidence for Norway is reported (though not emphasized) in Black, Devereux, and Salvanes (2005). While these responses can reflect equilibrium adjustments to policy reforms in line with models of educational signaling (Spence, 1973), these may also reflect the sequential and uncertain nature of educational decisions, as argued by Altonji (1993) and James J Heckman, John E. Humphries, and Veramendi (2018).

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

We implement our modelling approach and provide evidence on the ex-ante returns and the option values of education using Norwegian administrative data with career-long earnings information and education histories. We combine these data with detailed demographic information, including measures on individual ability for males collected as part of the compulsory military recruitment testing. This dataset has several advantages, as this provides (i) complete annual information on educational track choices and earnings histories for selected cohorts across 44 years, (ii) allows us to capture several sources of persistent heterogeneity, and (iii) only suffers from natural sample attrition due to either death or out-migration. Our dataset further covers a compulsory schooling reform that increased the minimum requirement schooling from seven to nine years across different municipalities at different points in time (Black, Devereux, and Salvanes, 2005). The latter feature of our setting allows us to estimate our model on individuals that were not exposed to the reform and rely on the reform-induced variation to evaluate our model in an out-of-sample validation and to shed light on "inframarginal" responses to educational policy reforms. Specifically, we compare the predictions about policy impacts based on the model estimated on pre-reform data to the observed impacts post-reform (Todd and Wolpin, 2021).[‡‡]

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

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

[‡‡] The recent review by Galiani and Pantano (2021) also emphasizes the need for model validation and provides a structured review of the small literature.

[§] A negative return to a choice alternative in our model reflects that an individual expects to receive a higher reward from another choice alternative; i.e., the respective choice alternative is thus not chosen.

highest in the earliest years of schooling and relatively similar across ability groups.

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

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

The structure of our paper is as follows. We outline our structural model in Section 2.2. Section 2.3 describes our data and institutional setting, and discusses model implementation and provide evidence on model fit and validation. Section 2.4 presents our main findings. Section 2.5 concludes.

2.2 Model

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

2.2.1 Setup

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

A policy $\pi = (d_1, \dots, d_T)$ provides the individual with instructions for choosing an action in any possible future state. It is a sequence of decision rules d_t that specify the planned action at a particular time t for any possible state s_t. The implementation of a policy generates a sequence of utilities that depends on the transition probability distribution $p(s_t, a_t)$ for the evolution of state s_t to s_{t+1} induced by the model. To fix ideas, Figure 2.1 illustrates the timing of events in the model for two generic periods. At the beginning of period t, an individual fully

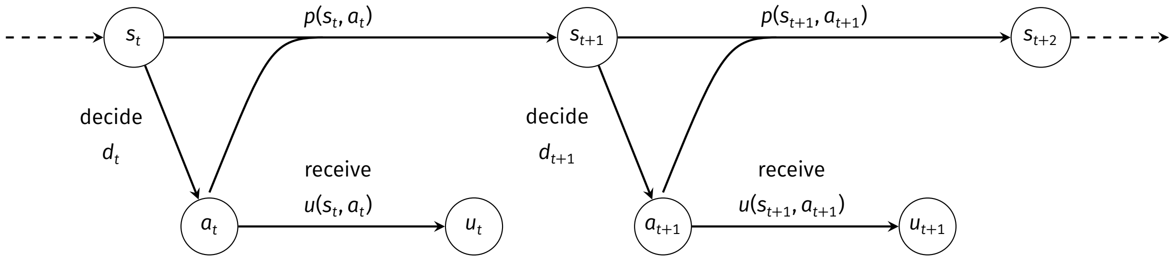


Figure 2.1. Timing of Events.

learns about each alternative's immediate utility, chooses one of the alternatives, and receives its immediate utility. Then, the state evolves from s_t to s_{t+1} and the process is repeated in $t+1$.

Individuals make their decisions facing uncertainty about the future and seek to maximize their expected total discounted utilities over all remaining decision periods. They have rational expectations (Muth, 1961), so their subjective beliefs about the future agree with the objective probabilities for all possible future events determined by the model. Immediate utilities are separable between periods (Kahneman, Wakker, and Sarin, 1997), and individuals discount future over immediate utilities by a discount factor δ (Samuelson, 1937). Equation (2.1) provides the formal representation of an individual's objective function. Given an initial state s_1, they implement a policy π^* from the set of all possible policies Π that maximizes the expected total discounted utilities over all decision periods given the information available at the time.

$$\max_{\pi \in \Pi} \mathrm{E}_{s_1}^{\pi} \left[\sum_{t=16}^{T} \delta^{t-16} u(s_t, d_t(s_t)) \right] \tag{2.1}$$

When entering the model, all individuals have seven years of basic compulsory schooling, but they are one of the three $\mathcal{J} = \{1, 2, 3\}$ latent types that capture alternative-specific skill endowments $\boldsymbol{e} = \left(e_{j,a}\right)_{\mathcal{J} \times \mathcal{A}}$ (Heckman and Singer, 1984). In addition, individuals can be of either low, medium, or high level of ability. Individuals know their own ability and latent type.*

* As researchers, we observe each individual's ability group, but must infer their latent types based on choices. To classify individuals in ability groups, we rely on an IQ test score available in our data. See further details in Section 2.3.1 below. The ability measures capture observed heterogeneity while latent types capture persistent unobserved heterogeneity across individuals. The model is specified and estimated separately for each ability group but we refrain from making this distinction while outlining the model here to ease the exposition.

The immediate utility $u(\cdot)$ of each alternative consists of a non-pecuniary utility $\zeta_a(\cdot)$ and, for the working alternative, an additional monetary wage component $w(\cdot)$. Both depend on an individual's level of human capital as measured by work experience k_t, years of completed schooling in each track $\boldsymbol{h_t} = (h_{a,t})_{a\in\{A,V\}}$, and the alternative-specific skill endowment $\boldsymbol{e}$. The immediate utilities are also influenced by the decision a_{t-1} in the previous period, a time trend t, and alternative-specific shocks $\boldsymbol{\epsilon_t} = \left(\epsilon_{a,t}\right)_{a\in\mathscr{A}}$. Their general form is given by:

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

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

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

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

Individuals' skill endowments $\boldsymbol{e}$ and their level of ability are the two sources of persistent heterogeneity in this model. All remaining differences in life-cycle decisions result from differences in the transitory shocks $\boldsymbol{\epsilon_t}$ over time. Thus, our setup allows for learning-by-doing (Altuğ and Miller, 1998). In each period, individuals can increase their stock of human capital $(k_t, \boldsymbol{h_t})$ by either working in the labor market or enrolling in school. However, we only incorporate individuals learning about themselves in a limited fashion (Miller, 1984). From the beginning, individuals are aware of their level of ability and alternative-specific skill endowments $\boldsymbol{e}$. They

** While in principle, one could also allow persistence in these shocks over time, the estimation problem becomes computationally more cumbersome as this would increase the state space dramatically. However, as discussed below, since the model includes persistent heterogeneity *and* adjustment costs in moving across states, adding persistence in transitory shocks can also pose challenges for identification (Heckman and Singer, 1984).

only learn about the realizations of shocks $\boldsymbol{\epsilon_t}$ at the beginning of each period. As the shocks are distributed independently over time, individuals do not update their prior beliefs about their productivity or alternative-specific tastes (Arcidiacono, 2004; Arcidiacono et al., 2016).

Previous research on the determinants of life-cycle wages and schooling decisions (Keane and Wolpin, 1997; Meghir and Pistaferri, 2011) informs our specification of the immediate utility functions. We specify the wage component $w(\cdot) = rx(\cdot)$ in the immediate utility from working as the product of the market-equilibrium rental price r and a skill level $x(\cdot)$. The skill level $x(\cdot)$ is determined by a skill production function, which includes a deterministic component $\Gamma(\cdot)$ and a multiplicative stochastic productivity shock $\epsilon_{W,t}$, as follows:

$$x(k_t, \boldsymbol{h_t}, t, a_{t-1}, e_{j,W}, \epsilon_{W,t}) = \exp\big(\Gamma(k_t, \boldsymbol{h_t}, t, a_{t-1}, e_{j,W}) \cdot \epsilon_{W,t}\big)$$

The specification above leads to a standard logarithmic wage equation in which the constant term is the skill rental price $\ln(r)$ and wages follow a log-normal distribution. Equation (2.2) shows the parametrization of the deterministic component $\Gamma(\cdot)$ of the skill production function:

$$\Gamma(k_t, \boldsymbol{h_t}, t, a_{t-1}, e_{j,W}) = e_{j,W} + \underbrace{\beta_{1,w} \cdot h_t^A + \beta_{2,w} \cdot h_t^V + \beta_{3,w} \cdot k_t + \beta_{4,w} \cdot (k_t)^2}_{\text{Mincer-inspired returns to schooling and experience}} \tag{2.2}$$

$$+ \underbrace{\sum_{d \in \{9,12,16\}} \gamma_{d,w}^A I[h_t^A \geq d] + \sum_{d \in \{9,12\}} \gamma_{d,w}^V I[h_t^V \geq d]}_{\text{non-linear rewards to diplomas or degrees}} \tag{2.3}$$

$$+ \underbrace{\eta_{1,w} \cdot I[a_{t-1} = W]}_{\text{skill depreciation}} + \nu_{1,w}$$

The first part of the skill production function is motivated by Mincer (1974) and hence linear in years of completed schooling by track ($\beta_{1,w}, \beta_{2,w}$), quadratic in experience ($\beta_{3,w}, \beta_{4,w}$), and separable between the two of them. We include diploma effects ($\gamma_{d,w}^A, \gamma_{d,w}^V$) that capture the non-linear rewards associated with a degree d beyond the years of schooling (Hungerford and Solon, 1987; Jaeger and Page, 1996). Skills depreciate by η_1 if the individual didn't work in the previous period. Finally, there is a time-trend ν_1 and a penalty when working as a minor ν_2.

In the following, we briefly highlight some salient aspects of how we parametrize the immediate non-pecuniary reward of working and the immediate utilities of attending academic and vocational schooling, and staying at home, respectively. The Appendix, Section A.1, provides more details on the parametrizations, while Section 2.3.3 discusses model solution and implementation.

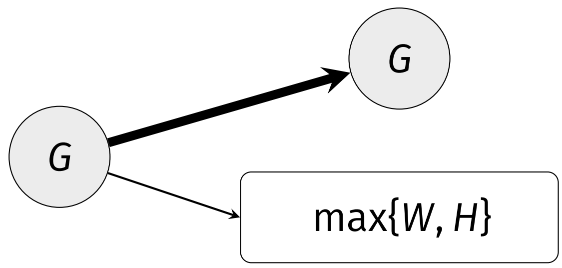


Figure 2.2. Choice Alternatives Isolating the Ex-ante Return to Schooling.

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

2.2.2 Objects of Interest

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

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

$$v(s_t, a) \;=\; u(s_t, a) + \delta \; \mathrm{E}^{\pi}_{s_t}\left[v^{\pi^*}(s_{t+1})\right]$$

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

Ex-ante Return. In Figure 2.3, we illustrate the choice alternatives that are needed to isolate the ex-ante return to an additional year of schooling. The thought-experiment we perform is to compare the total value of schooling $v(s_t, G)$ against the value of choosing the best alternative choice. Notably, the alternative choice can also contain the option of taking more schooling at a later stage in the life-cycle through re-enrollment. Quantifying the ex-ante return requires making comparisons of counterfactuals as a given individual in state s_t in the estimated model only chooses one of the available alternatives. We construct such counterfactuals through model simulations, where we require each individual to make alternative choices in state s_t, but restrict the realizations of shocks in each period to be held fixed across comparisons.

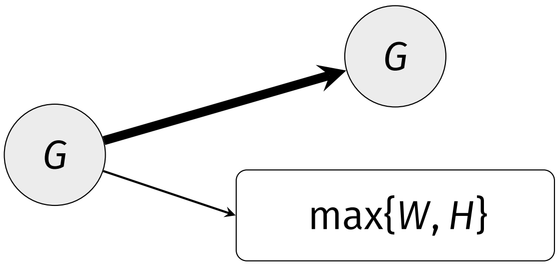


Figure 2.3. Choice Alternatives Isolating the Ex-ante Return to Schooling.

We denote by $ER(s_t)$ the ex-ante return capturing the value of an additional year of schooling against the best alternative choice in state s_t. Formally, we can express this object as follows:

$$ER(s_t) = \frac{v(s_t, G) - \tilde{v}(s_t)}{\tilde{v}(s_t)}, \quad \text{where} \quad \tilde{v}(s_t) = \max_{a \neq G}\{v(s_t, a)\}. \tag{2.4}$$

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

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

$$OV(s_t) = v^{\pi^*}(s_t, G) - v^{\hat{\pi}}(s_t, G)$$

The option value of schooling is non-negative at all states and zero once an individual attains the maximum schooling level. The option value increases with the future benefits of pursuing higher education and the probability of doing so. Figure 2.4 shows the decision problem facing the individual for whom we calculate the option value. We compare the total value of continued schooling under the scenario that the individual *may* continue to increase their schooling level in the future periods and the counterfactual scenario where it is impossible to do so.

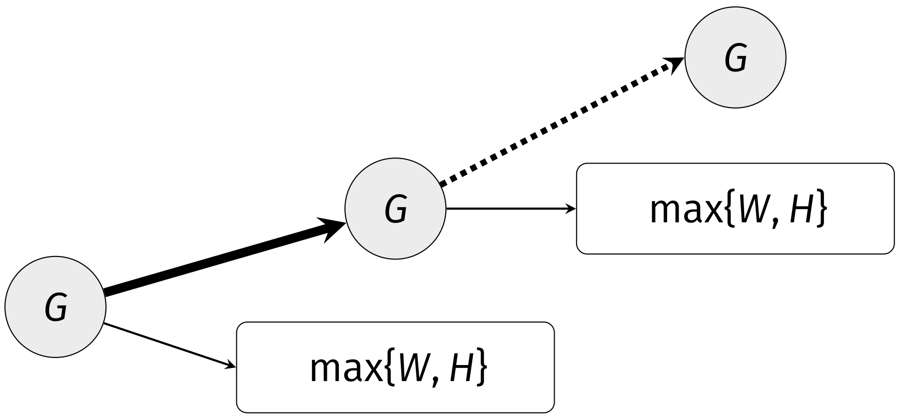


Figure 2.4. Choice Alternatives Isolating the Option Value of Schooling.

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

$$OVC(s_t) = \frac{OV(s_t)}{v^{\pi^*}(s_t)}. \tag{2.5}$$

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

2.3 Data and Implementation

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

2.3.1 Data Sources

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

Sample construction. We restrict our sample to Norwegian males born between 1955 and 1960. We can follow each of these individuals' educational choices and earnings from age 15 and up to age 58.[*] Our initial sample consists of 176,804 Norwegian-born males. Dropping individuals with missing information on childhood municipality of residence, exposure to compulsory schooling reform and education enrollment or attainment, we retain 165,171 individuals. Further dropping individuals with missing information on IQ test scores in the Norwegian military records, we retain 136,292 individuals (i.e., around 77% of the initial sample). Using annual information on individuals' educational choices and earnings, we create a weakly-balanced panel of individuals entering our sample across 44 annual observations, which an individual can exit only due to natural attrition (i.e., death or out-migration). Our panel dataset thus consists of 5,840,243 person-year observations.

[*] We observe educational choices annually for birth cohort 1955 at age 15 and onwards since the National Education Database was established in 1970. Educational histories are partially observed for earlier cohorts.

We further split the analytical sample in two parts, depending on the type of compulsory schooling system each individual was subject to, exploiting variation in the timing of a compulsory schooling reform across different municipalities in Norway (see details in Section 2.3.4). Specifically, there are 9,156 individuals in our sample (i.e., around 7%) who grew up in one of the 200 (out of 732) municipalities which hadn't implemented the compulsory schooling reform by the year they turned age 14 (threshold age for completely compulsory schooling) and as such were subject to the pre-reform education system. We will utilize of this sample of 9,156 individuals and 392,941 person-year observations to estimate our structural model, accounting for key features of the pre-reform education system, and refer to this as the *estimation sample*. We will use the remaining sample of 127,136 post-reform individuals and 5,447,302 person-year observations to validate the structural model, and refer to this as the *validation sample*.

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

Combining information obtained from the NUDB and Statistics Norway's Education Register, where the latter also comprises information on compulsory education attainment, we can classify individuals' educational choices in a detailed manner across all education levels.[**] Noteworthy, information in both the NUDB and the Education Register is based on the annual reports submitted by educational establishments for each of their attendants directly to Statistics Norway, which minimizes the chance of misreporting. In comparison, survey-based data that are often used to study enrollment, drop-out and completion behavior may suffer from non-response or other biases due to misreporting.

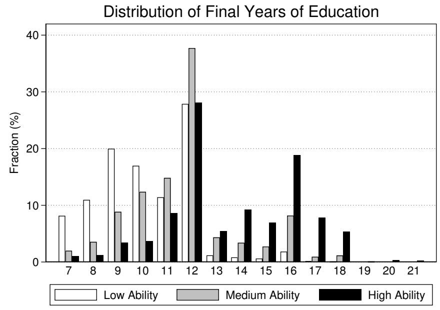
[**] Earlier studies on the returns to education in Norway have relied on Statistics Norway's Education Register and used information on an individual's highest completed education level or the years of schooling corresponding to the highest level of education, see, e.g., Aryal, Bhuller, and Lange (2021), Bhuller, Mogstad, and Salvanes (2017) and Aakvik, Salvanes, and Vaage (2010). Neither of these studies consider the ex-ante returns or the option value of educational choices.

Earnings. Our earnings data are based on annual tax records. Our earnings measure is the sum of labor income (from wages and self-employment) and work-related cash transfers (such as unemployment benefits and short-term sickness benefits). This dataset have several advantages over those available in most countries. First, there is no attrition from the original sample other than natural attrition due to either death or out-migration. Second, our earnings data pertain to all individuals, and are not limited to some sectors or occupations. Third, we can construct long earnings histories that allow us estimate the returns to education across the life-cycle.

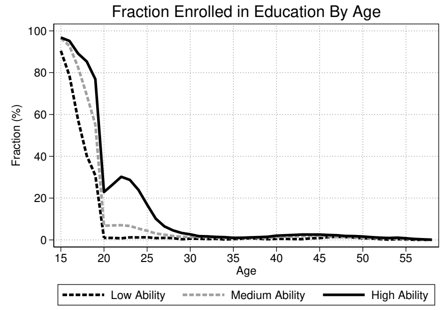
Ability. An important measure we exploit in our analysis to capture observational heterogeneity is an IQ test score accessed from the Norwegian Armed Forces. In Norway, military service was compulsory for all able males in the birth cohorts we study. Before each male entered the service, his medical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

Statistics. Figure 2.5 provides descriptive statistics for key variables in our dataset. In each panel, we categorize individuals as either low (scores 1-4), medium (scores 5-6) or high (scores 7-9) ability. Panel (a) shows the distributions of final years of education, where we find clear associations between education and ability. Panel (b) shows the fraction of individuals enrolled in education at each age. Individuals are more likely to attend education during the early part of their life-cycle, with gradual declines in the enrollment rate up to age 30, and virtually no enrollment beyond age 33. Next, in panels (c)-(d), we consider the conditional exit and re-enrollment rates, focusing on the earlier part of the life-cycle. The exit rate is substantially higher among low- and medium-ability individuals, while high-ability individuals have consistently higher re-enollment. Panel (e) illustrates the choices of academic and vocational tracks in middle and high school, reflecting clear ability-related differences in track choices.

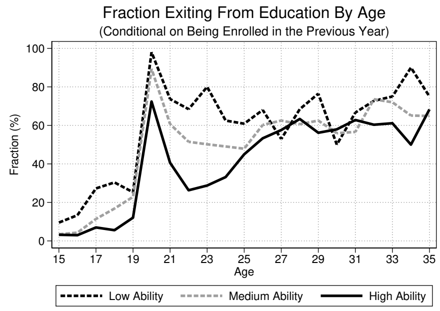
Next, panel (f) in Figure 2.5 shows the work-participation rates by ability. While low-ability individuals reach an employment rate of 96 percent already at age 20, high- and medium-ability individuals gradually increase their employment rates until age 30. Beyond age 30, the employment rates remain relatively stable across all groups, though low-ability have earlier labor market exits. Panels (g)-(h) show age-specific means and standard deviations of annual earnings (in 1000s,



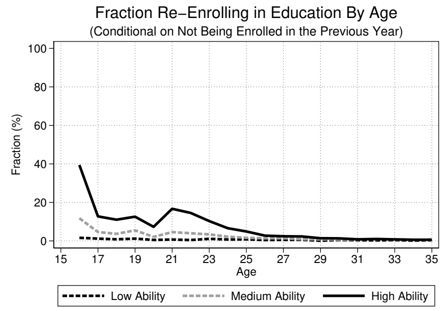
(a) Distribution of Final Years of Education



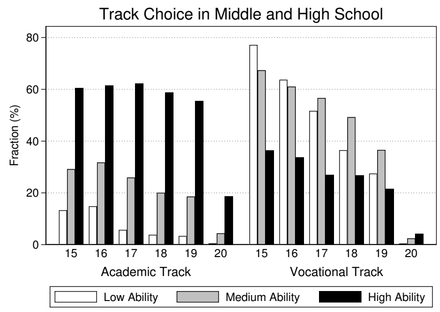
(b) Fraction Enrolled in Education by Age



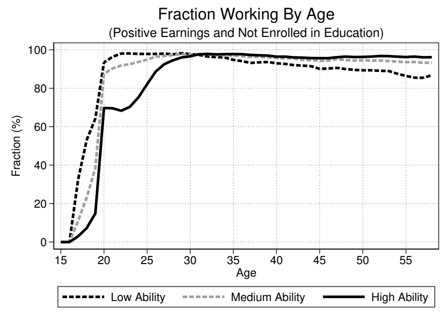
(c) Exit Rate By Age



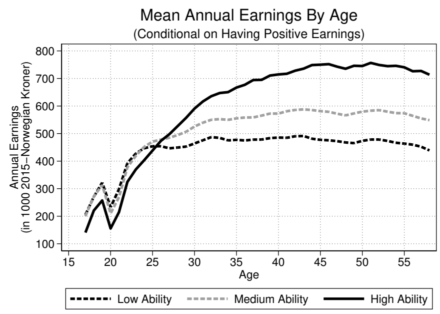
(d) Re-enrollment Rate by Age



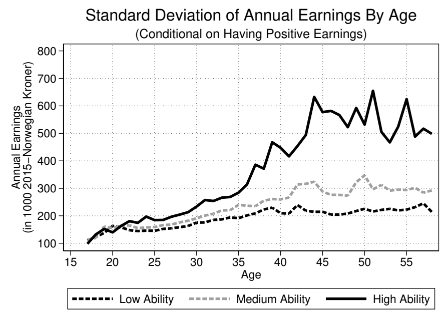
(e) Track Choice in Middle/High School



(f) Fraction working by age



(g) Mean Earnings by Age

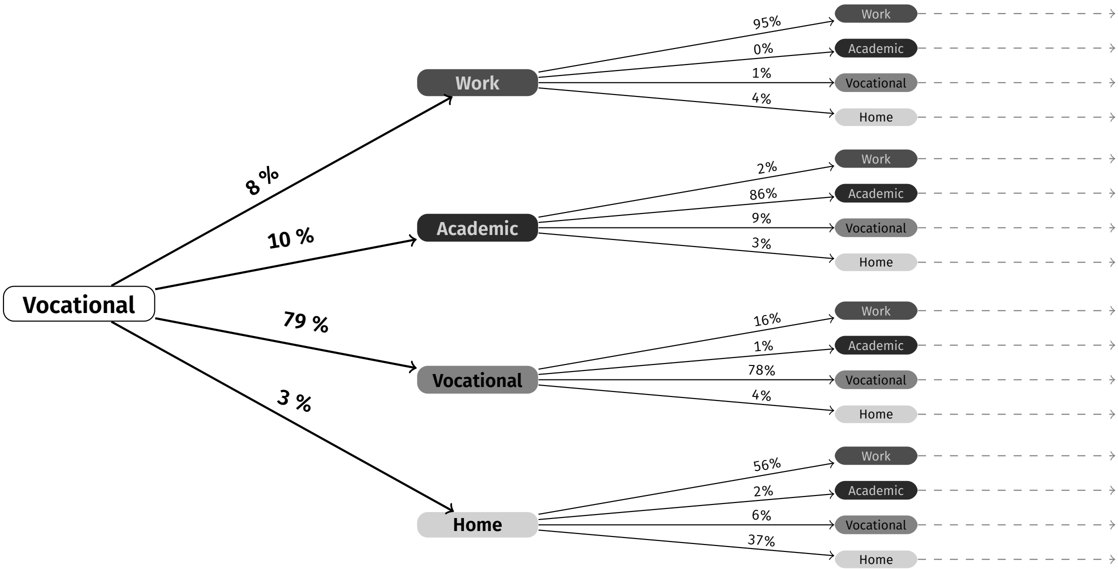


(h) Standard Deviation of Earnings by Age

Note: The sample consists of Norwegian males born 1955-1960, who grew up up in a municipality which hadn't implemented the compulsory schooling reform by the year they turned age 14 (see details in Section 2.3.2). Individual are followed over ages 15–58, corresponding to calendar years 1970–2018, unless there is natural attrition due to death or out-migration. Individuals' ability is split in three discrete categories, constructed as low (stanine IQ scores 1-4), medium (scores 5-6) and high (scores 7-9). N=9,143.

Figure 2.5. Descriptive Statistics.

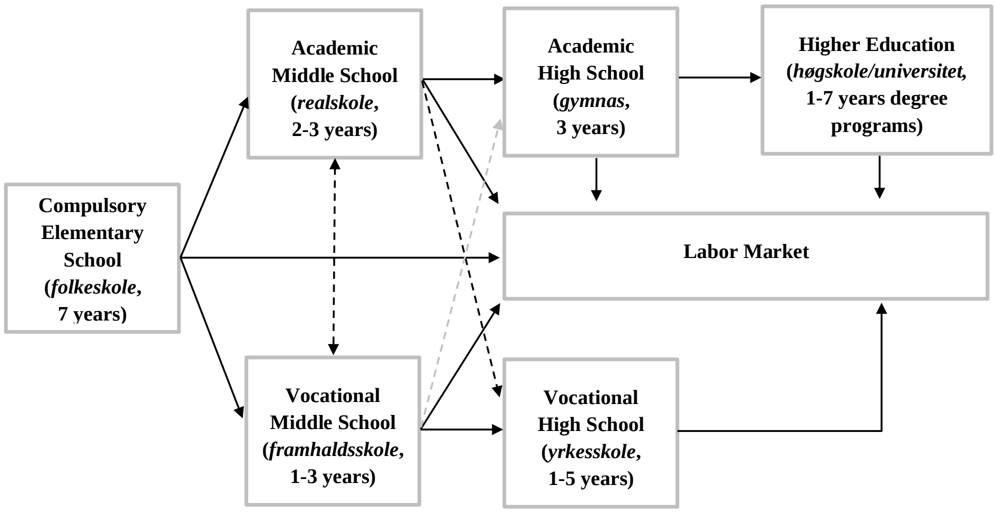
2015-Norwegian Kroner) conditional on working, respectively, by ability. The age-earnings profiles are increasing for all ability groups up to age 45, aside from a temporary drop in earnings at ages 19/20 due to military service. Standard deviations of earnings are quite stable in the earlier parts of the life-cycle and relatively similar across ability groups, while there is a large increase after age 35, especially among high-ability individuals.



Note: This figure shows the decision tree between ages 17 to 19 for individuals who attended the vocational track at ages 15 and 16, after having completed compulsory schooling. This also shows the fraction transiting from one state to another at each age.

Figure 2.6. Illustration of the Decision Tree and Transition Rates.

Besides some of the key moments of our dataset that are illustrated in Figure 2.5, our model implementation will also rely crucially on the fractions of individuals who transit between different choices over their life-cycle. To illustrate the rich transition patterns present in our data, in Figure 2.6, we consider individuals who were enrolled in the vocational track at ages 15 to 16 after having compulsory schooling at age 14, and follow their transition histories over the following three years in our data. Around 79% of these individuals continue in the vocational track for a third year while 10% switch to an academic track. Only 8% enter the labor market, and 3% stay at home. Among the 3% that decide to stay at home for one period, roughly 8% re-enroll in an academic or vocational school. These rich patterns of (i) persistence in choices over time, (ii) presence of track switching, and (iii) re-enrollment after spells of work or home stay provide a motivation for the flexible modelling of schooling choices in Section 2.2.



Note: This figure illustrates the Norwegian education system following the 1959 legislation (*Lov om folkeskolen 1959*), when only seven years of elementary schooling was compulsory. Solid black arrows indicate the typical paths that pupils could take as they traverse through the school system, while dotted black (gray) arrows indicate switching between tracks (considered particularly difficult or associated with additional requirements). Following the subsequent legislation in 1969 (*Lov om grunnskolen 1969*), the compulsory schooling was extended to nine years, which was rolled-out in a staggered manner between 1960 and 1975 (see details in Section 2.3.4). Our baseline analysis uses individuals born between 1955-1960, who faced the pre-reform education system. In 1974, a new type of comprehensive high school (*videregående* skole) was introduced, which made track switching easier. The latter system remained in place up to the mid-1990s, when two reforms (Reform 94 and Reform 97) were enacted, which altered the structure of high school education and lowered the school starting age to six, respectively. See further details in Bertrand, Mogstad, and Mountjoy (2020).

Figure 2.7. Illustration of the Norwegian Education System in 1960s.

2.3.2 The Norwegian Education System

We describe here the structure of the Norwegian education system that existed in the 1960s, which our model is specified to fit. This system had four main stages, as shown in Figure 2.7.

The first stage consisted of seven years of compulsory elementary education. The second stage involved tracking, where pupils could attend either a vocational middle school (*framhaldsskole*) or an academic middle school (*realskole*). The vocational middle school could be either one, two or three years, with most attending two years, while the academic middle school could be either two or three years, where the final year was only required for those who wanted to later pursue further academic education. The third stage corresponded to a high school education, which again was track-specific. After attending the academic middle school, students could move on to attend a academic high school (*gymnas*). In contrast, pupils attending the vocational middle school normally didn't quality for the academic high school, but could rather attend a vocational high school (*yrkesskole*). The academic high school was required to be three years, while the vocational high school could be of varying lengths, depending on the particular vocational field. Finally, the fourth stage involved higher education, leading up to an academic degree at a college or a university, enrollment to which was typically contingent on having completed the academic high school. There existed two main degrees in tertiary education; a 4 year degree (*cand.mag*) and a 6 year degree (*hovedfag*), while degrees of other durations also existed.

2.3.3 Model Implementation and Estimation

The model we described in Section 2.2 is set up as a standard Markov decision process (MDP), which can be solved by a simple backward induction procedure (White, 1993; Puterman, 1994; Rust, 1994). In the final period T, there is no future to consider, and the optimal action is choosing the alternative with the highest immediate utility in each state. With the decision rule for the final period, we can determine all other optimal decisions recursively.*

We use the method of simulated moments (Pakes and Pollard, 1989; Duffie and Singelton, 1993) to estimate the 61 parameters $\hat{\boldsymbol{\theta}}$ of the model for each ability group, i.e., a total of $61 \times 3 = 183$ parameters. Equation 2.6 shows our criterion function. We select the parameterization for our analysis that minimizes the weighted squared distance between our specified set of moments computed on the observed $\boldsymbol{M_D}$ and the simulated data $\boldsymbol{M_S(\theta)}$. We weigh the moments with a diagonal matrix $\boldsymbol{W}$ that contains the variances of the observed moments (Altonji and Segal, 1996) and use estimagic (Gabler, 2022) for the optimization of the criterion function**. We simulate a sample of 50,000 individuals based on the candidate parameterizations of the model.

$$\hat{\boldsymbol{\theta}} = \underset{\boldsymbol{\theta} \in \boldsymbol{\Theta}}{\arg\min}\, (\boldsymbol{M_D} - \boldsymbol{M_S}(\boldsymbol{\theta}))\boldsymbol{W}^{-1}(\boldsymbol{M_D} - \boldsymbol{M_S}(\boldsymbol{\theta}))' \tag{2.6}$$

Table 2.1 provides an overview of the 1,692 empirical moments used in our estimation. These consist of aggregate moments of annual earnings (type I and II), aggregate annual choice proportions in each alternative (type III to VI), and the distribution of final years of schooling (type VII). Moments of type I to VI each have 264 moments that are calculated for each of the 44 periods in our model between ages 15 to 58, the three ability groups, and an indicator for residing in

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

** Estimagic is a Python package for the estimation of scientific models. We use a global version of the BOBYQA algorithm within estimagic(Powell et al., 2009).

an area with a local high school during childhood, i.e., $44 \times 3 \times 2 = 264$ unique moments. Type VII captures the distribution of final years of schooling, which can take a total of 18 values between 7 and 25 years of completed schooling at the end of the life-cycle, calculated for the three ability groups by local high school availability, i.e., $18 \times 3 \times 2 = 108$ unique moments.[‡]

These moments are selected to determine the various components of our model. While as described above all moments are used jointly in the estimation procedure, we can nonetheless provide some heuristic arguments for how these various moments aide identification. The information on average earnings in each period along with information on the proportion of individuals attending schooling by year in each track allows us to pin down the parameters of the wage component that determine the immediate pecuniary utility from working. Intuitively, the movements in aggregate wages across periods where people with more schooling enter the labor market allow us to identify the wage rewards to additional years of schooling. And, aggregate wages across periods where more high school graduates enter the labor market allow us to identify the wage rewards to a high school degree. Including the distribution of final years of schooling as an additional set of moments further allows recovering non-linearities in the wage-schooling relationship and associated bunching at specific degrees.[‡‡] Similar arguments apply for the identification of wage rewards to additional years of labor market experience.

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

‡ To ease the computational burden, we impose an upper limit of 25 years of completed schooling.

‡‡ Note that we do not rely on the cross-sectional wage-schooling relationship directly in our estimation, as these moments usually suffer from problems related to endogeneity of schooling and sample selection bias. Using the distribution of final years of schooling and average earnings and choice shares by period, we can nonetheless recover the parameters of the wage-schooling relationship in a relatively flexible manner.

Table 2.1. Summary of Moments Used in the Estimation.

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

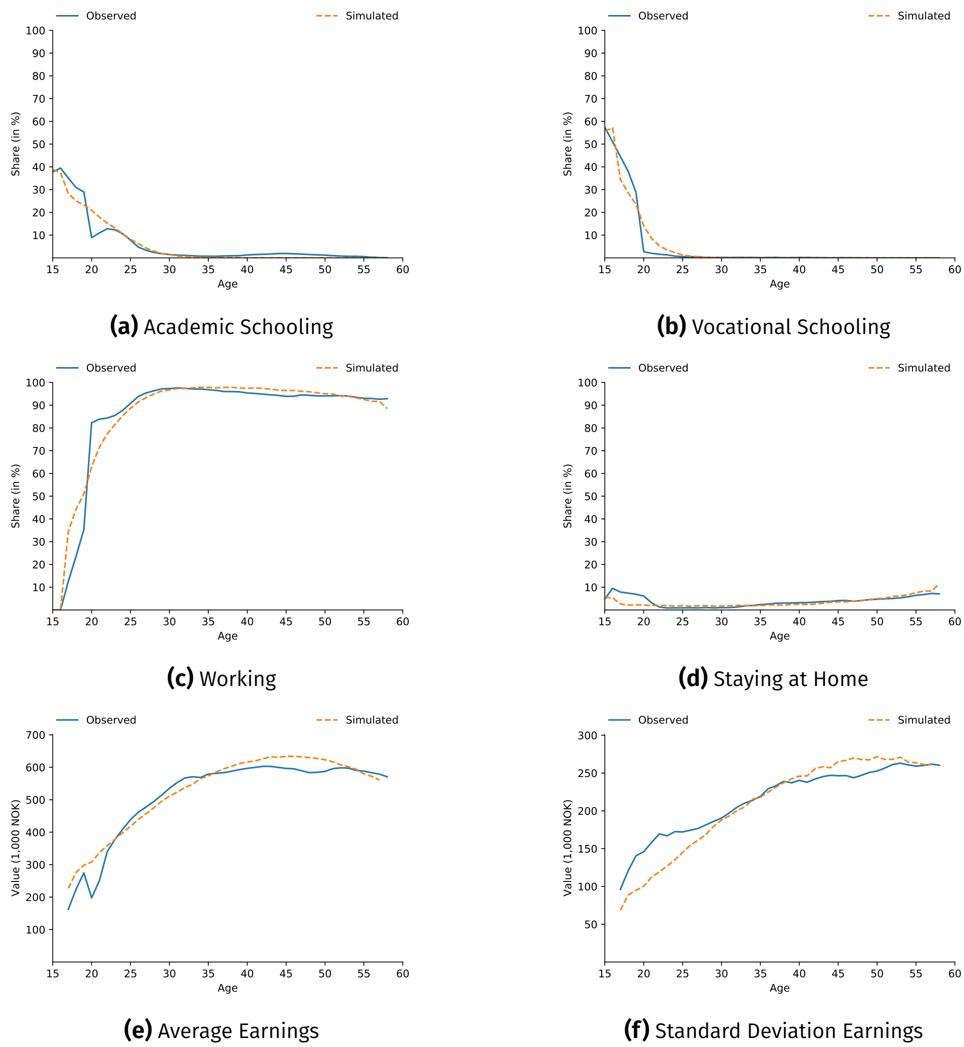
Note: This table provides an overview of the 1,692 moments used in the estimation by the type of moment. Moments of type I to VI are each calculated for the 44 periods in our model between ages 15 to 58, high/medium/low ability type, and an indicator for residing in an area with a local high school during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

for the identification of taste shocks associated with the other alternatives. Finally, the latent heterogeneity types are identified as the set of discrete taste shifters that capture persistence in choices over time and minimize residual heterogeneity.

2.3.4 Model Validation

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

Parameter Estimates:. All parameter estimates are reported in Appendix, Section A.2, along with the associated standard errors based on simulation-based inference. In the following, we discuss some of these estimates. Most of our parameter estimates are standard and in line with the previous literature (Keane and Wolpin, 1997; Eisenhauer, Heckman, and Mosso, 2015). The annual discount rate is about 4% for all ability levels. Returns to experience are concave and unobserved types play an important role in shaping schooling decisions even within ability groups. The cost of re-enrollment in school after dropping out is very high. There are interesting differences in the wage rewards to academic and vocational schooling by ability. For the vocational choice, the wage rewards are highest for low ability individuals where wages increase by 16% with an additional year compared to only 13% for high ability individuals. The pattern reverses for the academic choice, where the wage rewards are highest for high ability individuals, for whom another year of



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

Figure 2.8. Model Fit.

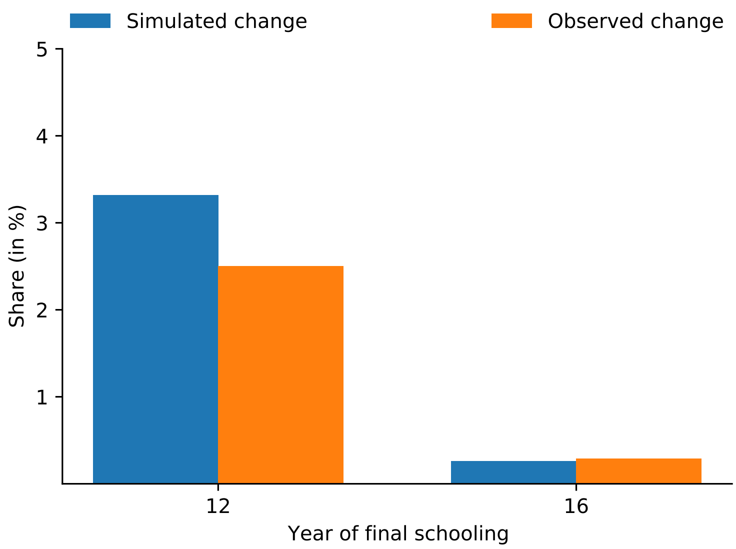
schooling increases wages by 18%, but only by 11% among low ability individuals. The associated non-pecuniary rewards reinforce the sorting of high-ability individuals into academic and low-ability individuals into a vocational school. For example, the non-pecuniary benefits from an academic education are negative for low ability individuals but positive for high ability.

In-Sample Model Fit. We now assess our model's ability to reproduce the overall patterns of choices and earnings by comparing our simulated sample to the observed data. Figure 2.8 shows the shares of individuals deciding to either attend academic (panel a) or vocational (panel b) school, work (panel c) or stay at home (panel d). The model predictions (black solid lines) are closely aligned with the observed patterns in our data (dotted gray lines), but we fail to account for the stark drop in academic schooling at ages 19/20, which in the data is associated with compulsory military service not captured in our model. Next, we show the model fit for the average (panel e) and standard deviation (panel f) of annual earnings by age. Our model does an excellent job of reproducing these basic patterns over the life cycle as well.

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

We exploit the Norwegian compulsory schooling reform to validate our model in the following manner. First, as described in Section 2.3.1, our model is estimated solely using data on individuals born 1955–1960 who were subject to the pre-reform education system, and is geared to capture the schooling system that exited pre-reform. Second, for the purposes of model validation, we constrained the choice sets in a modified version of our model where individuals cannot leave schooling before nine years to reflect the implementation of a nine year compulsory schooling. We then compare the predicted changes in education choices in our model to the observed differences in education choices across pre- and post-reform cohorts born 1955–1960, respectively. Finally, in order to provide an insightful and strong validation of our model, we focus on "inframarginal" responses beyond the new minimum schooling requirement. We focus on such responses as the reform is mechanically expected to induce increases in educational attainment up to the new minimum schooling requirement among those who otherwise would have had less than nine years of schooling, both in the observed data and in our model,

* The staggered roll-out of the compulsory schooling reform in Norway has led to extensive literature relying on quasi-experimental designs to study the causal effects of schooling on various outcomes, see, e.g., Black, Devereux, and Salvanes (2005), Monstad, Propper, and Salvanes (2008), Aakvik, Salvanes, and Vaage (2010), Machin, Salvanes, and Pelkonen (2012), Bhuller, Mogstad, and Salvanes (2017), and Aryal, Bhuller, and Lange (2021). None of these studies consider the ex-ante returns or the option values of schooling choices.



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

Figure 2.9. Out-of-Sample Validation Using Compulsory Schooling Reform.

while it is less clear how educational choices beyond the new minimum schooling requirement are affected.

Figure 2.9 provides the results of our validation exercise. We compare the predicted changes in the fractions of individuals leaving with 12 years (high school degree) of schooling and 16 years (college), respectively, in model simulations pre- and post-reform to the corresponding changes observed in actual data. This exercise highlights the main motivation of our modelling approach as there are indeed changes in the distribution of education attainment across margins that are not directly affected by the policy reform, and the model does predict that there will be such “inframarginal” responses. We predict an increase in graduation rates of 3.2% for high school and 0.3% for college. In the validation sample, the share of individuals with a high school degree increases by 2.5% and the share of college graduates by 0.3%. Thus, our model predictions slightly exceed the increase in high school graduates, while we are spot-on for college graduation. In a nutshell, the predictions from our model line up with the observed changes. We return to these findings in

Section 2.4.3, where we provide additional evidence on economic mechanisms from our model that shed more light on the nature of these responses.

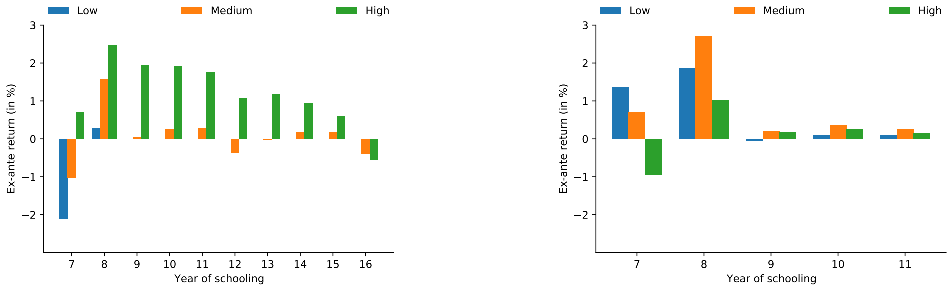
2.4 Empirical Results

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

2.4.1 Evidence on Ex-ante Returns

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

Ex-ante Returns By Track and Ability. Figure 2.10 shows our main evidence on the ex-ante returns to continue schooling in academic or vocational track for another year and individual ability type. The returns are shown for each year of schooling along the horizontal axis and are computed for individuals that have reached this particular stage and are faced with the decision to continue schooling, i.e., the bars at 10 years illustrate the average ex-ante returns of attending the 10th grade by track and ability for individuals who have completed 9 years of schooling in this track in an uninterrupted spell. As we move towards right in each panel, the illustrate returns pertain to only individuals who actually reach those stages in our model. At each stage, these returns capture both the immediate rewards and the discounted future rewards. In this sense, the model allows us to estimate the aver-



(a) Academic Schooling

(b) Vocational Schooling

Note: The figure is based on samples of 10,000 simulated schooling careers for each ability group based on the estimated model. This figure contains average ex-ante returns for each year-track-ability cell. The left figure shows how ex-ante returns to academic schooling develop over time for each group while the right figure shows the same for the vocational track. Each bar shows the average ex-ante return to a particular year of schooling for the individuals in the respective ability group that reaches the relevant transition in our model. For instance, the bar for the high-ability group in the academic panel in year 11 shows the average ex-ante return of the 12th year for high-ability individuals that have had an uninterrupted academic schooling career until the 11th year. We compute the ex-ante return as defined in Equation (2.4). Whenever there are only a few people of a particular ability group that reach a particular transition we do omit this group from the calculation.

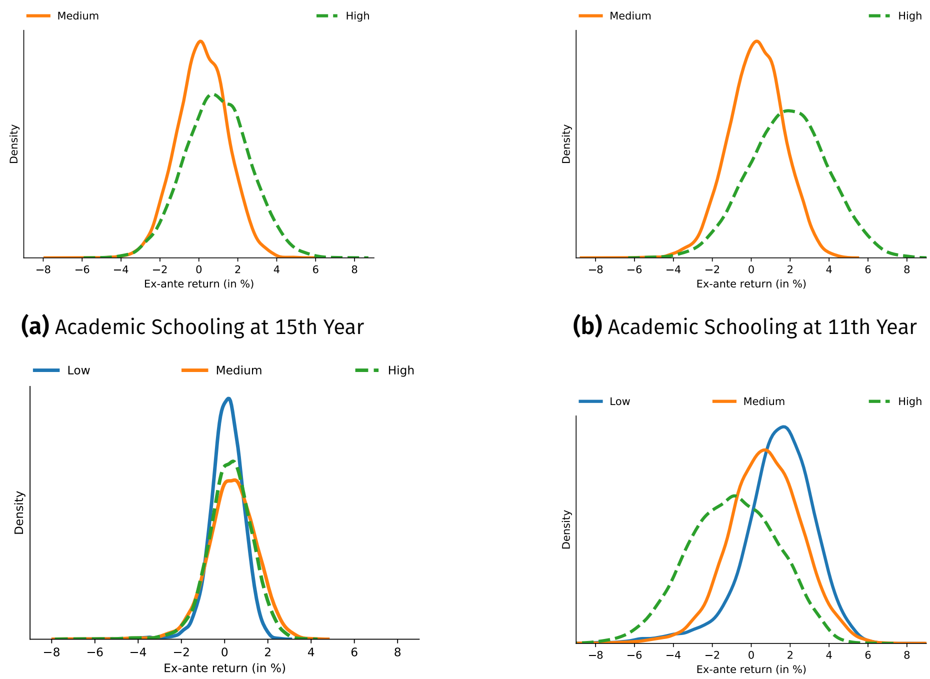
Figure 2.10. Average Ex-ante Returns to Academic and Vocational Schooling.

age dynamic treatment effect for those facing this treatment choice (Heckman and Navarro, 2007; James J. Heckman, John Eric Humphries, and Veramendi, 2016). We find substantial heterogeneity in the average ex-ante returns by ability, track choice and year of schooling. The returns range from −2% for the 8th grade in the academic track for low-ability individuals up to 3% for medium-ability for the 9th year in the vocational track. Underlying this heterogeneity is a strong pattern of sorting into academic and vocational tracks by ability, which in our model is both caused by differences in wage rewards and preference heterogeneity. Indeed, the structure of the 8th grade returns reflects the separation of the ability groups in the different schooling tracks at an early stage of the educational pathways, consistent with the descriptive evidence in Figure 2.5, panel (e). The average return to vocational track at the 8th year is negative at −1% for high-ability individuals, so the majority of them never enter vocational school. The opposite is true for low-ability individuals, for whom the returns to an academic track are negative initially, pushing them into vocational schooling instead. Indeed, about 83% of low-ability individuals never attend an academic school. As we move towards right in panel (a), we notice that the returns to academic schooling remain consistently positive only for high-ability individuals. In each track, we find the highest returns for transitions that entail a middle school degree at the 9th year, with gradually decreasing returns as we progress further.

The Distributions of Ex-ante Returns. The average returns in Figure 2.10 can mask considerable heterogeneity in returns by track choice across individuals with the same ability facing identical choices. For instance, Wiswall and Zafar (2015) and Attanasio and Kaufmann (2017) document substantial heterogeneity in ex-ante returns using survey data on subjective expectations. In our model, heterogeneous returns across observationally similar individuals, i.e., those from the same ability group who have reached the same stage of the decision tree after an uninterrupted spell, are represented through the presence of heterogeneous latent types and different realizations of shocks to productivity and tastes associated with different choices.

To illustrate heterogeneity in ex-ante returns, we now focus in Figure 2.11 on individuals in each ability group who in our model faced the choices of 11th and 15th year of academic schooling and 8th and 11th year of vocational schooling, respectively. In panel (b), we see that the average return of the 11th year of academic schooling is positive for both high- and medium-ability groups, but also that a considerable share within each group has negative returns. In our model, all individuals with negative returns to academic schooling would decide not to attend academic schooling as this choice is (in expectation) dominated by the best alternative choice. They might, however, pursue academic school later as this does not rule out the possibility of re-enrollment. In panel (b), we also see that the distributions overlap, so there are many individuals of medium-ability for whom returns to the 11th year of academic schooling are higher than for high-ability individuals. Overall, the distribution of returns is more spread out among high-ability individuals at that transition. In panel (a), we see the distributions of returns to the 15th year of academic schooling are more similar across ability groups, reflecting that fewer among the high-ability group go on to attend the 15th year as compared to the 11th year.

Next, in Figure 2.11, panels (c)-(d), we consider the distributions of returns to 11th and 8th year of vocational schooling, respectively. In these plots, we include all three ability groups as sufficiently many from each group are present at these transitions in our model. We find interesting ability-related patterns in panel (d), where the majority of low-ability individuals have positive returns to 8th year of vocational schooling, while the majority of high-ability individuals have negative returns. These results reflect the strong patterns of ability-related sorting at the 8th year schooling tracks. By contrast, the distributions of returns are much more similar in panel (c), reflecting that conditional on having reached the 10th year of vocational schooling, the transition rates to 11th year of vocational school do not differ substantially across ability groups. This finding may reflect that there are latent types among high- and medium-ability individuals with a high propensity to attend vocational schooling, and these types stay in vocational schooling throughout middle and high school, conditional on having enrolled.



(a) Academic Schooling at 15th Year

(b) Academic Schooling at 11th Year

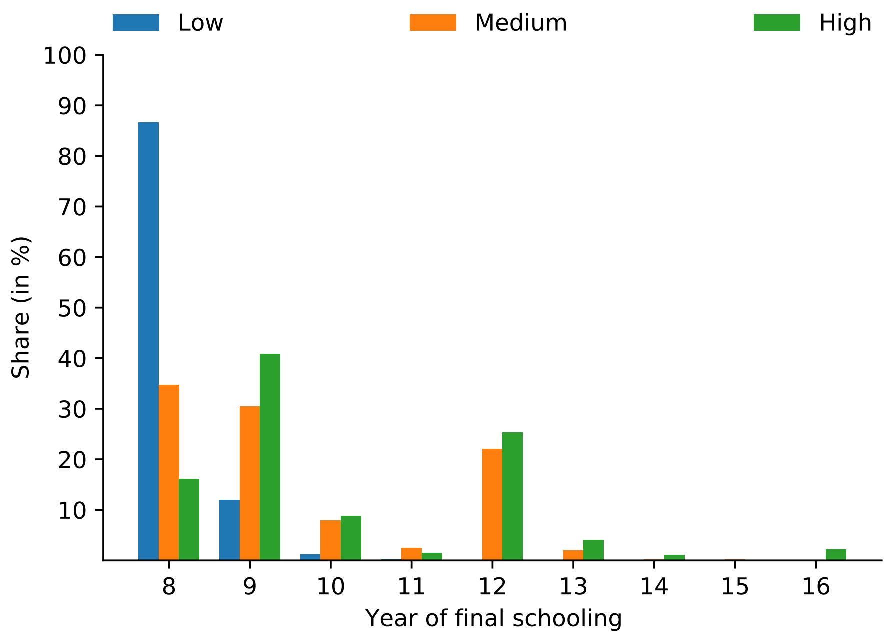
(c) Vocational Schooling at 11th Year

(d) Vocational Schooling at 8th Year

Note: The figure is based on samples of 10,000 simulated schooling careers for each ability group based on the estimated model. Each panel shows the distribution of ex-ante returns to a particular schooling choice by ability who those with an uninterrupted schooling career up to that point who have reached this transition. For instance, in panel (a), we show the distribution of ex-ante returns to the 15th year of academic schooling for all individuals with uninterrupted schooling careers up to that point. We compute the ex-ante return as defined in Equation (2.4). The heterogeneity in returns follow from the permanent differences across latent types $\boldsymbol{e}$ and the realizations of transitory shocks $\boldsymbol{\varepsilon_t}$. Whenever there are only a few people of a particular ability group that reach a particular transition we do omit this group from the calculation.

Figure 2.11. Distributions of Ex-Ante Returns to Academic and Vocational Schooling.

The Role of Re-enrollment. A salient aspect of our model–crucial in interpreting the results above–is the individuals' ability to re-enroll in school after having exited and undergone a non-schooling spell. Indeed, the relatively low average ex-ante returns in Figure 2.10 can be partly attributed to the fact that many individuals come back to school to pursue more education. In an attempt to illustrate this feature of our model, we show the final schooling level for individuals that initially leave school after the 8th grade in either track by ability in Figure 2.12. Among low ability individuals, dropping out at that stage determines the final schooling level for about 90%. Only 10% do still acquire their middle school degree at a later stage. For high-ability individuals, however, the large majority do continue their schooling at some point. Roughly 85% do eventually end up with at least a middle school degree, and 30% even continue to obtain at least a high school degree. We need to keep this feature of our model in mind when interpreting average ex-ante returns at each transition that are presented above.

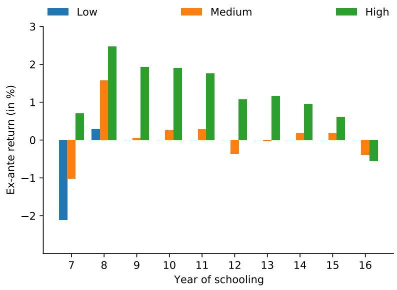


Note: The figure is based on samples of 10,000 simulated schooling careers for each ability group based on the estimated model. We further restrict the sample to 1,580 individuals who continue their schooling for only one additional year and then initially drop out of school at the 8th year of schooling,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

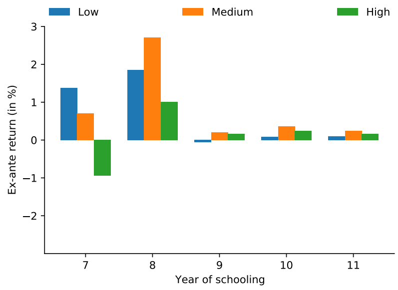
Figure 2.12. The Final Years of Schooling for those Exiting School at the 8th Grade.

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

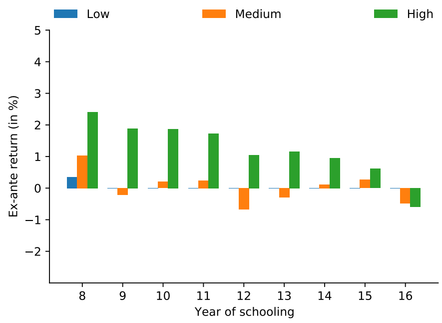
Figure 2.13 summarizes our findings from these exercises. To facilitate comparison, panel A reports estimates of average ex-ante returns by ability and track from our baseline model (as in Figure 2.10), while panel B shows the corresponding estimates from a version of the model where we remove shocks to productivity (i.e., no wage risk), while in panel C we further also remove unobserved transitory shocks related to tastes for schooling, working or staying at home. This illustration provides a few additional insights. While high-ability individuals have the highest



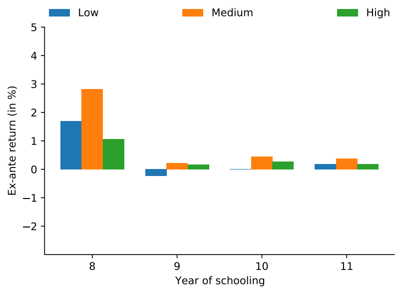
(a) Academic Schooling



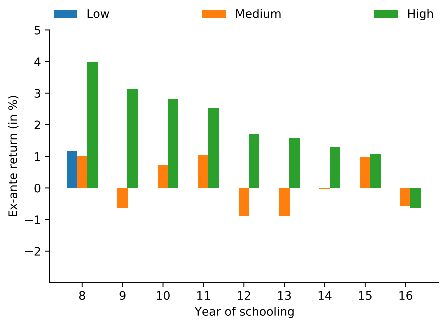
(b) Vocational Schooling



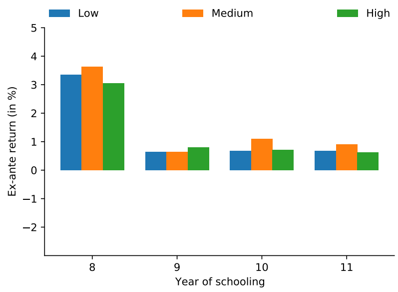
(c) No Laborrisk: Academic Schooling



(d) No Laborrisk: Vocational Schooling



(e) No Risk: Academic Schooling



(f) No Risk: Vocational Schooling

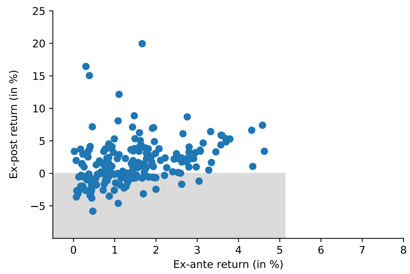
Note: The figure is based on samples of 10,000 simulated schooling careers for each ability group based on the estimated model under different specifications of transitory shocks. Each panel contains average ex-ante returns for each year-track-ability cell for alternative model specifications. Panel A shows results based on the baseline model, while panel B removes shocks to productivity (i.e., no wage risk) and panel C further also removes taste shocks. In each panel, the left figure shows how ex-ante returns to academic schooling develop over time for each group while the right figure shows the same for the vocational track. Each bar shows the average ex-ante return to a particular year of schooling for the subset of the respective ability group that has reached the relevant transition in our model. For instance, the bar for the high-ability group in the academic panel in year 11 shows the average ex-ante return of the 11th year for those that have had an uninterrupted academic schooling career until the 10th year. We compute the ex-ante return as defined in Equation (2.4). Whenever there are only a few people of a particular ability group that reaches a particular transition we do omit this group from the calculation

Figure 2.13. Average Ex-ante Returns – The Role of Shocks to Productivity and Tastes.

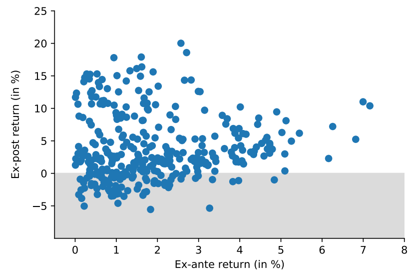
ex-ante returns to academic schooling across all panels, the returns to the 8th year of academic (vocational) schooling for low (high) ability individuals are no longer negative once productivity shocks are turned off (panel B). This pattern becomes even stronger once we also remove taste shocks (panel C). These comparative statics imply that the strong patterns of ability-related sorting into tracks in the early stage of educational careers in our model are partly explained by (i) positive returns to academic schooling for high-ability types, irrespective of their taste preferences or presence of wage risk, (ii) negative returns to academic schooling for low-ability types stemming from a combination of taste and productivity shocks, and (iii) negative returns to vocational schooling for high-ability types stemming from a combination of taste and productivity shocks. Indeed, when both taste and productivity shocks are removed, the returns to vocational schooling are relatively homogeneous across ability groups (panel C).

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

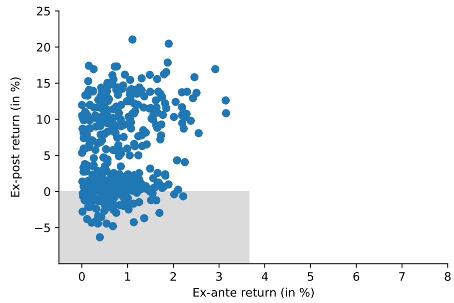
Figure 2.14 presents the joint distribution of ex-ante and ex-post returns for a random set of 500 individuals from our model at each transition. As expected, the ex-ante return are always positive by construction in each panel. However, the shaded areas indicate that the ex-post returns from pursuing an education were negative for some individuals, i.e., they faced regret due to the actual shock realizations. We also note that the ex-post returns to the 8th year of vocational schooling are relatively dispersed. As this decision made early in the life-cycle, agents face very different life-time trajectories subject to the future shock realizations and choices. By contrast, the ex-post returns to the 15th year of academic schooling are relatively compressed. As most individuals would go on to attend the 16th year to



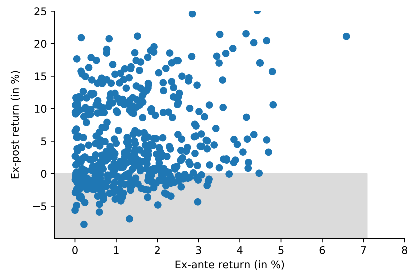
(a) Academic Schooling at 15th Year



(b) Academic Schooling at 11th Year



(c) Vocational Schooling at 11th Year



(d) Vocational Schooling at 8th Year

Note: The figure is based on samples of 10,000 simulated schooling careers for each ability group based on the estimated model. We then restrict the sample to 500 random individuals with uninterrupted careers in the respective period for a particular track. Each panel shows the joint distributions of ex-ante and ex-post returns to a particular schooling choice in either academic or vocational track. Ex-post returns are the realized total discounted utilities over the remaining decision periods relative to the value function of the best alternative. The gray area shows all points where the realized return is smaller than the expected return from the second best option. Ex-ante return as defined in Equation (2.4). Whenever there are only a few people of a particular ability group that reaches a particular transition we do omit this group from the calculation.

Figure 2.14. Joint Distributions of Ex-Ante and Ex-post Returns.

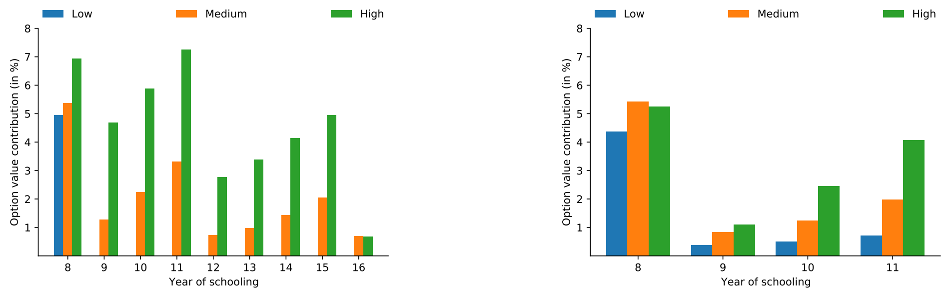
attain a college degree and then enter the labor market, these ex-post returns are associated with more similar life-time trajectories. These findings also demonstrate how uncertainty is highest at the beginning of the life-cycle and the choices made early on are more consequential in a dynamic setting like ours.

2.4.2 Evidence on Option Values

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

Option Value Contributions By Track and Ability. Figure 2.15 shows the contribution of the option value to the overall value of a schooling track by the year of schooling and ability. The option value contributions in the academic track range from 7% for the 11th year to almost zero beyond the 15th year of schooling. A recurring pattern is that the option value contribution is always the highest for the year of schooling right before the completion of an academic degree that entails considerable "diploma" effects. We also find sizeable heterogeneity by ability level. The option value contributions in the academic track tend to be the highest for high-ability individuals, as they are also likely to benefit the most from the additional schooling opportunities that open up from taking an extra year of schooling. By contrast, in the vocational track, the option value contributions are the highest at the 8th year of schooling and of a comparable order of magnitude across ability groups. This pattern may reflect that most attending this track go on to complete the 9th year in vocational school, irrespective of ability. Among those who progress further in vocational schooling, we again find a strong ability gradient. This likely reflects that among this group, also the high-ability individuals have the highest gain from attending the 10th and 11th year, and reach a vocational high school degree.

While the previous illustration provides evidence on the option value contributions, measured as a fraction of the overall value of a choice, we now provide more direct evidence on how the option value channel can play a crucial role in shaping schooling careers. To get at this, we perform counterfactual experiments based on our model where we turn on and off the option value of a choice and characterize the schooling decisions made by the agents in our model under each scenario. Based on these comparisons and inspired by the IV/LATE complier characterizations done in the program evaluation literature (e.g., Angrist, Imbens, and Rubin (1996)), we perform a characterization of agents into three groups; always-takers, never-takers and marginal agents (or compliers). Agents that always (never) decide to take another year of schooling when faced with this choice, irrespective of the option value, are characterized as always-takers (never-takers). While, agents that decide to take another year of schooling when the option value is turned on but not when it is off are characterized as marginal (i.e., compliers). By construction, monotonicity is satisfied, as for given shock realizations, agents in our model are never more likely to take more schooling when the option value is turned off



(a) Academic Schooling

(b) Vocational Schooling

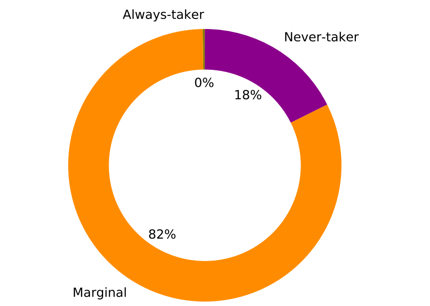
Note: The figure is based on samples of 10,000 simulated schooling careers for each ability group based on the estimated model. We restrict the sample to individuals with uninterrupted schooling careers up the relevant transition using the estimated model. The left figure shows how option value contributions for academic schooling develop over time for each group while the right figure shows the same for the vocational track. The option value contribution is defined in Equation (2.5). Whenever there are only a few people of a particular ability group that reaches a particular transition we do omit this group from the calculation.

Figure 2.15. The Option Value Contributions of Academic and Vocational Schooling.

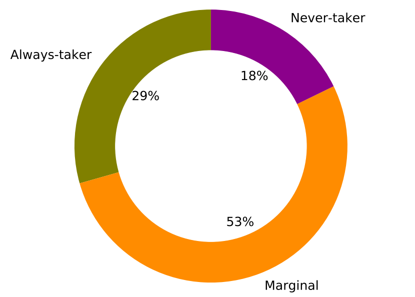
compared to when it is on.

Figure 2.16 illustrates our evidence based on the complier characterizations described above. In panels (a)-(b), we focus on high-ability individuals who faced the decision to continue their schooling for the 11th and 12th year in the academic track. These figures provide interesting illustrations of how important option values can be close to the degree-rewarding schooling choices. Among those facing the decision to continue their academic schooling in the 11th year, we find that a large majority at 82% among the high-ability individuals consists of marginal compliers, i.e., individuals who continue for another year of schooling only because of the option value stemming from being able to complete a high school degree right afterwards. By contrast, fewer than 1% are always-takers, who move ahead with their schooling even when no future schooling opportunities are available, and about 18% are never-takers, who drop out regardless. The picture is somewhat different at the 12th year of academic schooling. The fraction of always-takers rises drastically to 29% as completing the high school degree provides immediate considerable wage rewards. For 53% the option value of the high school diploma is crucial to complete the 12th year, as receiving this diploma opens up the possibility of attending college. Still, 18% drop-out and do not complete high school regardless of the option value.

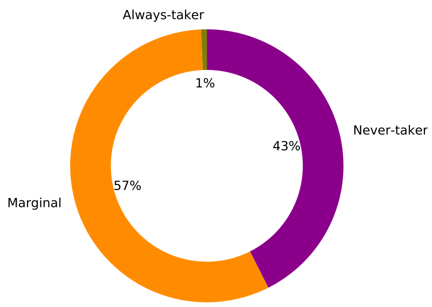
Next, in panels (c)-(d) of Figure 2.16, we consider all individuals (irrespective of ability) who faced the decision to continue their schooling for the 8th and 9th year in the vocational track. Option values in the vocational track arise primarily at the



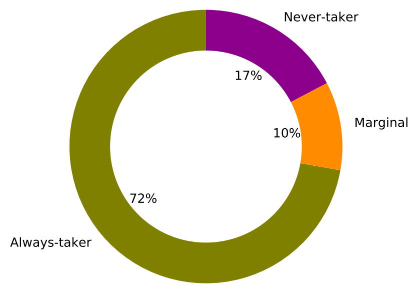
(a) Academic Schooling at 11th Year



(b) Academic Schooling at 12th Year



(c) Vocational Schooling at 8th Year

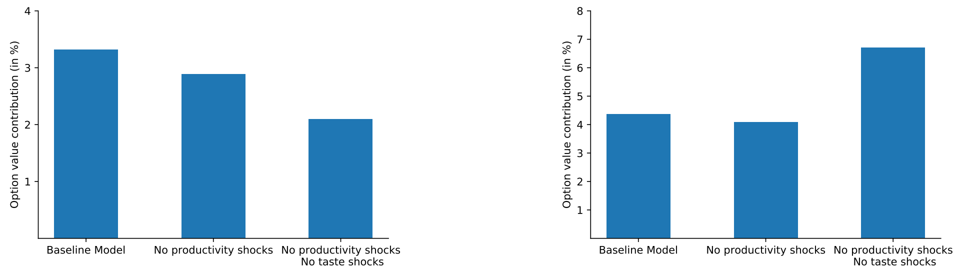


(d) Vocational Schooling at 9th Year

Note: The figure is based on samples of 10,000 simulated schooling careers for each ability group based on the estimated model. Panels (a)-(b) are restricted to high-ability individuals, while panels (c)-(d) average across all ability groups. Each panel provides a complier characterization based on model simulations where we turn off the option value of a particular schooling choice. This calculation compares the total value of schooling and the value of schooling net of the option value contribution to the next best alternative. The option value contribution is defined in Equation (2.5). Always-takers (never-takers) always (never) choose to continue with another year of schooling, irrespective of the option value contribution, while marginal individuals take the additional year only because of the option value contribution. Whenever there are only a few people of a particular ability group that reaches a particular transition we do omit this group from the calculation.

Figure 2.16. 'Complier' Characterization – Switching Off the Option Value.

8th year of schooling as this gives the option to continue later on with the 9th year of vocational schooling, i.e., receive a two-year vocational diploma. At the 9th year of vocational schooling, the large majority at 72% of individuals facing this choice are characterized as always-takers, who attend this year due to the immediate wage



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

Note: The figure is based on samples of 10,000 simulated schooling careers for each ability group based on alternative model specifications. The left panel shows the different option value contributions for medium-ability individuals for the 11th year of academic schooling, while the right panel shows the option value contributions for low-ability individuals for the 8th year of vocational schooling. The option value contribution is defined in Equation (2.5). The bars correspond to different model specification; the first bar corresponds to the estimated model, the medium bar corresponds to an adapted version of the estimated model where productivity shocks (i.e., wage risk) is turned off and the final bar to a model where both productivity and taste shocks are turned off. Whenever there are only a few people of a particular ability group that reaches a particular transition we do omit this group from the calculation.

Figure 2.17. Option Value Contributions – The Role of Shocks to Productivity and Tastes.

gains associated with this choice, while the option value associated with the possibility to continue with a vocational high school matters for only 10% of individuals.

Uncertainty and the Option Value Contributions. In our model, transitory shocks to productivity (i.e., wage risk) and tastes for alternative schooling-work-home choices give rise to uncertainty in agents' decision-making. We now consider how these sources of uncertainty contribute to the option values associated with different educational choices.** As in Figure 2.13, we now perform a series of comparative statics to assess the role of such uncertainty, where we re-compute option values shutting off the various sources of shocks in our model.

We present in Figure 2.17 two different scenarios where the presence of transitory shocks has opposite signed effects on the option value contribution in our model. In

** The existing literature on learning and educational choices in dynamic settings actually emphasizes uncertainty as the primary source of option values, i.e., individual learn about their own ability and preferences as they progress in their schooling career (Stange, 2012; Stinebrickner and Stinebrickner, 2014; Trachter, 2015; Arcidiacono et al., 2016). As the shocks in our model are distributed independently over time, individuals do not update their prior beliefs about their productivity or alternative-specific tastes, i.e., our model does not feature learning over time. We rather focus on the overall value attached to a schooling choice stemming from the possibility of pursuing further education, and not only the value associated with resolution of uncertainty and learning. The presence of transitory shocks may nonetheless affect individuals' schooling choices and alter the likelihood of attending further schooling, i.e., option values can depend on the presence of shocks.

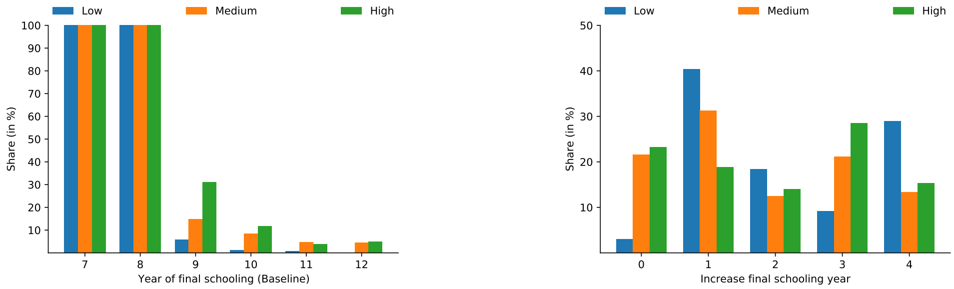
panel (a), we consider the option value of the 11th year in the academic track for individuals of medium ability under different sources of uncertainty. We first turn off the productivity shocks and then also turn off the taste shocks. In the baseline model, the option value contribution amounts to about 3.2% as most individuals of medium ability continue to at least a high school degree. When we turn off the productivity shocks alone, the option value contribution shrinks by about 0.3 percentage points. It further decreases to about 2.1% in a scenario without any uncertainty. This pattern reflects that the continuation of schooling becomes less likely when we reduce the extent of uncertainty. Specifically, for some of the medium-ability individuals facing the decision to attend 11th year of academic schooling, the decision to further attend college is driven by the realization of productivity and/or taste shocks. These individuals decide to attend college only as a result of receiving a low productivity shock, thus facing low opportunity cost of continued schooling, or a high taste shock for schooling. As we successively remove these realizations, the option value of attending the 11th academic year thus declines for these individuals.

In panel (b) of Figure 2.17, we consider another scenario showing how the presence of transitory shocks affects the option value contribution in our model. Here, we consider the option value of the 8th year in the vocational track for individuals of low ability under different sources of uncertainty. In the baseline model, the option value contribution is sizeable at above 4%. When we turn off the productivity shocks alone, the option value remains almost unchanged, but when we remove taste shocks this value increase to almost 7%. This pattern reflects that some among the low-ability individuals in our baseline model who drop-out at the 8th year of vocational schooling do so due to the realization of taste shocks. Once we remove these shocks from our model, their likelihood of continuing beyond the 8th year increases even further, so that the option value of this choices increases further.

2.4.3 Policy Evaluation

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

The Norwegian Compulsory Schooling Reform. As described in Section 2.3.4, the Norwegian compulsory schooling reform increased the minimum schooling requirement from seven to nine years, and was gradually introduced in different



(a) By Ability **(b)** By Ability, Among Early Drop-outs

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

Figure 2.18. Compliance to the Norwegian Compulsory Schooling Reform.

municipalities in different years. In our analysis thus far we used individuals born 1955-1960 who were not exposed to the reform and relied on the reform variation in an out-of-sample validation of our model. We now use our estimated model to shed light on the compliance to this reform by ability and early drop-out status. In panel (a) of Figure 2.18, we show the fractions of individuals by their final year of schooling in the baseline scenario (i.e., pre-reform) along the horizontal axis that change their schooling choices due to the reform. By construction, since the post-reform compulsory schooling is nine years, all individuals that previously decided to stop after seven or eight years are affected. Notably, as discussed in Section 2.3.4, some of these individuals even increase their schooling beyond the new minimum requirement. Such "inframarginal" responses in our model can be explained by the presence of option values; by forcing individuals to attend nine years of schooling, we also bring them closer to transitions that make a high school diploma within reach.[‡]

More interestingly, our model also predicts alterations in the educational trajectories among those who in the baseline scenario actually had attended nine or more years of schooling. While the presence of option values can trigger the "inframarginal" responses discussed above among those with less than nine years of

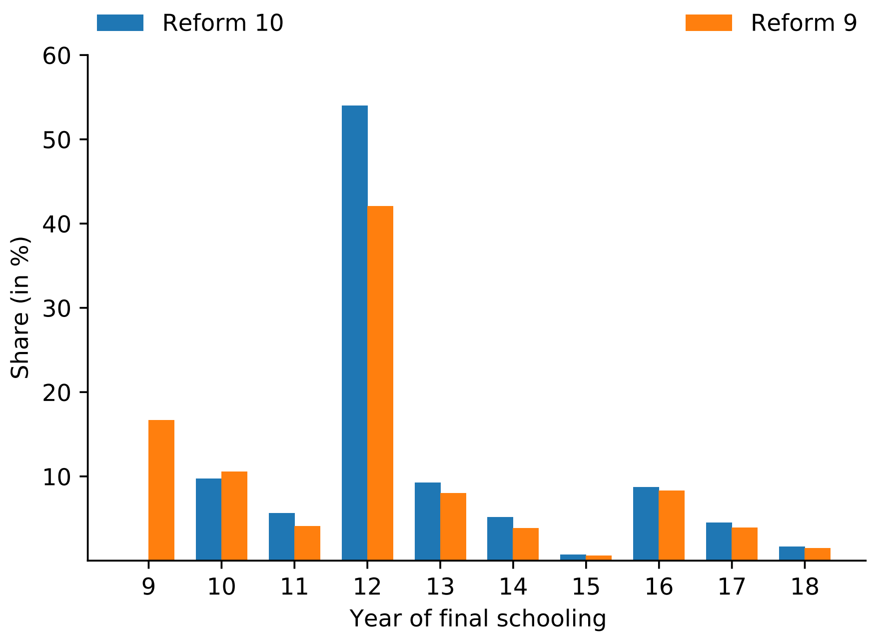
[‡] Indeed, we relied on the extent of such "inframarginal" responses for the model validation in Section 2.3.4.

schooling, an additional mechanism of re-enrollment possibilities is at play when we consider those having nine or more years of schooling pre-reform. Prior of the reform, 10% of individuals had dropped out either after the 7th or 8th grade but then re-enrolled at a later time. Since the reform rules out any interruptions between 7th and 9th year of schooling, the educational trajectories individuals who earlier dropped out after the 7th or 8th grade and re-enrolled are also affected. Indeed, about 40% of those who end up with only nine years of schooling in the baseline scenario increase their final schooling level after the reform. They do so because they no longer face the considerable re-enrollment costs they had to incur in the baseline scenario where they dropped out after the 7th or 8th year.

In panel (b) of Figure 2.18, we show that the compulsory schooling reform affects individuals who initially dropped out after the 8th year of schooling in our model. Around 20% of the early drop-outs with medium- and high-ability do not increase their final years of schooling post reform; these individuals all re-enrolled even in the baseline scenario and attained at least nine years of schooling in the end. Around 30% increase their schooling by one year and thus only meet the new requirement, while around 25% increase their schooling level by four years and thus attain a high school degree after the reform. Taken together, option values and re-enrollment are important channels that are useful to explain these compliance patterns.

Compulsory High School Enrollment Policy. Another policy we consider next is the introduction of compulsory high school enrollment, which requires all individuals to attend ten years of schooling, i.e., one more year than the Norwegian compulsory schooling reform. Figure 2.19 compares the distributions of final years of schooling in our model between the simulated reform with the nine year of compulsory schooling ('Reform 9') and the compulsory high school enrollment policy ('Reform 10'). On average, the latter policy increases schooling by yet another 0.5 years and has impacts along the distribution of schooling.

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



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

Figure 2.19. Compliance to Compulsory High School Enrollment ('Reform 10').

2.5 Conclusion

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

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

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

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

Appendix

A.1 Specifications of Immediate Reward Functions

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

Choice Alternative: Work.

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

$$\underbrace{\zeta_W(k_t, \boldsymbol{h_t}, t, a_{t-1}, e_{j,W})}_{\text{Non-Pecuniary Component}} + \underbrace{w(k_t, \boldsymbol{h_t}, t, a_{t-1}, e_{j,W}, \epsilon_{W,t})}_{\text{Wage Component}}$$

Wage Component

$$\begin{aligned}
w(k_t, \boldsymbol{h_t}, t, a_{t-1}, e_{j,W}, \epsilon_{W,t}) &= r \cdot x(k_t, \boldsymbol{h_t}, t, a_{t-1}, e_{j,W}, \epsilon_{W,t}) \\
x(k_t, \boldsymbol{h_t}, t, a_{t-1}, e_{j,W}, \epsilon_{W,t}) &= \exp\big(\Gamma(k_t, \boldsymbol{h_t}, t, a_{t-1}, e_{j,W}) \cdot \epsilon_{W,t}\big) \\
\Gamma(k_t, \boldsymbol{h_t}, t, a_{t-1}, e_{j,W}) &= e_{j,W} + \beta_{1,w} \cdot h_t^A + \beta_{2,w} \cdot h_t^V + \beta_{3,w} \cdot k_t + \beta_{4,w} \cdot (k_t)^2 \\
&\quad + \sum_{d \in \{9,12,16\}} \gamma_{d,w}^A \cdot I[h_t^A \geq d] + \sum_{d \in \{9,12\}} \gamma_{d,w}^V \cdot I[h_t^V \geq d] \\
&\quad + \eta_{1,w} \cdot I[a_{t-1} = W] \\
&\quad + \nu_{1,w} \cdot (t - 15) + \nu_{2,w} \cdot I[t < 17]
\end{aligned}$$

Non-Pecuniary Component

$$\begin{aligned}
\zeta_w(k_t, \boldsymbol{h_t}, t, a_{t-1}, e_{j,W}) &= e_{j,W} + \beta_{2,W} \cdot I[k_t > 0] + \beta_{3,W} \cdot I[t < 17] \\
&\quad + \beta_{4,W} \cdot k_t + \beta_{5,W} \cdot h_t^A + \beta_{6,W} \cdot h_t^V \\
&\quad + \sum_{d \in \{9,12,16\}} \vartheta_{d,W}^A \cdot I[h_t^A \geq d] \\
&\quad + \sum_{d \in \{9,12\}} \vartheta_{d,W}^V \cdot I[h_t^V \geq d]
\end{aligned}$$

Choice Alternative: Academic Schooling.

$$\begin{aligned}
\zeta_A(k_t, \boldsymbol{h_t}, t, a_{t-1}, e_{j,A}, \epsilon_{A,t}) &= e_{j,A} + \beta_{1,A} \cdot I[a_{t-1} = A] + \beta_{2,A} \cdot I[a_{t-1} = V] \\
&\quad + \beta_{3,A} \cdot (t - 15) + \beta_{4,A} \cdot (h_t^V - 7) \\
&\quad + \beta_{6,A} \cdot I[a_{t-1} = A] \cdot I[h_t^A \geq 12] \\
&\quad + \beta_{7,A} \cdot I[\text{HS Proximity} = 1] \\
&\quad + \sum_{d \in \{9,12,16\}} \vartheta_{d,A}^A \cdot I[h_t^A \geq d] \\
&\quad + \epsilon_{A,t}
\end{aligned}$$

Choice Alternative: Vocational Schooling.

$$
\begin{aligned}
\zeta_V(k_t, \boldsymbol{h_t}, t, a_{t-1}, e_{j,V}, \epsilon_{V,t}) \ = \ & e_{j,V} + \beta_{1,V} \cdot I[a_{t-1} \ = \ A] + \beta_{2,V} \cdot I[a_{t-1} \ = \ V] \\
& + \beta_{3,V} \cdot (t - 15) + \beta_{4,V} \cdot (h_t^A - 7) \\
& + \beta_{7,V} \cdot I[\text{HS Proximity} \ = \ 1] \\
& + \sum_{d \in \{9,12\}} \vartheta_{d,V}^A \cdot I[h_t^V \ \geq \ d] \\
& + \epsilon_{V,t}
\end{aligned}
$$

Choice Alternative: Staying at Home.

$$
\begin{aligned}
\zeta_H(k_t, \boldsymbol{h_t}, t, a_{t-1}, e_{j,H}, \epsilon_{H,t}) \ = \ & e_{j,H} + \beta_{1,H} \cdot I[t \ < \ 17] \\
& + \sum_{d \in \{12,16\}} \vartheta_{d,H}^A \cdot I[h_t^A \ \geq \ d] + \vartheta_{12,H}^V \cdot I[h_t^V \ \geq \ 12] \\
& + \epsilon_{H,t}
\end{aligned}
$$

A.2 Estimation Results

Choice Alternative: Work.

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

Table A.1. Choice Alternative: Work – Wage Component.

		Low Ability	**Medium Ability**	**High Ability**
Constant Term		10.3	10.1	9.7
		(0.00074)	(0.00077)	(0.00085)
Years of Academic Schooling	$\beta_{1,w}$	0.11372	0.15632	0.18123
		(0.00007)	(0.00002)	(0.00003)
Years of Vocational Schooling	$\beta_{2,w}$	0.16168	0.13436	0.13707
		(0.00007)	(0.00005)	(0.00002)
Academic Middle School Diploma	$\gamma^{A}_{9,w}$	0.09542	0.05577	0.06588
		(0.00025)	(0.00021)	(0.00015)
Vocational Middle School Diploma	$\gamma^{V}_{9,w}$	0.00862	0.01748	0.02278
		(0.00033)	(0.00013)	(0.00014)
Academic High School Diploma	$\gamma^{A}_{12,w}$	-	0.05320	0.10376
		(-)	(0.00024)	(0.00020)
Vocational High School Diploma	$\gamma^{V}_{12,w}$	0.02199	0.00614	0.11436
		(0.00021)	(0.00011)	(0.00016)
College Degree	$\gamma^{A}_{15,w}$	-	0.00940	0.05349
		(-)	(0.00034)	(0.00021)
Years of Work Experience	$\beta_{3,w}$	0.10725	0.13831	0.15012
		(0.00005)	(0.00003)	(0.00004)
Years of Work Experience Squared	$\beta_{4,w}$	-0.05463	-0.07934	-0.10123
		(0.00011)	(0.00009)	(0.00010)
Period	$\nu_{1,w}$	-0.07726	-0.09627	-0.10092
		(0.00003)	(0.00001)	(0.00001)
Lagged Choice: Work	$\eta_{1,w}$	0.34907	0.32721	0.22061
		(0.00046)	(0.00031)	(0.00058)
Latent Type 1	$e_{1,w}$	-0.00454	-0.00107	0.15594
		(0.00099)	(0.00112)	(0.00096)
Latent Type 2	$e_{2,w}$	-0.02594	0.00379	-0.08258
		(0.00085)	(0.00097)	(0.00093)

Table A.2. Choice Alternative: Work – Non-Pecuniary Component.

		Low Ability	**Medium Ability**	**High Ability**
Constant Term		172902.6	149525.8	189391.9
		(521.6)	(350.9)	(443.9)
Years of Academic Schooling	$\beta_{5,W}$	1401.4	-1473.3	1307.3
		(52.5)	(36.3)	(43.1)
Years of Vocational Schooling	$\beta_{6,W}$	11101.5	13889.9	12560.2
		(33.4)	(30.7)	(36.2)
Academic Middle School Diploma	$\theta^{A}_{9,W}$	1854.0	-14817.8	-5530.7
		(111.0)	(86.0)	(71.9)
Vocational Middle School Diploma	$\theta^{V}_{9,W}$	-1400.6	3053.7	12320.1
		(123.1)	(64.6)	(61.5)
Academic High School Diploma	$\theta^{A}_{12,W}$	-	4824.3	5677.8
		(-)	(106.4)	(107.1)
Vocational High School Diploma	$\theta^{V}_{12,W}$	-1356.1	27757.1	14234.4
		(115.0)	(68.9)	(67.9)
College Degree	$\theta^{A}_{16,W}$	-	16702.5	23311.4
		(-)	(350.9)	(157.1)
Years of Work Experience	$\beta_{4,W}$	11976.9	5536.4	6688.2
		(25.5)	(22.7)	(21.3)
Any Past Work Experience	$\beta_{2,W}$	117431.5	116545.1	81132.1
		(400.3)	(298.4)	(302.0)
Latent Type 1	$e_{1,W}$	3375.7	2306.1	-15816.0
		(949.2)	(560.4)	(865.9)
Latent Type 2	$e_{2,W}$	-11346.0	1865.5	2609.0
		(1096.6)	(635.5)	(476.3)

Choice Alternative: Academic Schooling.

Table A.3 presents the point estimates and the standard errors for the parameters determining the immediate utility from academic schooling.

Table A.3. Choice Alternative: Academic Schooling.

		Low Ability	Medium Ability	High Ability
Constant Term		-83055.2	45869.0	-39418.3
		(442.5)	(428.8)	(343.8)
Academic High School Diploma	$\theta^{A}_{12,A}$	-	103657.6	110434.9
		(-)	(883.4)	(454.3)
Academic Middle School Diploma	$\theta^{A}_{9,A}$	-	52943.8	87702.0
		(-)	(221.4)	(522.8)
Post High School Diploma Return	$\beta_{6,A}$	-	17196.0	41794.8
		(-)	(439.9)	(289.1)
College Degree	$\theta^{A}_{16,A}$	-	135069.8	146769.2
		(-)	(1910.9)	(475.5)
Lagged Choice: Academic Schooling	$\beta_{1,A}$	47152.9	56605.9	84114.3
		(577.2)	(268.5)	(153.8)
Lagged Choice: Vocational Schooling	$\beta_{2,A}$	-550.9	-11344.4	63379.8
		(1448.4)	(1083.2)	(727.4)
Years of Vocational Schooling, Lagged	$\beta_{4,A}$	-38108.7	-89136.7	-
		(457.8)	(550.7)	(-)
Local High School Proximity	$\beta_{7,A}$	17157.6	21213.7	21299.7
		(429.1)	(283.4)	(238.3)
Period	$\beta_{3,A}$	-17150.2	-11194.6	-53514.6
		(107.9)	(52.1)	(80.4)
Type 1	$e_{1,A}$	-3080.6	-2304.3	12779.2
		(1115.5)	(870.2)	(845.2)
Type 2	$e_{2,A}$	-9954.3	2433.7	-12441.0
		(992.4)	(702.1)	(622.3)

Choice Alternative: Vocational Schooling.

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

Table A.4. Choice Alternative: Vocational Schooling.

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

Choice Alternative: Staying at Home.

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

Table A.5. Choice Alternative: Staying at Home.

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

Time Preferences and the Distribution of Shocks.

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

Table A.6. Time Preferences and Distribution of Shocks.

	Low Ability	Medium Ability	High Ability
Discount Rate	0.96586	0.95933	0.95850
	(0.00006)	(0.00005)	(0.00003)
Shock SD Work	0.30237	0.33056	0.15257
	(0.00066)	(0.00053)	(0.00041)
Shock SD Academic	263544.4	244771.0	366191.6
	(0.00099)	(0.00042)	(0.00045)
Shock SD Vocational	143429.8	183672.8	154709.2
	(0.00041)	(0.00017)	(0.00030)
Shock SD Home	1008774.6	916222.1	789137.5
	(0.00026)	(0.00024)	(0.00023)

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Chapter 3

Macroeconomic Expectations in Turbulent Times

Joint with Hans-Martin von Gaudecker

3.1 Introduction

Effective macroeconomic policy in times of increased economic uncertainty requires understanding how households will adjust their expectations in the presence of such uncertainty. Macroeconomic models usually assume full information rational expectations to derive optimal policy responses to various economic shocks. Past research on subjective expectations has generally rejected full-information rational expectations and identified various factors that drive households' macroeconomic expectations. They have found that personal experiences, cognitive skills, media consumption, and differences in political preferences matter for household expectations[⋆]. Hence, there are many factors that could drive household expectations, according to the literature, but it is unclear which of them matters the most in times of increased uncertainty.

This paper provides a comprehensive summary of household's macroeconomic expectations in times of increased economic uncertainty. In particular, we assess

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⋆. See Bachmann, Topa, and Klaauw (2022) for a summary. Detailed credits are given below.

which economic scenarios households expect in the presence of different shocks, what factors explain heterogeneity in expected economic scenarios during uncertain times, and how stable household expectations are in times of increased uncertainty.

We analyze a representative household panel of macroeconomic expectations between 2020 and 2022. The panel starts at the onset of the coronavirus pandemic in April 2020 and goes until April 2022, when inflation was rising, and the Russian invasion of Ukraine had just begun. Hence, our data contains two episodes characterized by increased economic uncertainty, making it an ideal setting to address our questions. We collect data on household expectations for unemployment, GDP growth, and inflation. At each of the four survey dates, we have asked people to indicate their expectations for the current year and two upcoming years. This leaves us with a detailed panel of macroeconomic expectations between April 2020 and April 2022.

People are unlikely to think about economic aggregates in isolation. Their current perception of the economy and the set of relevant news they consider probably have implications for several macroeconomic aggregates. Even if they are unable to come up with proper economic expectations or do not want to put effort into answering the survey questions, considering the combination of expectations is informative as they are more likely to produce combinations that make little sense. Thus, if we track the combination of economic aggregates that individuals choose in response to an economic shock, we get a more detailed picture of what drives changes in average expectations. We refer to a combination of economic expectations in different dimensions as an expected economic scenario. We use a k-means clustering algorithm to summarize and track scenario choice over time. The k-means algorithm identifies a predefined number of scenarios as cluster centers and assigns each expected scenario to the closest cluster center. This method approximates each expected scenario with one element in a vector of scenarios with a predetermined length, making it easy to summarize and follow scenario choice over time. We separately cluster expectations indicated in 2020 and 2022 as they have been indicated under different economic circumstances. We then document what economic scenarios people expect during the COVID-19 pandemic and after the surge in inflation in early 2022. Then, we associate scenario choice with various characteristics at different points in time. Lastly, we consider how individuals update their economic scenarios and associate updating patterns with background characteristics.

In the first step, we summarize the distribution of economic scenarios across interview dates and time horizons in 2020 and 2022, respectively. With the advent of the pandemic in 2020, most individuals anticipated scenarios with combinations of unemployment and growth that align with an economic downturn in 2020. However, the extent and duration of this impact are subjects of significant disagreement. Around a third of respondents expected a scenario close to the pre-pandemic average for 2022, while around two-thirds expected the pandemic to have a more permanent impact. We document that a significant part of the increase in disagreement in early 2020 is driven by excessively pessimistic scenarios and by scenarios that make little sense. Furthermore, we find that inflationary expectations are associated with a combination of unemployment and growth expectations corresponding to a strong economic downturn. Considering scenario choice in December and September reveals that people updated their expectations at different rates. Many people switched to a more optimistic assessment in September, while others still chose pessimistic scenarios in December.

In 2022, people disagree on whether inflation will be associated with a significant deterioration of the real economy. Around 40 % expect scenarios for 2022, which feature increased inflation and either negative growth or a significant increase in unemployment. People who expect inflation to be associated with an economic downturn also believe that inflation will be persistent. In contrast, around one-third of the people who did not associate inflation with an economic downturn expect inflation to return to normal levels until 2024.

In the next step, we use a LASSO procedure to explain scenario choice at different points in time. We find that lower statistical reasoning abilities predict excessively pessimistic scenarios or scenarios that make little sense at a particular time. This finding confirms that people have varying abilities to express their expectations accurately and that part of the observed disagreement is due to noise, limited understanding, or heuristics. People in a less comfortable economic situation chose more pessimistic scenarios. Stock market participants had more accurate expectations in December 2020 and were more likely to believe that the economy would recover from the pandemic in the medium run. Disagreement about the impact of the shock and the most relevant economic news to consider are other important drivers of scenario choice. Expecting longer restrictions at the onset of the pandemic predicts more pessimistic expectations. At the same time, people who considered supply-side factors into account in 2022 were more likely to pick a scenario that features an economic downturn. Lastly, we document that different variables indicating trust in various institutions strongly predict pessimistic long-term expectations in 2020 and 2022.

In the last part of the paper, we analyze how individuals update their expected scenarios across time. This allows us to analyze the stability of expected scenarios in uncertain times. Furthermore, we can relate some of the relevant predictors of scenario choice with sequences of scenarios that people choose over time, which allows us to dig deeper into how various background characteristics affect belief formation. We first consider transitions for 2020 expectations between September and December 2020 to measure how noisy macroeconomic expectations are on the individual level. In both cases, there has been little uncertainty about the realization of outcomes. In December 2020, the correct values were already known. We document that around 15% of the respondents update to a scenario that is further away from the truth than what they indicated in September, which implies that expectations are volatile on a personal level even in the short run without the resolution of any relevant information.

Next, we associate background characteristics with the sequence of scenarios people choose across different interview dates, which we refer to as scenario patterns. We focus on scenario patterns of 2022 expectations during 2020 since they are less noisy and contain less uncertainty about the current economic situation than shorter-term expectations. We differentiate between people who are consistently pessimistic or optimistic across the year, people who update from pessimistic to optimistic scenarios in September or December, and people who indicate other patterns that are largely at odds with the dynamics of information revelation in 2020. We find that consistently pessimistic people have lower trust in institutions. Optimistic people and people who update from a pessimistic to an optimistic scenario in September or December mainly disagree about the length of restrictions related to the pandemic, and people with other patterns have lower statistical reasoning abilities. These results show that different relevant background characteristics are associated with different scenario patterns. We also find that scenario patterns in 2020 predict scenario choice in 2022 in a way consistent with their definition, which shows that belief formation is at least partly persistent. Pessimistic individuals are more likely to associate inflation with negative growth and unemployment. People who were optimists during the pandemic are more likely to expect that inflation will return to normal levels until 2024 and are less likely to associate inflation with an economic downturn. People who chose any other sequence of scenarios in 2024 are likelier to indicate scenarios with no inflation for 2022 in April 2022.

The distribution of scenario sequences and their correlation with background characteristics suggest that different types of heterogeneity drive disagreement in times of economic uncertainty. Most of the disagreement in early 2020 is associated with different opinions about how current developments will affect the economy. However, this disagreement fades as more information is resolved over time. Other people are more persistently pessimistic and less likely to change their scenario as new information appears. They tend to have lower trust in institutions than others and are more likely to sympathize with the right-wing populist party in the Netherlands. Finally, there are people with volatile expectations, many of whom have lower statistical reasoning abilities.

This paper contributes to a literature that aims to explain how households form macroeconomic expectations. Kuchler and Zafar (2019) and Malmendier and Nagel (2016) document the importance of personal experiences for macroeconomic expectations. Weber, Gorodnichenko, and Coibion (2022) and D'Acunto et al. (2021) document how exposure to grocery prices drives macroeconomic expectations of households. Andre et al. (2023) and Andre et al. (2022) relate heterogeneity in macroeconomic expectations to differences in narratives and mental models of the macroeconomy. Gerber and Huber (2010) document that partisan preferences in the US drive economic expectations. D'Acunto et al. (2019) find that cognitive skills are associated with people's inflation expectations. Our paper combines a panel of macroeconomic expectations through two years and two distinct times of economic uncertainty with a broad set of background characteristics. This allows us to document how the mechanisms identified in the literature jointly drive macroeconomic expectations in a broad population. Some papers have analyzed macroeconomic expectations during the pandemic or other times of increased economic uncertainty. Dietrich et al. (2022) analyze a repeated cross-section of macroeconomic expectations at the onset of the pandemic. They use subjective expectations as identified moments in a macroeconomic model and find that the economic shock associated with the pandemic must be significant to justify the change in expectations. Fofana, Patzelt, and Reis (2024) summarize the most important characteristics of disagreement in inflation expectations across households. They document important variables, the implications of significant disagreement, and the evolution of disagreement during economic shocks. We consider a more detailed panel and focus on expected scenarios instead of individual dimensions of macroeconomic expectations. This, for example, allows us to conclude that a significant portion of the change in average expectations at the beginning of the pandemic is driven by excessively pessimistic scenarios and scenarios that make little sense. The empirical strategy we use in this paper is inspired by Gaudecker and Wogrolly (2022), who use a method proposed by Bonhomme, Lamadon, and Manresa (2017) to explain dynamic heterogeneity in stock market beliefs.

3.2 Data, Summary Statistics and Method

3.2.1 Data

Between April 2020 and 2022, we fielded four questionnaires about macroeconomic expectations in the Longitudinal Internet Studies for the Social Sciences (LISS) panel. The first three questionnaires were fielded in April, September, and December 2020, respectively, while the last questionnaire was fielded in April 2022. At each point, we asked people about their unemployment, GDP growth, and inflation expectations for the current year and the two subsequent years. In April 2020, we additionally asked people to recall their expectations from February 2020. In April 2022, we additionally asked people to recall unemployment, GDP growth, and inflation in 2020 and 2021. The LISS panel is based on a probability sample of individuals registered by Statistics Netherlands; it has been running since 2007 and consists of roughly 4,000 Dutch households comprising about 7,000 individuals. It is administered by CentERdata, a Dutch survey research institute affiliated with Tilburg University. All five modules were addressed to all panel members at the age of at least 16 years. The response rate was more than 80% in all surveys. While not all respondents participated in all five waves, the distribution of demographic variables is very stable over time. All questions of the surveys during 2020 are documented at https://liss-covid-19-questionnaires-documentation.readthedocs.io. Individuals were asked to provide answers in a multiple-choice format, as shown in Figure 3.1

We would like to know what you expect the unemployment rate to be in the Netherlands. The unemployment rate in the period 2017-2019 was about 4% per year. What are your expectations about the unemployment rate?

	less than 3.0%	3.0% to 6.0%	6.0% to 9.0%	9.0% to 12.0%	12.0% or greater
2020	❑	❑	❑	❑	❑
2021	❑	❑	❑	❑	❑
2022	❑	❑	❑	❑	❑

Notes: Question from 2020. In April 2022, we asked: "We willen graag weten wat u verwacht dat het werkloosheidscijfer in Nederland zal zijn. Gemiddeld was het werkloosheidspercentage in de periode 2017-2019, dus voor de coronapandemie, ongeveer 4% per jaar.

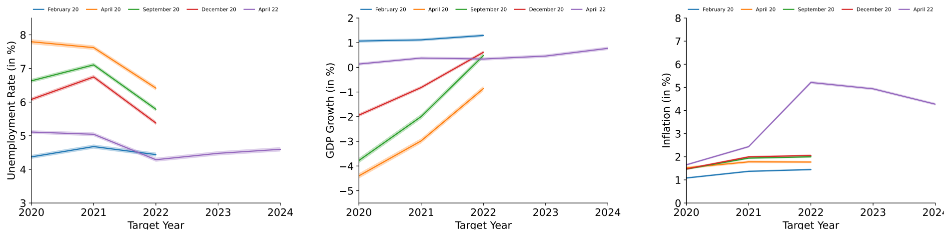
Wat denkt u dat het werkloosheidscijfer was in de afgelopen twee jaar? En wat denkt u dat het dit jaar en de komende twee jaar zal zijn?

Figure 3.1. Example question: Unemployment rate for 2020, 2021, and 2022 as expected before the Coronavirus pandemic

We use a spline-based procedure to map the multiple-choice answers into numerical expectations. First, we use the pchip algorithm (Fritsch and Butland, 1984) to impute the probability density function of the distribution of the economic expectation. We then use the probability density function to assign each multiple-choice response the mean expectation within the interval. We apply this procedure separately for each dimension, expectation horizon, and interview date.

3.2.2 Average expectations

Figure 3.2 shows the average expectations for 2020–2024. There is one line per survey date; the values for 2020 and 2021 for the April 2022 questionnaire are backward-looking. Expectations strongly changed at the onset of the pandemic. On average, people expect 8% unemployment and 5% negative growth. While average expectations for 2022 are a bit less extreme, people expect the pandemic to have a lasting effect initially. In strong contrast, average inflation hardly reacted to the pandemic. The average increase is less than one percentage point, which is still below the ECB target. Expectations only recovered slowly over the year. In December 2020, average expectations for 2020 were still more pessimistic than the realization, which should have been mostly public information at this point. People are moderately optimistic on average in 2022. They expect unemployment to be around 4.5%



(a) Unemployment Expectations **(b)** Growth Expectations **(c)** Inflation Expectations

Note: This figure shows average macroeconomic expectations between 2020 and 2022. Each panel represents a different macroeconomic aggregate. The lines differ in length since we asked people for different time horizons over time. In 2020, they were asked for their expectations for 2020, 2021, and 2022. In 2022, they were asked to recall 2020 and 2021 and indicate their expectations for 2022, 2023, and 2024. The expectations for February 2020 were asked as recall questions in April 2020.

Figure 3.2. Mean Macroeconomic Expectations

and zero growth in 2022, which will increase in 2023-2024. However, they expect substantially higher and persistent inflation, which is consistent with the news situation in early 2022.

3.2.3 Method

Identifying Scenarios: We want to document how people form economic expectations in several dimensions simultaneously. However, descriptively tracking several dimensions is not straightforward. Conventional methods, such as linear regressions, will likely miss essential patterns in higher dimensions if different variables share a nonlinear relationship. To circumvent this issue, we use a k-means clustering algorithm. The algorithm identifies different combinations of macroeconomic aggregates as cluster centers and assigns each expected scenario to one of these clusters. The number of clusters that the algorithm identifies needs to be specified ex-ante. The algorithm reduces each expected economic scenario to one of the few scenarios identified as cluster centers. This makes it substantially easier to track scenario choice over time since we reduce a high-dimensional expectation to one element in a vector of scenarios with a predetermined length. However, each assigned scenario only approximates the actual scenario that people have indicated. In the result section, we will show the spread within each cluster and discuss the precision of the approximation.

In our dataset, we observe unemployment, inflation, and growth expectations at four different time points for several expectation horizons. We consider the 2020 and 2022 interview dates separately. First, we use the interpolation procedure described in the previous section to map stated categories into numerical beliefs. We let the clustering algorithm run over all combinations of unemployment, growth, and inflation expectations for each category, disregarding the expectation horizon and interview date. For 2020, we thus cluster over a dataset that contains people's expectations in February, April, September, and December 2020 for time horizons 2020, 2021, and 2022. For 2022, we cluster over a dataset that contains people's expectations in April 2022 for time horizons 2022, 2023, and 2024. We choose the number of groups in each environment based on the tractability and precision of the resulting approximation. Details will be provided in the result section. The objective of our clustering algorithm looks as follows:

$$\min_{C,\{\mu_j\}} \sum_{j=1}^{k} \sum_{i \in C_j} \|x_i - \mu_j\|^2 \tag{3.1}$$

k is the number of clusters. C_j is the set of indices of data points in cluster j. x_i corresponds to a triple of unemployment, inflation, and growth expectations at a particular time for a certain expectation horizon. μ_j denotes the center of cluster j, which is also a combination of unemployment, inflation, and growth expectations. The algorithm finds the combination of cluster centers or scenarios in our case μ_j and scenario assignments C_j that minimizes Equation 3.1.

Heterogeneity: The LISS data contain a range of background variables that are potentially relevant to household's macroeconomic expectations. These variables include various indicators of a household's economic situation, trust in institutions, expectations in other domains, education, and a measure of statistical reasoning skills. Since there are many potentially relevant variables, we propose to use a LASSO procedure for variable selection. This allows us to focus on the most relevant set of variables. In particular, we estimate a multinomial logit regression with a LASSO penalty term:

$$\min_{\beta_1,\ldots,\beta_K} \left(-\sum_{i=1}^{N} \sum_{k=1}^{K} y_{ik} \log \left(\frac{e^{\beta_k^T x_i}}{\sum_{j=1}^{K} e^{\beta_j^T x_i}} \right) + \lambda \sum_{k=1}^{K} \|\beta_k\|_1 \right) \tag{3.2}$$

y_{ik} is the indicator variable that is 1 if the i-th observation belongs to class k and 0 otherwise. x_i is the vector of predictors for the i-th observation. λ is the regularization parameter controlling the strength of the Lasso penalty. This objective drives weak predictors to zeros and keeps stronger variables. We remove all variables whose absolute average over all categories is lower than a constant. After that, we estimate a regular multinomial logit regression with all remaining variables.

3.3 Results

In this section, we present the results of the clustering analysis. First, we present the clusters for expectations in 2020 and 2022, respectively. Then, we present the most important determinants of cluster choice. In the last section, we consider expectations patterns across time.

3.3.1 Scenarios

We identify four expectation scenarios for 2020 and 2022, respectively. Figure 3.3 and 3.5 show the identified belief scenarios together with the corresponding observations that belong to each scenario. The number of scenarios is motivated by keeping the problem tractable while capturing the most important dimensions of heterogeneity. We show the resulting scenarios if we increase the number of groups to 5 in Section 3.A.2. Adding a group mainly splits one of the scenarios and does not fundamentally change people's assignment to groups in 2020 and 2022.

3.3.1.1 Covid Scenarios

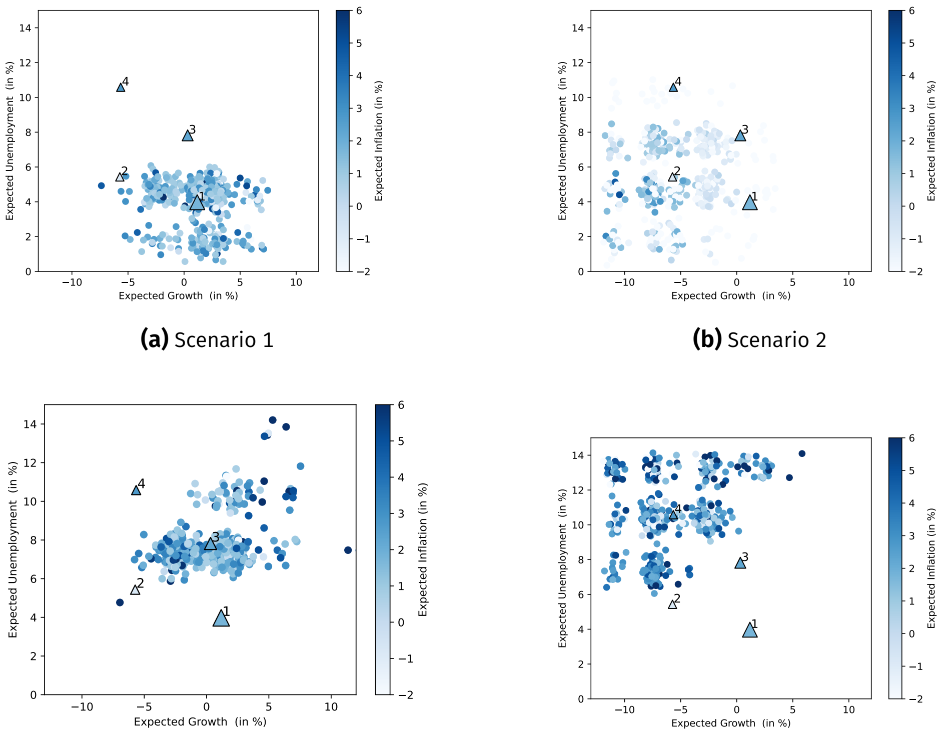
Figure 3.3 shows the four belief scenarios for expectations indicated in 2020. We will first discuss each of the identified scenarios. After that, we will show a summary of scenario choices during 2020.

Scenario 1: Business as Usual: The first scenario corresponds to expecting business as usual and is close to the anchoring scenario we provided. It also includes more pessimistic expectations with an elevated unemployment rate or moderately negative growth. This scenario is most frequently chosen across all interview dates and horizons. One important reason for that is that most respondents indicate this scenario when asked to recall what they expected in February 2020 in April 2020.

Scenario 2: Recession and Low Inflation: The second scenario is characterized by low growth, low inflation, and variable unemployment. Observations at the left part of the cluster indicate a combination of deflation, a strong recession, and comparably low unemployment. At the onset of the pandemic, it is unlikely that people actually referred to a scenario featuring precisely this combination of economic aggregates. It is possible that many people who checked this scenario had something else in mind and associated the scenario with an economic downturn. One potential explanation is that people ticked the lowest option possible for each category. Some observations that are closer to the center and do not feature deflation are close to the actual macroeconomic scenario at the end of 2020. In fact, we observe that expected scenarios in December that are assigned to this cluster tend to be closer to the realization of 2020, while expected scenarios in April are more likely to feature combinations of significant negative growth, deflation, and low unemployment[**]. The interpretation of this scenario thus changes over time.

Scenario 3: Higher Unemployment + Slight Recession: The most salient feature of this scenario is substantially higher unemployment than in the status quo. Growth fluctuates around zero, although the majority is negative, and inflation

⋆⋆. See Figure 3.A.3



(a) Scenario 1 **(b)** Scenario 2

(c) Scenario 3 **(d)** Scenario 4

Note: This figure summarizes identified belief scenarios along with the corresponding observations. The figure shows the result of using a k-means clustering algorithm with five groups on the set of expected scenarios between February and December 2020 for expectation horizons 2020, 2021, and 2022. The y-axis of each panel represents the expected unemployment rate, the x-axis represents the expected growth rate, and the color of each point represents the expected inflation rate. In each panel, all four clusters are indicated as triangles. Each triangle is scaled according to the size of the cluster. Each panel also contains a random sample of the respective group. The random samples are slightly perturbed to improve the visualization.

Figure 3.3. Cluster during Covid.

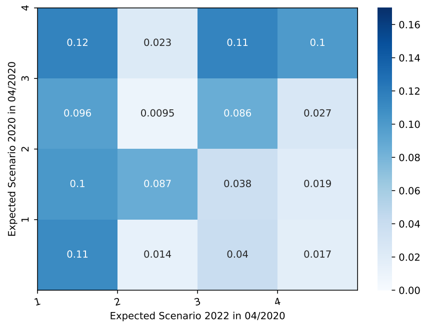
is positive and close to zero. This scenario includes both scenarios featuring a recession and elevated unemployment and scenarios corresponding to a slight recovery of the economy without a decrease in unemployment. Earlier in 2020 and for shorter-term expectations, this scenario is more likely to feature negative growth, while it is more likely to feature positive growth for two-year expectations.

Scenario 4: Mass Unemployment: This scenario includes most expectations with unemployment above 10 percent. The majority of these expectations also feature a severe recession and higher inflation. This scenario contains the most pessimistic expectations, some of which imply economic downturns that have not been observed in the Netherlands since World War 2. At the onset of the pandemic in April, when uncertainty was significant, even some experts predicted large increases in unemployment rates likely to fall into this scenario (see, e.g., Centraal Planbureau (2020)). Expecting this scenario for any time horizon in September or December seems at odds with the state of the economy and the pandemic at that point.

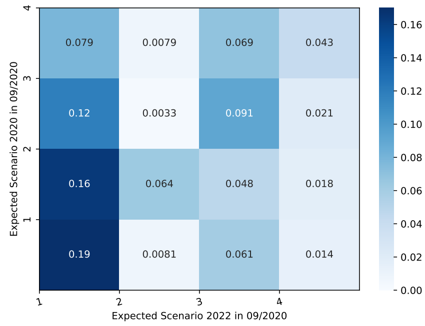
Transitions across expectation horizon: Figure 3.4 shows how individuals transited between scenarios for the current year and two years ahead. While most people believed that the pandemic will lead to an economic downturn in April 2020, there is considerable disagreement about the severity of this impact and its duration. One-third of all respondents chose the mass unemployment scenario, which confirms that many people associated the pandemic and the corresponding policy measures with a massive increase in unemployment. Many of these expectations also feature increased inflation rates, which shows that increased inflation is associated with expecting a relatively strong economic downturn. Around 20% picked the third scenario, which features a less severe economic downturn, while another 25% picked the second scenario, which includes a range of different expectations, some of which combine deflation with negative growth and low unemployment. Since some of the scenarios in the second group feature unrealistic combinations of economic aggregates, it is likely that part of the disagreement in April 2020 is driven by noise.

People also have differing views about whether the economy will recover after two years or whether the pandemic will permanently impact the economy. In April, around a third of respondents believed the economy would recover until 2022, while around two-thirds expected the pandemic to have a more permanent impact. We observe persistence across time horizons, as people who chose the mass unemployment scenario are also more likely to believe that the pandemic will have a permanent impact on the economy. Many people indicated excessively pessimistic scenario patterns. It is unlikely that people actually expected negative economic growth of more than 5% for three years in a row.

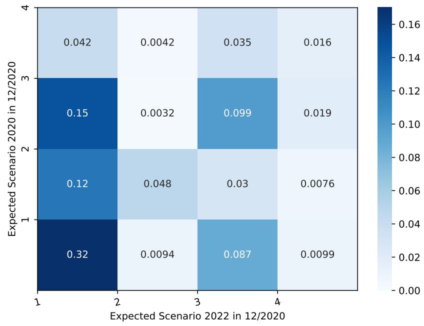
Scenario choice in September and December shows that updating happens at different rates. While people chose more optimistic scenarios in September and December, on average, around 10 % still indicated the mass unemployment scenario for 2020 in December. This is remarkable since it should have been public knowledge in December that the pandemic has not substantially increased unemployment rates in 2020. Around a third of all respondents held pessimistic expectations for 2022 in December. Many individuals who held a biased expectation in December 2020 also believe in a permanent effect on the economy. These people still associated the current economic environment and restrictions with a bad development of the economy. At the end of 2020, around ten percent of the respondents believed that the economic situation would become worse in the medium run.



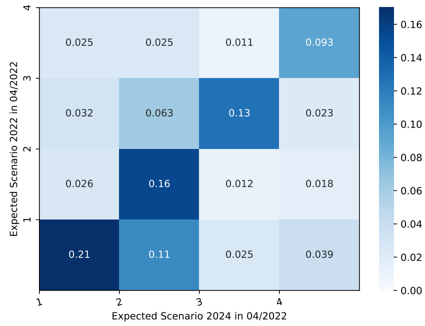
(a) Transition 2020 - 2022 in April 2020



(b) Transition 2020 - 2022 in September 2020



(c) Transition 2020 - 2022 in December 2020



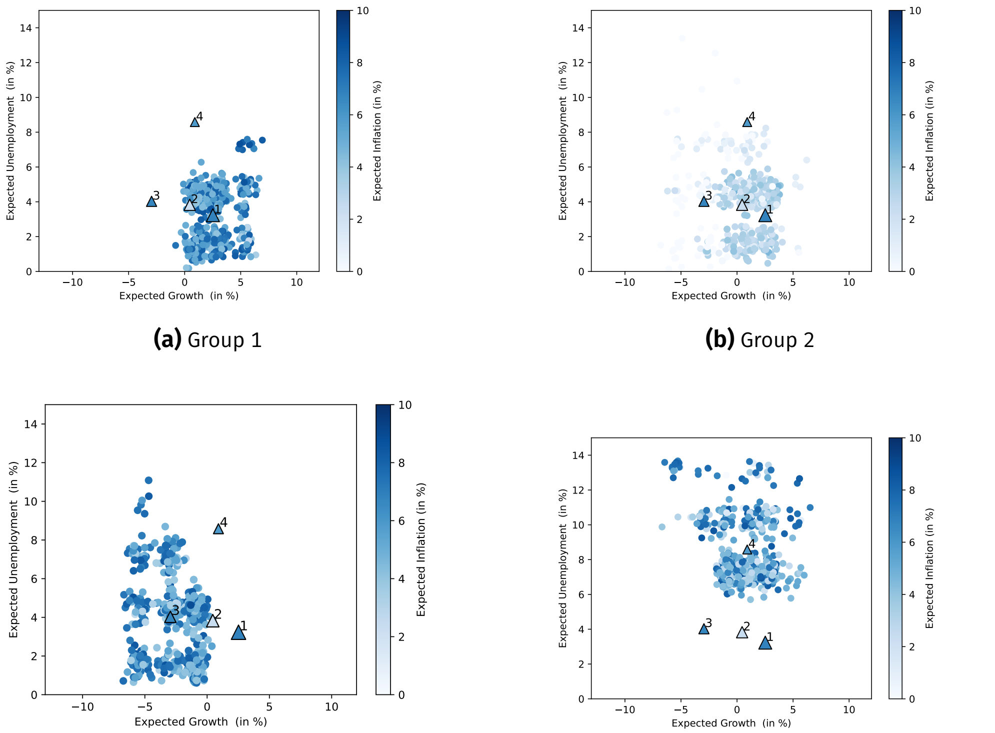
(d) Transition 2022 - 2024 in April 2022

Note: This figure shows transitions between expected scenarios in the year where the survey was taken and two years ahead. People were asked to indicate their expectations for the corresponding year and the two upcoming years at each point. The first three panels show the transition between expected scenarios for 2020 and 2022 for the three interview dates in 2020. The last panel shows the transition between the expected scenario for 2022 and 2024 people that people have indicated at the interview date in 2022. Each of the four panels contains a heatmap with the short-run scenario on the y-axis and the medium-run scenario on the x-axis. Each cell represents a transition between scenarios for the short-run and medium-run. The color of each cell is scaled according to its relative frequency, and each cell is annotated with its relative frequency.

Figure 3.4. Cluster Transition: Current Year.

3.3.1.2 Inflation Scenarios

The second set of scenarios is based on survey responses from 2022 and covers expectations for 2022, 2023, and 2024. We cluster expectations indicated in 2022 separately because the economic environment was different from that in 2020. While the economy largely recovered from the pandemic in 2021, the inflation rate started to rise at the end of that year. Furthermore, the Russian invasion of Ukraine had just started when the survey was fielded. We increase the weighting of the inflation rate relative to the other two factors by 25%. Since the inflation rate was particularly salient in 2022, an essential feature of expectations was how large respondents believed inflation would become in 2022 and whether respondents believed that inflation would cede until 2024. Increasing the importance of inflation makes it more



(a) Group 1

(b) Group 2

(c) Group 3

(d) Group 4

Note: This figure summarizes identified belief scenarios along with the corresponding observations. The figure shows the result of using a k-means clustering algorithm with five groups on the set of expected scenarios in April 2022 for expectation horizons 2022, 2023, and 2024. The y-axis of each panel represents the expected unemployment rate, the x-axis represents the expected growth rate, and the color of each point represents the expected inflation rate. In each panel, all four clusters are indicated as triangles. Each triangle is scaled according to the size of the cluster. Each panel also contains a random sample of the respective group. The random samples are slightly perturbed to improve the visualization.

Figure 3.5. Cluster during Inflation.

likely to pick up these differences in the identified scenarios. We first discuss the identified scenarios. Then, we discuss scenario choice across the expectation horizon.

Scenario 1: Positive Outlook + Inflation This scenario features positive growth, low unemployment, and relatively high inflation. Most of the expected scenarios in this group forecast little change in growth and unemployment, together with a high inflation rate. The scenario also includes a few observations which forecast very high growth rates. These observations frequently also feature inflation above 6 percent.

Scenario 2: Neutral / Positive Outlook + Low Inflation This scenario is close to the anchoring scenario we indicated in the questions. Most expectations in this scenario include a low inflation rate, a low positive growth rate, and relatively low unemployment. A few observations also contain higher unemployment rates or a slight recession alongside low inflation. People who believed that inflation is only temporary would select this scenario for 2024. At the time of the survey, it was highly likely that the inflation rate would be substantial by the end of the year. Anyone who chose this scenario for 2022 has not incorporated this information in her expected scenario.

Scenario 3: Recession + High Inflation This scenario features a recession, significant inflation, and variable changes in unemployment. Many scenarios in this group feature high inflation, a recession, and comparably low unemployment. Given consistently low unemployment numbers and labor shortages between 2020 and 2022, it may make sense to believe in a recession without a significant increase in unemployment. People who chose this scenario may have believed that the Russian invasion of Ukraine or continued supply problems from China have a detrimental impact on GDP.

Scenario 4: High Unemployment The high unemployment scenario is characterized by high unemployment, high inflation, and growth rates around zero. There was little reason to believe the labor market situation would deteriorate sufficiently to justify choosing this scenario. Respondents who indicated this scenario for any of the horizons must either believe that some of the shocks will have a significant short-run impact on the labor market or have a biased assessment of the current situation.

Cluster Choice: The last panel in Figure 3.4 shows how individuals transited between scenarios for 2022 and 2024 in April 2022. 80% chose a scenario with a significant inflation increase for 2022. 40% of all respondents indicated the third and fourth scenarios, which feature negative growth and high unemployment, respectively, while a third chose the first scenario. Thus, a substantial number believed that the rise in inflation would be associated with an economic downturn. These individuals may have been influenced by the Russian invasion or supply chain issues when they indicated this assessment. Another theory is that people who experience a decrease in real purchasing power due to inflation form a more pessimistic outlook. Particularly, the fourth scenario could be driven by a pessimistic sentiment as there was little reason to believe in a significant short-run increase in unemployment rates in early 2022. We document strong persistence across time horizons, as people who chose the third or fourth scenario for 2022 are most likely to choose the same scenario for 2024. This persistence suggests that disagreement about economic scenarios in 2022 is driven by very different views on the economy's current state and future development. People who indicated the third and fourth scenarios for 2022 also believed that inflation would persist. In contrast, around one-third of the people who selected scenario one expected inflation to return to normal until 2024.

3.3.2 Heterogeneity

Next, we discuss the determinants of scenario choice in 2020 and 2022. Our procedure allows us to associate background characteristics with economic scenarios that people expect rather than just individual economic aggregates. We run a separate LASSO for each expectation horizon in 2020 and 2022, respectively. However, to keep regressions comparable, we use the same penalty term for the 2020 and 2022 scenarios indicated in 2020 and for the 2022 and 2024 scenarios indicated in 2022, respectively. Penalty terms are chosen such that around 50% of the variables that we include are removed[‡]. Since we use the same penalty term for expectations indicated in the same period, the number of coefficients differs across expectation horizons. Tables 3.1 and 3.2 show marginal effects from re-estimated multinomial logit regressions for scenarios in 2020 and Tables 3.A.1 and 3.A.2 show marginal effects from re-estimated multinomial logit regressions for scenarios in 2022. Each number in one of the tables shows the change in the probability of selecting a specific scenario if a particular characteristic is increased by one unit. Whenever we refer to a percentage increase associated with changing a variable, we mean the absolute change in the probability. We have also re-estimated the models for each interview date in 2020 and have visualized the importance of various coefficients over time in Figures 3.6 and 3.7.

We first consider the role of statistical reasoning abilities. The measure that we use goes from zero to four and reflects the result of a series of questions that test statistical reasoning abilities. Statistical reasoning is a relevant aspect of cognitive skills, indicating how well respondents can reason with numbers and probabilities. Table 3.1 shows that in 2020, higher statistical reasoning ability is associated with a one percent lower probability of selecting either the business-as-usual scenario or the second scenario and a 2.5% increase in the likelihood of choosing the mass unemployment scenario for the expectation horizon 2020. People who expected the business-as-usual scenario in April 2020 may have just checked the anchor indicated in the question. The fact that lower statistical reasoning predicts choosing the second scenario supports our earlier assertion that some scenarios, particularly those indicated in April 2020, approximated by this scenario make little sense.

Increasing our measure of statistical reasoning by one unit increases the probability of choosing the first scenario for 2022 by 2.5% and decreases the probability of choosing the second and fourth scenario for 2022 by 1.5% and 0.6%, respectively. This finding supports our assessment that some scenario choices are excessively pes-

‡. We cannot use cross-validation because we want the specification to remain symmetric across categories. We plan to use a group lasso to make this procedure more formal.

Table 3.1. LASSO: Scenarios 2020 during 2020

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Wave September	7.648***	5.148***	-0.479	-12.316***
	(1.502)	(1.341)	(1.344)	(1.113)
Wave December	25.197***	-3.140**	3.942***	-26.000***
	(1.285)	(1.376)	(1.246)	(1.325)
Female	-1.351	-6.379***	3.060***	4.670***
	(1.185)	(1.181)	(1.121)	(1.059)
Couple without children	2.495**	0.434	-2.205*	-0.724
	(1.181)	(1.173)	(1.132)	(1.067)
Income 1500-2500	0.354	-0.463	1.821	-1.712
	(1.501)	(1.520)	(1.437)	(1.340)
Income > 2500	-3.124*	1.296	2.548	-0.720
	(1.727)	(1.708)	(1.642)	(1.524)
Owns Risky Assets	-4.109**	2.637*	1.014	0.458
	(1.704)	(1.600)	(1.641)	(1.534)
Real Estate	2.441*	1.844	-0.954	-3.331***
	(1.414)	(1.421)	(1.313)	(1.225)
3rd Wealth Tercile	2.832**	3.278**	-4.048***	-2.061*
	(1.315)	(1.308)	(1.277)	(1.200)
Statistical Literacy	-0.969*	-1.560***	0.174	2.355***
	(0.568)	(0.565)	(0.543)	(0.521)
Interested Politics	-0.389	2.738***	-2.087**	-0.262
	(0.998)	(0.996)	(0.945)	(0.891)
N	5872	NaN	NaN	NaN
Pseudo R2	0.049534	NaN	NaN	NaN

Note: This table shows marginal effects obtained from a multinomial logit regression of the expected cluster for 2020 during 2020 on a set of background characteristics selected by LASSO. In the first step, we run the LASSO procedure to select variables. In the second step, we run a multinomial logit regression with the selected variables. The marginal effects show the increase in the probability that a person chooses the respective outcome level if the variable in question increases by one unit. See Section 3.A.1 for a description of the scale of each variable.

simistic. People who choose scenarios that feature significant negative growth for three years in a row are likely unaware of the implications of their choice. Figures 3.7 and 3.6 show how the effect of statistical reasoning abilities on scenario choice changes over the year 2020. For 2020 expectations, statistical reasoning abilities are most predictive in April. Contrary to the short-run expectations, the variable becomes more critical towards the end of the year for scenarios 2022. Table 3.A.1 shows that in 2022, lower statistical reasoning abilities predict choosing the high unemployment scenario. This is consistent with the observation that there was little probability of a quick rise in unemployment at the onset of 2022.

Table 3.2. LASSO: Scenarios 2022 during 2020

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Wave September	14.117***	-5.399***	-3.263**	-5.456***
	(1.444)	(0.831)	(1.353)	(0.824)
Wave December	23.704***	-7.542***	-3.763***	-12.399***
	(1.424)	(0.917)	(1.347)	(1.100)
College Educated	0.670	0.067	-0.737	0.000
	(1.370)	(0.814)	(1.272)	(0.847)
Female	-9.788***	1.988***	3.707***	4.093***
	(1.236)	(0.720)	(1.151)	(0.767)
Age 30-50	2.693*	-0.620	-1.019	-1.055
	(1.595)	(0.930)	(1.476)	(0.973)
Income > 2500	-4.035***	-1.765*	4.755***	1.046
	(1.458)	(0.906)	(1.338)	(0.907)
Working	3.249**	0.336	-1.575	-2.011**
	(1.532)	(0.886)	(1.415)	(0.929)
Owns Risky Assets	5.771***	-1.656	-3.483**	-0.632
	(1.759)	(1.136)	(1.670)	(1.156)
Real Estate	1.732	0.110	-1.476	-0.366
	(1.462)	(0.816)	(1.337)	(0.845)
Expect Long Restrictions	-8.259***	2.138***	3.351**	2.770***
	(1.513)	(0.814)	(1.377)	(0.846)
Statistical Literacy	2.540***	-1.490***	-0.398	-0.652*
	(0.634)	(0.356)	(0.586)	(0.375)
Confidence Democracy	3.257***	-0.386**	-1.364***	-1.508***
	(0.327)	(0.177)	(0.295)	(0.173)
Follow Internet News	3.243**	-1.573**	-2.070*	0.400
	(1.368)	(0.765)	(1.254)	(0.809)
Probability Low Income	-0.063***	0.022*	0.010	0.031***
	(0.022)	(0.011)	(0.020)	(0.012)
N	5872	NaN	NaN	NaN
Pseudo R2	0.060607	NaN	NaN	NaN

Note: This table shows marginal effects obtained from a multinomial logit regression of the expected cluster for 2022 during 2020 on a set of background characteristics selected by LASSO. In the first step, we run the LASSO procedure to select variables. In the second step, we run a multinomial logit regression with the selected variables. The marginal effects show the increase in the probability that a person chooses the respective outcome level if the variable in question increases by one unit. See Section 3.A.1 for a description of the scale of each variable.

Past research has demonstrated that individuals extrapolate from their economic experiences. We have included household wealth, income, and subjective measures of economic anxiety and financial comfort. At the beginning of the pandemic, people were asked about the probability that they would receive no or very little income due to the pandemic. A unit increase in this probability leads to a

0.06% decrease in the probability of choosing the first scenario for 2022, which implies that the economy will have recovered by 2022. According to Figure 3.7, this effect becomes stronger over the year. People who experienced more significant economic anxiety at the onset of the pandemic take longer to update their expectations than others. Higher income predicts more pessimistic scenarios for both time horizons. Figures 3.6 and 3.7 show that this is mainly driven by expected scenarios in September. In December, they are similar to the rest for 2022 and more likely to choose a scenario close to the realization for 2020. Table 3.A.1 shows that people who would have a hard time spontaneously paying a 500-euro bill are more likely to choose the third or fourth scenario for 2022 in 2022, which associates inflation with an economic downturn. These people are likely to be particularly affected by an increase in inflation, which would explain why they chose more pessimistic scenarios in early 2022. It is important to note that the regressions contain several measures of the household's economic situation that are likely to be covariant, making it challenging to interpret individual effects. However, the overall relevance of many of these variables shows the importance of the economic situation for a household's macroeconomic expectations.

Stock market participation is a relevant driver of scenario choice in our data. Successful participation in the stock market may require people to be informed and to have reasonable expectations about the future development of the economy. Individuals who hold risky assets are 5 percent more likely to believe that the economy will have recovered until 2022 in 2020, and they are less likely to associate the rise in inflation with negative growth or higher unemployment. At the end of 2020, they are more likely to select the second scenario, which contains many observations close to the actual realization. Furthermore, they are more likely to believe that inflation will return to normal levels until 2024. In general, stock market participants appear to be better informed and more likely to believe that the economy will return to the status quo after a shock.

Our data also contains measures of interest in politics and the general news. If some people hardly follow the news, part of the observed disagreement could be driven by a lack of information. In 2020, politically interested people were more likely to choose the second scenario at the year's end, as seen in Figure 3.6. Furthermore, individuals who follow the news online were 3% more likely to expect the economy to recover from the pandemic until 2022. In 2022, individuals who indicated interest in the news were less likely to choose the scenario with no inflation for 2022. Thus, some of the scenarios featuring low inflation for 2022 in April 2022 may originate from people who have no idea what is currently going on. The questions we use are likely insufficient to give a complete picture of a person's media usage and political interest. Some people may be very engaged but mostly follow news from dubious sources. The regressions, however, show that heterogeneity in information across individuals plays an important role.

The LASSO procedure also chooses questions where individuals indicate their expectations about policies or other relevant mechanisms. These beliefs may hint at different opinions or narratives about how the current shock will affect the economy. People who expected longer restrictions during the pandemic were eight percent less likely to believe that the economy would have recovered by 2022. People who indicated that they considered the decrease in imports from China when they formed their expectation are 8 percent more likely to select the third scenario in 2022, which features negative growth. Similarly, increasing the expected government deficit at the end of 2022 increases the probability of choosing the third scenario by two percent. Thus, some of the disagreement among people can be traced to disagreement about how current events will affect the economy and to differences in the news they consider when forming their expectations.

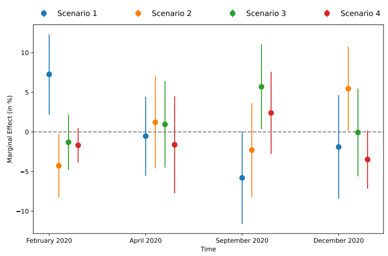
Finally, we show that trust in institutions matters for scenario choice in 2020 and 2022. We find that trust in democracy significantly predicts medium-term expectations in 2020. People with higher trust in democracy are likelier to choose the first scenario and are less likely to select scenarios that postulate a permanent economic impact of the pandemic. Increasing trust in democracy by one unit[‡‡] increases the probability of choosing the first scenario by 3.2%. Figure 3.7 shows that this effect becomes stronger during 2020. These findings suggest that fundamental beliefs about society are important for expectation formation. People who think the system is flawed and unfair will likely project this assessment on their economic outlook.

3.3.3 Determinants of Expectations across time

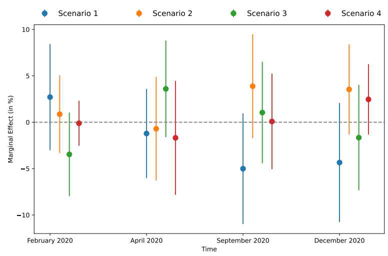
One key advantage of our data is that we can observe the same respondents over two years. Observing expectation updates at the individual level allows us to document how individuals respond to different economic circumstances and update their expectations in the presence of new information. Furthermore, we can assess how much noise individual-level expectations contain by comparing expectations in the short term. We will first document the distribution of scenario updates during 2020 and then use these statistics to determine how noisy short-term expectations are. Next, we will identify different expectation types and relate them to various background variables. Finally, we consider expectation updates across 2020 and 2022 and relate patterns to background variables.

Belief Patterns during Covid - 2020: Figure 3.8 shows scenario transitions for scenarios indicated in 2020. Consistent with the resolution of uncertainty, people updated their expectations towards more optimistic scenarios for both 2020 and 2022. For 2020 expectations, they updated to the first and second scenarios, and for 2022

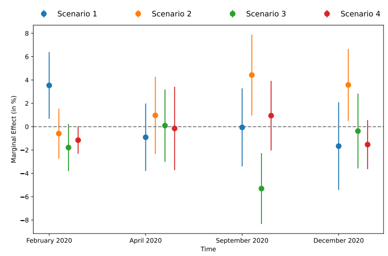
‡‡. The variable is coded from 0-10.



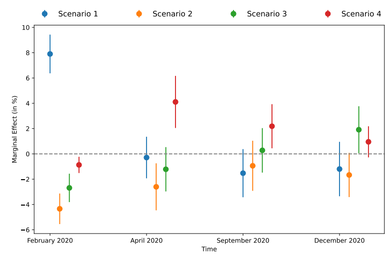
(a) (Equivalized) Household Income above 2500



(b) Risky Assets



(c) Political Interest



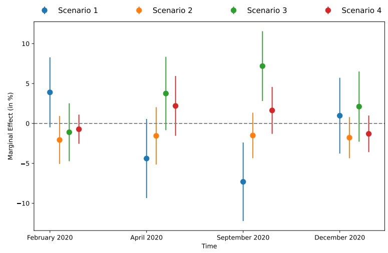
(d) Statistical Reasoning

Note: This figure shows the development of some marginal effects over time. Each panel contains the marginal effects of a certain variable on scenario choice for 2020 from February 2020 until December 2020. Each set of marginal effects at a particular point in time is obtained by running the regression featured in Table 3.1 only with observations at the particular interview date. Each panel shows the marginal effect on each of the four scenarios that we have identified for 2020. The marginal effects show the increase in the probability that a person chooses the respective outcome level if the variable in question increases by one unit. See Section 3.A.1 for a description of the scale of each variable.

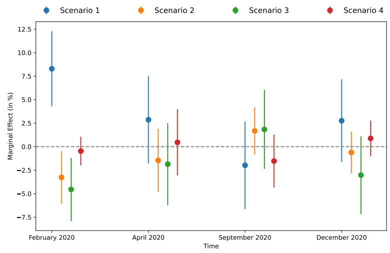
Figure 3.6. Predictors of 2020 Expectations in 2020.

expectations, they mainly updated to the first scenario, which implies that the economy will recover until 2022. Figure 3.8 also shows persistence in pessimistic expectations, as people who initially chose the fourth scenario are more likely to keep pessimistic expectations in September. Only about one-third of the people who chose scenario four for 2022 in April updated to scenario one in September, while more than half of those who chose scenario three updated to the first scenario.

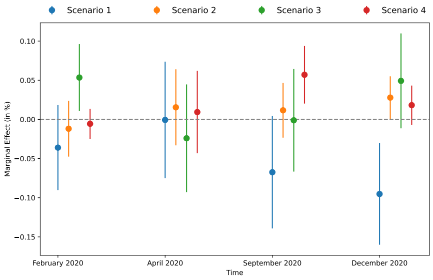
Individual Level Volatility: We can compare scenario choices for 2020 in September and December to assess how volatile individual expectations are. In both months, there has been little uncertainty about the realization of outcomes. In December 2020, the correct values were already known. We thus assume that between September and December 2020, no new information about outcomes should appear, which leads households to update their expectations further away from the truth. Looking at Figure 3.8, we see that around 15 % of all individuals updated their expectations to a scenario that is further away from the truth than their previous scenario. Unless many individuals received information about the current situation contrary to the observable realization, the movements are due to the variability of



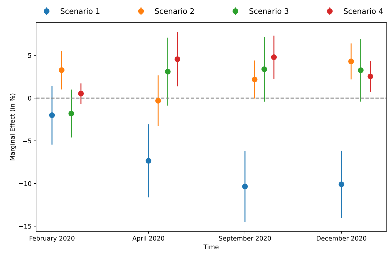
(a) (Equivalized) Household Income above 2500



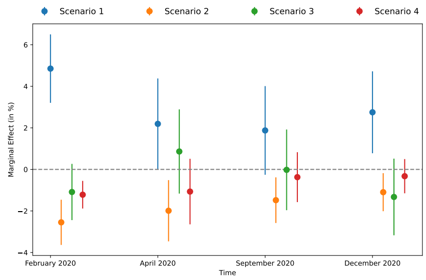
(b) College Educated



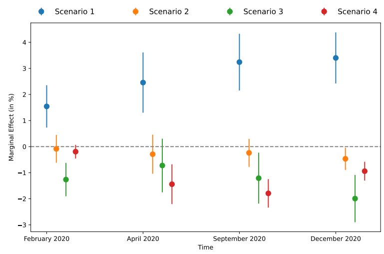
(c) Economic Anxiety (in %)



(d) Gender



(e) Statistical Reasoning



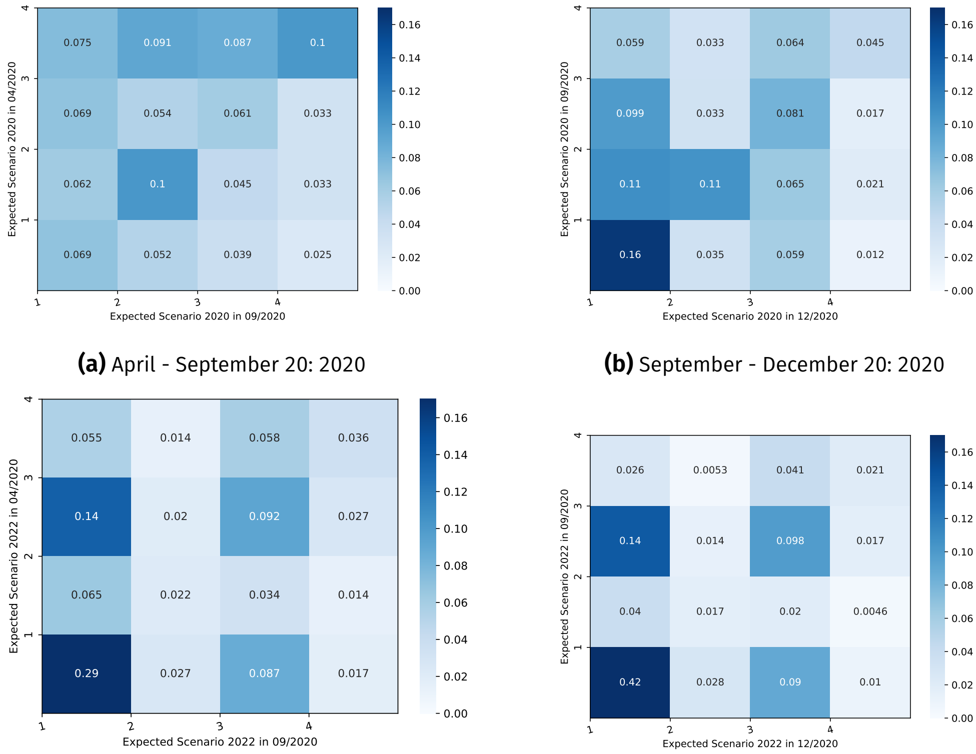
(f) Trust in Democracy

Note: This figure shows the development of some marginal effects over time. Each panel contains the marginal effects of a certain variable on scenario choice for 2022 from February 2020 until December 2020. Each set of marginal effects at a particular point in time is obtained by running the regression featured in Table 3.2 only with observations at the particular interview date. Each panel shows the marginal effect on each of the four scenarios that we have identified for 2020. The marginal effects show the increase in the probability that a person chooses the respective outcome level if the variable in question increases by one unit. See Section 3.A.1 for a description of the scale of each variable.

Figure 3.7. Predictors of 2022 Expectations during 2020.

expected scenarios. This finding shows that expectations are volatile on a personal level, even in the short run, without the resolution of any relevant information.

Scenario Patterns: In this section, we classify people based on the scenarios they chose for the three 2020 interview dates. We refer to a scenario pattern as the sequence of scenarios people indicate over several dates or time horizons. We focus on scenario patterns of 2022 expectations during 2020 since they are less noisy and contain less uncertainty about the current economic situation than shorter-term ex-



(a) April - September 20: 2020

(b) September - December 20: 2020

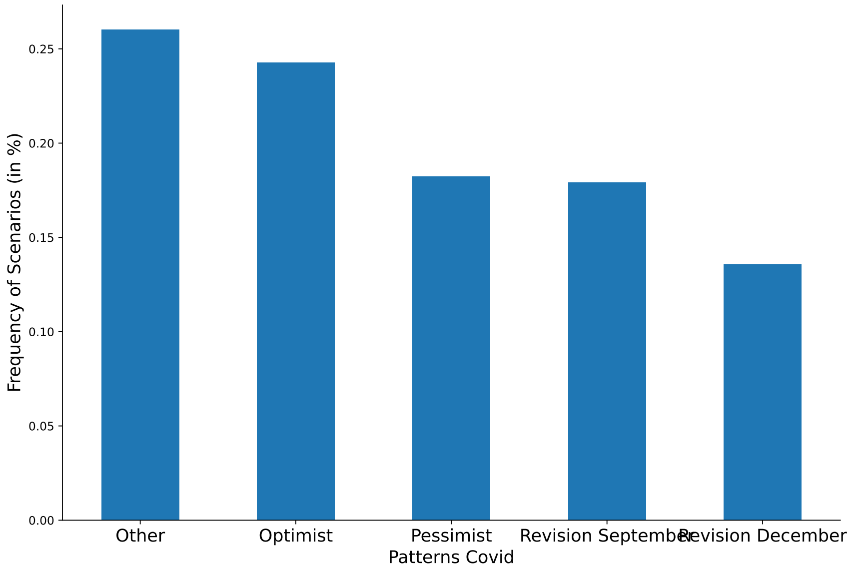
(c) April - September 20: 2022

(d) September - December 20: 2022

Note: This figure shows transitions of expected scenarios across different interview dates in 2020. Each of the four panels contains a heatmap with a scenario at one interview date on the y-axis and a scenario at a later interview date on the x-axis. Each cell represents a transition between scenarios indicated at two different interview dates. The color of each cell is scaled according to its relative frequency, and each cell is annotated with its relative frequency.

Figure 3.8. Cluster Transition: Across Interview Time in 2020.

pectations. We base our classification on the observation that the second, third, and fourth scenarios for 2022 feature no recovery from the pandemic in the medium run, while the first scenario implies a recovery until 2022. Individuals who indicated the first scenario three times are labeled “Optimists”, and those who always believed in one of the other three scenarios are labeled “Pessimists”. Individuals who changed their assessment to the first scenario in September or December are labeled “Recovery September” and “Recovery December”, respectively. The rest, which includes all the assessments where individuals became more pessimistic over the year, are labeled as “Other”. While a few of the “Other” patterns could be justified by the fact that people thought the pandemic would end soon, in April, most of these patterns are not in line with the resolution of information throughout the year. Figure 3.9 summarizes the distribution of scenario patterns for 2022 in 2020. Around 25% are “Optimists”, around 20% are “Pessimists”, and around 25% are labeled as “Other”.



Note: This barplot shows the distribution of scenario patterns for 2022 during 2020. People are classified based on the sequence of scenarios they indicated for 2022 between April 2020 and December 2020. The classification is based on whether they expected the economy to recover until 2022, which corresponds to scenario 1, or expected the pandemic to have a permanent effect, corresponding to any other scenario, at each point in time.

Figure 3.9. Expectation Patterns during Covid.

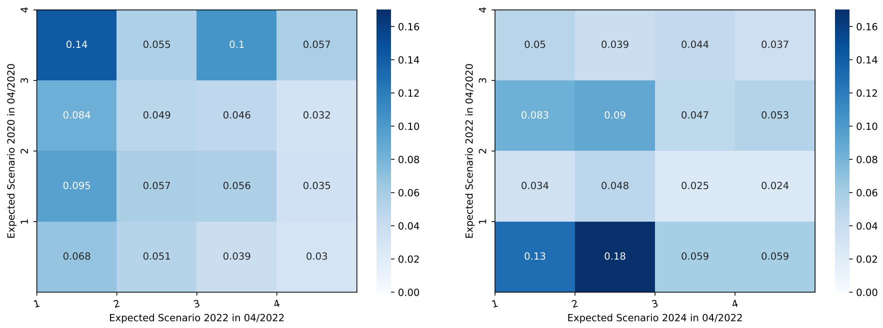
Most people switch from a pessimistic assessment to an optimistic one either in September or December.

Heterogeneity in Scenario Patterns: We associate scenario patterns with background characteristics to understand what drives dynamic behaviors. Table 3.3 shows the marginal effects of a multinomial logit regression of scenario patterns on several variables that we found relevant for scenario choice in the lasso procedure. The table shows that "Pessimists" have lower trust in institutions and are likelier to vote for the right-wing populist party. This finding is consistent with our earlier assessment that some people's expected scenario reflects their fundamental disagreement with how the economy and society work.
Consistent with our interpretation of the "Other" type, we find that it is associated with lower statistical reasoning abilities on average. The frequent occurrence of this type, the documented importance of noise, and the importance of statistical reasoning abilities all suggest that limited understanding and noise play an important role in shaping the distribution of expected scenarios. It is crucial to consider this finding when interpreting household expectations in times of increased economic uncertainty. "Recovery" types disagree with "Optimists" about how long restrictions

will take. This makes sense as people who think restrictions will be more severe will adjust their economic expectations downward. This disagreement, however, resolves as new information arrives and people update their scenarios. “Recovery December” types are less likely to work, which could hint at the fact that being a more active part of the economy potentially leads to quicker updates of expectations when new information appears. Taken together, the results show that there are different sources of heterogeneity. While disagreement about how the situation will impact the economy matters initially, it resolves as new information appears. Other people are more persistently pessimistic, and others are not good at quantifying their expectations.

Scenario Transition across Domains: We also compare expected scenarios in April 2020 and April 2022 to understand to what extent households behave similarly across domains or whether their assessment changes fundamentally with varying economic environments. Figure 3.10 shows expected scenarios in the present year and two years ahead for 2022 and 2024. The first panel shows the assessment of the present year. Individuals with more positive assessments in April 2020 are slightly more likely to expect either the first or second scenario for 2022 in April 2022. There is a lot of fluctuation across these two dates, which is not surprising considering the large amount of uncertainty at the beginning of the pandemic. The second panel shows the transition of two-year-ahead scenarios. It shows that people who expect a pessimistic scenario for the medium run in 2020 are substantially more likely to have pessimistic expectations in 2022. The first two scenarios in 2022 can be considered optimistic, while the third and fourth are pessimistic. The picture shows that around a quarter has consistently pessimistic medium-run expectations, while around 30 % has consistently optimistic expectations. The rest switches assessment between these times. Individuals who believe in a swift recovery in 2020 are more likely than anyone else to believe that inflation is only temporary.

Scenario Patterns 2020 and Expectations in 2022: We associate beliefs in 2024 with scenario patterns during 2022 to assess to what extent these patterns translate to another economic environment. Figure 3.11 summarizes expected scenarios in April 2022 by expectation pattern during 2020. The first panel shows expected scenarios for 2022 by expectation pattern during COVID-19. “Optimists” are substantially more likely to pick the first scenario for 2022 and least likely to choose any other scenario. Scenario 1 features inflation at around 4 percent and business as usual in the other dimension. At that point, individuals who believed in no inflation were either badly informed, unable to provide their expectations, or did not put effort into answering the question. The fact that optimistic people chose the no-inflation scenario the least shows that they are relatively well-informed and do not just indicate the anchoring scenario. In fact, the “Other” type indicates this scenario most frequently, which is consistent with the fact that people in this group



(a) April 20 2020 - April 22 2022 **(b)** April 20 2022 - April 22 2024

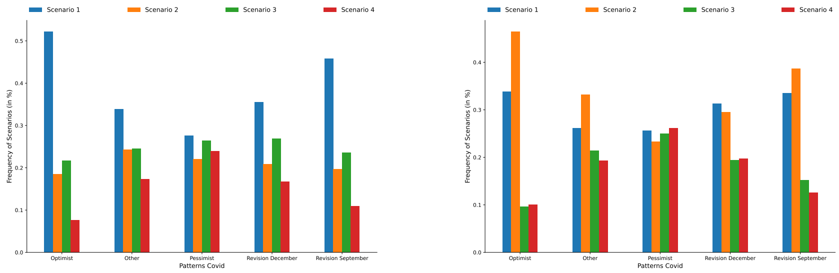
Note: This figure shows transitions of expected scenarios across different interview dates in 2020 and 2022. The first panel shows the transition between 2020 scenarios in April 2020 and 2022 scenarios in 2022. The second panel shows the transition between 2022 scenarios in April 2020 and 2024 scenarios in April 2022. Note that we identify scenarios separately for expectations indicated in 2020 and expectations indicated in 2022. Thus, the transitions depicted in this figure are between two different sets of scenarios. Each of the two panels contains a heatmap with a scenario indicated in April 2020 on the y-axis and a scenario indicated in April 2022 on the x-axis. Each cell represents a transition between scenarios in April 2020 and April 2022. The color of each cell is scaled according to its relative frequency, and each cell is annotated with its relative frequency.

Figure 3.10. Cluster Transition: Between 2020 and 2022

have previously indicated scenarios that were inconsistent with the resolution of information. The "Recovery" types are more likely than the "Optimists" to choose the third or fourth scenario for 2022. Similar to their behavior at the onset of the pandemic, they are more likely to adjust their expectations downward in the presence of economic uncertainty. This finding suggests that some people are more prone to overreacting in the presence of uncertainty than others. "Pessimists" are most likely to choose the third and fourth scenarios, which both imply an economic downturn in 2022.

The second panel shows expectations for 2024 by belief pattern. "Optimists" are most likely to believe inflation will fade after two years. Similar to their behavior in 2020, they revert to the anchor in the medium run. "Pessimists" and "Others" sill hold more pessimistic long-term expectations. The "Recovery" types chooses pessimistic scenarios slightly more often than the "Optimists".

Long-Term Scenario Patterns: We also run regressions based on expectation transitions between April 2020 and 2022. By comparing expectations in April 2020 and 2022, we can contrast the initial reactions to two distinct economic shocks. We could also derive patterns with scenarios from all four interview dates. However, there are fewer observations with expectations in 2020 and 2022, and more categories would be needed to summarize four dimensions instead of three. In 2022, we will consider anyone who selected the third and fourth scenario pessimistic and anyone who selected the first and second scenario optimistic. We then label people based on their



(a) 2022 Scenarios in April 2022 **(b)** 2024 Scenarios in April 2022

Note: This figure shows the distribution of expected scenarios for 2022 in 2022 by scenario pattern for 2022 scenarios in 2020. The first panel plots the distribution of expected scenarios for 2022 in April 2020 by scenario pattern during 2020. The second panel shows the same figure for expected scenarios for 2024 in April 2022.

Figure 3.11. Scenario patterns 2020 and expected scenarios in 2022

behavior in April 2020 and 2022. We categorize individuals who maintain their optimism or pessimism from 2020 to 2022 as “Optimists’ or “Pessimists”, respectively. Those who switch their outlook are labeled “Pessimists-covid” or “Pessimists-22”. We create two different patterns, one based on the expected scenario for 2022 in April 2022 and one based on the expected scenario for 2024. The reason for defining both is that the COVID pandemic was initially more salient. In 2022, there were fewer people with a very pessimistic scenario in the medium run and more disagreement about how the economy would develop in the short run.

Table 3.A.3 and 3.A.4 contain marginal effects derived from multinomial logit regressions of background variables on patterns based on transitions across April 2020 and April 2022. Table 3.A.4 shows results from patterns based on the transition of scenarios for 2022 in April 2020 and 2022 in April 2022. The table shows that people who switch to a pessimistic scenario in 2022 are more likely to consider Chinese imports and predict a larger government deficit. These people are thus more likely to associate current news with a scenario that hurts the real economy. People who switch to optimistic expectations expect longer restrictions at the onset of the pandemic in 2020. That shows that people react differently to various pieces of information, which partly explains the wide heterogeneity in scenario patterns across time.

Table 3.A.3 shows results for the transitions of two-year-ahead scenarios between April 2020 and 2022. In this instance, substantially fewer people are in the “Pessimist-22” group since long-term expectations are generally more optimistic in 2022. The only variable significantly affecting the “Pessimist-22” is the perceived comfort of household finances. This shows that the economic situation is essential in determining subjective expectations. In particular, during increased inflation, households with a sudden decrease in real purchasing power appear to update their expectations to more pessimistic scenarios.

3.4 Conclusion

We have analyzed macroeconomic expectations with a panel that starts in 2020 and runs until inflation rises in 2022. We find that a wide range of different economic scenarios drives disagreement in response to economic uncertainty. Scenario choice is associated with various characteristics shown to matter for subjective macroeconomic expectations in the prior literature. Most importantly, we document that different background characteristics are associated with distinct scenario patterns. A large part of the disagreement in economic scenarios in times of uncertainty can be traced to disagreement about how current events will affect the economy and what factors are relevant to consider. Some people, however, are generally pessimistic and change their expectations much less in response to news. Finally, there is a significant amount of people with very volatile expectations, often in stark contrast to the current economic situation. These findings have important implications for macroeconomic policymakers who work with subjective expectations. They need to consider that disagreement in times of increased economic uncertainty will likely be overstated. Furthermore, they should remember that people will likely react differently to policies, news, or communication campaigns. Persistently pessimistic people are less likely to change their expectations in response to news, policies, or communication initiatives. Our results also raise interesting questions for future research. Most importantly, it is unclear whether households differ in the extent to which they consider their macroeconomic expectations when making decisions. While past research has documented that subjective expectations matter for economic choices, it is unclear whether this holds across the population. If people with volatile or persistently pessimistic expectations do not consider their macroeconomic expectations to the same extent as others, their levels are less relevant to the macroeconomy.

Table 3.3. Long Term Expectation Patterns during 2020

	Optimist	Other	Pessimist	Recovery December	Recovery September
Upper Secundary Education	-2.045	-1.635	-1.891	-1.397	6.968***
	(2.805)	(2.606)	(2.139)	(2.157)	(2.593)
College Educated	-2.058	-1.685	-1.423	1.354	3.812
	(2.916)	(2.831)	(2.363)	(2.242)	(2.781)
Female	-10.275***	3.683*	8.469***	-0.391	-1.486
	(1.971)	(1.938)	(1.672)	(1.559)	(1.821)
Age 30-50	2.915	-4.574	0.134	2.203	-0.677
	(3.702)	(3.520)	(3.132)	(3.169)	(3.478)
Age > 50	-1.171	-6.926**	1.635	2.966	3.496
	(3.751)	(3.510)	(3.073)	(3.118)	(3.463)
Income 1500-2500	-0.632	-1.259	0.329	2.857	-1.294
	(2.719)	(2.517)	(2.113)	(2.198)	(2.474)
Income > 2500	-3.306	-3.728	3.495	6.353**	-2.814
	(3.107)	(3.030)	(2.530)	(2.516)	(2.861)
Working	2.883	-0.442	-2.564	-4.036**	4.159*
	(2.482)	(2.469)	(2.083)	(2.043)	(2.266)
Owns Risky Assets	7.567***	-0.139	-3.949	-2.372	-1.107
	(2.661)	(3.002)	(2.831)	(2.418)	(2.672)
Real Estate	3.145	-2.646	-2.559	2.415	-0.356
	(2.587)	(2.394)	(1.971)	(2.052)	(2.329)
2nd Wealth Tercile	3.702	-2.237	-3.067	-1.228	2.831
	(2.821)	(2.615)	(2.135)	(2.113)	(2.542)
3rd Wealth Tercile	1.203	1.185	-1.233	-2.102	0.948
	(2.998)	(2.805)	(2.310)	(2.261)	(2.722)
Expect Long Restrictions	-11.328***	-1.855	3.349*	5.044***	4.789**
	(2.717)	(2.423)	(1.898)	(1.804)	(2.191)
Household size	-1.100	0.063	0.397	0.243	0.397
	(0.950)	(0.949)	(0.812)	(0.784)	(0.883)
Statistical Literacy	3.799***	-2.596***	-0.489	-1.158	0.444
	(1.049)	(0.992)	(0.843)	(0.806)	(0.955)
Sympathy PVV	-0.496	0.048	0.521*	-0.169	0.096
	(0.396)	(0.376)	(0.307)	(0.305)	(0.360)
Confidence Economy	0.996	-0.753	-0.918	0.822	-0.147
	(0.840)	(0.780)	(0.628)	(0.637)	(0.752)
Confidence Democracy	1.963***	-0.290	-2.030***	-1.219**	1.576**
	(0.749)	(0.689)	(0.547)	(0.549)	(0.680)
Probability Low Income	-0.038	0.055*	0.040	-0.002	-0.054
	(0.037)	(0.033)	(0.027)	(0.027)	(0.034)
N	1922	NaN	NaN	NaN	NaN
Pseudo R2	0.049718	NaN	NaN	NaN	NaN

Note: This table shows marginal effects obtained from a multinomial logit regression of scenario patterns on a pre-selected set of background characteristics. Scenario patterns in this figure are based on the sequence of 2022 scenarios between April 2020 and December 2020. See Section 3.3.3 for details. The marginal effects show the increase in the probability that a person chooses the respective outcome level if the variable in question increases by one unit. See Section 3.A.1 for a description of the scale of each variable.

Appendix 3.A Appendix

3.A.1 Variable Guide

Scales: Most of the variables in the regression are categorical variables or dummy variables. In this section we classify all variables:

- Dummies: Wave September, Wave December, College Educated, Female, Age 30-50, Age > 50, Income 1500-2500, Income > 2500, Working, Expect Long Restrictions, Couple without children, Real Estate, Owns Risky Assets, Follow Internet News, 2nd Wealth Tercile, 3rd Wealth Tercile, No China Import, Less China Import, Comfortable Finances
- Integer from 0-10: Confidence Democracy, Confidence Economy , Sympathy PVV
- Probabilities (0-100): Probability Low Income
- Integer from 0-4: Statistical Literacy
- Integer from 0-2: Interested Politics, Interested News
- Integer from 0-7: Difficulty Paying 500
- Float: Expected Surplus (-6,2)
- Integer: Household Size

3.A.2 Robustness Cluster

This section discusses how the identified scenarios would look if we used five groups instead of four in the clustering procedure. Figure 3.A.1 shows the resulting scenarios for expectations in 2020. The figure shows that adding a group would mainly split the fourth scenario into a group that expects high inflation and a group that expects low inflation. Otherwise, scenario assignment would remain relatively stable. Figure 3.A.2 shows the resulting scenarios for expectations in 2022. The new group would split the first scenario into one scenario that features inflation of at least 6% and a group that expects inflation between 3 and 5%. The cluster centers slightly change, but the overall assignment remains relatively stable.

3.A.3 Additional Tables and Figures

Table 3.A.1. LASSO: Scenarios 2022 in 2022

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Female	-11.203***	4.554*	3.287	3.362
	(3.241)	(2.582)	(3.088)	(2.198)
Age > 50	6.761*	-3.900	-0.837	-2.024
	(3.528)	(2.657)	(3.301)	(2.264)
3rd Wealth Tercile	-0.484	0.148	6.560*	-6.224**
	(3.627)	(2.933)	(3.455)	(2.736)
Less China Import	-5.057	-2.978	8.541***	-0.506
	(3.306)	(2.582)	(3.029)	(2.155)
Statistical Literacy	7.249***	-3.932***	-0.437	-2.880***
	(1.510)	(1.142)	(1.434)	(0.974)
Difficulty Paying 500	-4.299***	0.968	1.581	1.750***
	(1.122)	(0.768)	(1.007)	(0.576)
Interested in News	9.917**	-8.090***	-2.825	0.998
	(3.884)	(2.840)	(3.559)	(2.319)
Interested Politics	2.413	0.309	0.682	-3.405
	(3.385)	(2.693)	(3.154)	(2.128)
Expected Surplus	1.780***	-0.466	-2.093***	0.780*
	(0.639)	(0.513)	(0.610)	(0.428)
N	831	NaN	NaN	NaN
Pseudo R2	0.082020	NaN	NaN	NaN

Note: This table shows marginal effects obtained from a multinomial logit regression of the expected cluster for 2022 in 2022 on a set of background characteristics selected by LASSO. In the first step, we run the LASSO procedure to select variables. In the second step, we run a multinomial logit regression with the selected variables. The marginal effects show the increase in the probability that a person chooses the respective outcome level if the variable in question increases by one unit. See Section 3.A.1 for a description of the scale of each variable.

Table 3.A.2. LASSO: Scenarios 2024 in 2022

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
College Educated	1.796	1.250	-1.470	-1.576
	(3.394)	(3.429)	(2.951)	(2.602)
Female	-6.133*	-2.524	5.533**	3.125
	(3.205)	(3.251)	(2.740)	(2.387)
Age > 50	7.785*	-5.042	0.010	-2.753
	(4.344)	(4.298)	(3.595)	(3.043)
Working	-1.633	6.561	-1.032	-3.896
	(4.194)	(4.187)	(3.504)	(3.068)
Owns Risky Assets	-5.160	6.889	-4.287	2.559
	(4.777)	(4.516)	(4.119)	(3.649)
2nd Wealth Tercile	6.435	1.110	-2.011	-5.534*
	(4.613)	(4.783)	(3.920)	(3.271)
3rd Wealth Tercile	-3.522	6.396	1.434	-4.308
	(5.045)	(5.107)	(4.178)	(3.642)
No China Import	-2.289	4.756	-3.486	1.018
	(3.214)	(3.238)	(2.747)	(2.392)
Difficulty Paying 500	-1.994*	1.080	-0.741	1.655**
	(1.168)	(1.197)	(0.974)	(0.750)
Confidence Politics	0.359	2.431***	-1.910***	-0.880*
	(0.701)	(0.714)	(0.572)	(0.489)
Expected Surplus	2.204***	-2.742***	-0.110	0.648
	(0.619)	(0.641)	(0.531)	(0.462)
N	831	NaN	NaN	NaN
Pseudo R2	0.049255	NaN	NaN	NaN

Note: This table shows marginal effects obtained from a multinomial logit regression of the expected cluster for 2024 in 2022 on a set of background characteristics selected by LASSO. In the first step, we run the LASSO procedure to select variables. In the second step, we run a multinomial logit regression with the selected variables. The marginal effects show the increase in the probability that a person chooses the respective outcome level if the variable in question increases by one unit. See Section 3.A.1 for a description of the scale of each variable.

Table 3.A.3. Long Term Expectation Patterns 2020-2022: Horizon 2022 - 2024

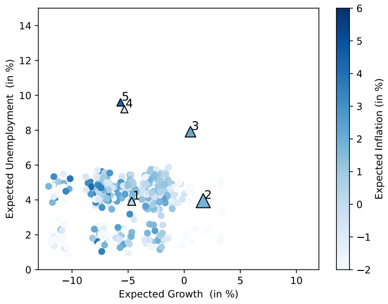
	Optimist	Pessimist	Pessimist 22	Pessimist Covid
Upper Secundary Education	-3.704	5.009	-0.971	-0.335
	(3.673)	(3.145)	(2.431)	(3.881)
College Educated	-2.474	4.486	-3.607	1.595
	(3.788)	(3.421)	(2.712)	(4.067)
Female	-11.715***	4.376*	1.620	5.719**
	(2.667)	(2.401)	(1.881)	(2.857)
Age 30-50	7.627	1.074	0.838	-9.539
	(7.020)	(7.055)	(5.041)	(7.106)
Age > 50	2.196	3.406	0.224	-5.827
	(7.121)	(7.054)	(5.081)	(7.174)
Income 1500-2500	-0.414	5.059	0.591	-5.236
	(3.548)	(3.086)	(2.422)	(3.748)
Income > 2500	-8.586**	5.046	1.871	1.670
	(4.333)	(3.837)	(2.985)	(4.492)
Working	0.425	-7.038**	1.384	5.230
	(3.478)	(3.091)	(2.429)	(3.651)
Comfortable Finances	6.813**	-2.968	-5.362**	1.517
	(3.292)	(2.750)	(2.159)	(3.456)
Owns Risky Assets	8.589**	-4.047	1.019	-5.560
	(3.758)	(3.907)	(2.814)	(4.349)
Expect Long Restrictions	-7.402**	6.469**	-1.528	2.461
	(3.535)	(2.812)	(2.485)	(3.605)
No China Import	-1.515	-2.255	-2.482	6.253
	(5.639)	(4.978)	(3.825)	(6.264)
Less China Import	-5.787	3.147	-2.098	4.738
	(5.759)	(4.998)	(3.875)	(6.374)
Statistical Literacy	3.890***	-3.984***	-0.161	0.255
	(1.348)	(1.166)	(0.937)	(1.432)
Confidence Economy	0.954	-2.002**	-0.089	1.137
	(1.098)	(0.907)	(0.750)	(1.157)
Confidence Democracy	1.009	-1.098	-0.051	0.141
	(0.901)	(0.761)	(0.623)	(0.957)
Probability Low Income	0.021	0.052	-0.059	-0.013
	(0.050)	(0.042)	(0.037)	(0.054)
Expected Surplus	0.272	0.108	-0.316	-0.064
	(0.527)	(0.463)	(0.370)	(0.560)
N	1138	NaN	NaN	NaN
Pseudo R2	0.042876	NaN	NaN	NaN

Note: This table shows marginal effects obtained from a multinomial logit regression of scenario patterns on a pre-selected set of background characteristics. Scenario patterns in this figure are based on the transition between scenario choice for 2022 in April 2020 and scenario choice for 2024 in April 2022. See Section 3.3.3 for details. The marginal effects show the increase in the probability that a person chooses the respective outcome level if the variable in question increases by one unit. See Section 3.A.1 for a description of the scale of each variable.

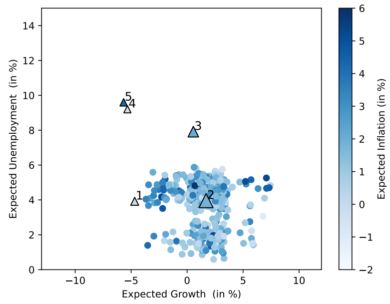
Table 3.A.4. Long Term Expectation Patterns 2020-2022: Horizon 2022

	Optimist	Pessimist	Pessimist 22	Pessimist Covid
Upper Secundary Education	-5.217	2.488	0.452	2.277
	(3.553)	(3.239)	(2.811)	(3.865)
College Educated	-6.201*	1.155	0.233	4.813
	(3.684)	(3.538)	(2.989)	(4.030)
Female	-7.359***	7.678***	-2.743	2.425
	(2.636)	(2.479)	(2.084)	(2.849)
Age 30-50	4.440	-8.661	5.096	-0.876
	(6.795)	(6.112)	(5.583)	(7.217)
Age > 50	2.020	-4.892	1.560	1.312
	(6.880)	(6.141)	(5.681)	(7.283)
Income 1500-2500	1.473	1.091	-1.166	-1.397
	(3.491)	(3.143)	(2.670)	(3.758)
Income > 2500	-2.893	1.649	-3.825	5.069
	(4.245)	(3.905)	(3.318)	(4.468)
Working	-0.228	0.338	1.999	-2.108
	(3.428)	(3.148)	(2.665)	(3.654)
Comfortable Finances	4.763	-4.140	-3.716	3.093
	(3.223)	(2.847)	(2.423)	(3.443)
Owns Risky Assets	6.249*	-4.694	3.710	-5.265
	(3.715)	(4.066)	(2.878)	(4.292)
Expect Long Restrictions	-4.769	4.701	-4.358	4.426
	(3.442)	(2.958)	(2.830)	(3.543)
No China Import	3.621	-4.738	-8.097**	9.214
	(5.611)	(5.003)	(4.055)	(6.368)
Less China Import	-6.059	-0.454	-2.443	8.956
	(5.780)	(5.063)	(4.045)	(6.478)
Statistical Literacy	2.408*	-3.503***	1.227	-0.132
	(1.317)	(1.209)	(1.051)	(1.419)
Confidence Economy	1.365	-1.427	-0.505	0.567
	(1.077)	(0.946)	(0.825)	(1.145)
Confidence Democracy	0.782	-1.523*	0.158	0.583
	(0.881)	(0.788)	(0.688)	(0.949)
Probability Low Income	0.030	0.023	-0.072*	0.019
	(0.049)	(0.044)	(0.042)	(0.053)
Expected Surplus	0.792	-0.417	-0.849**	0.474
	(0.513)	(0.480)	(0.412)	(0.553)
N	1138	NaN	NaN	NaN
Pseudo R2	0.039066	NaN	NaN	NaN

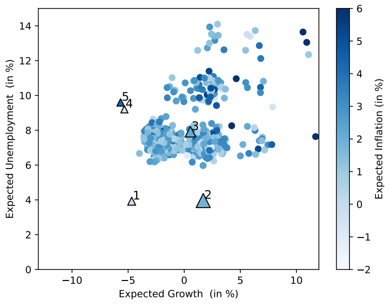
Note: This table shows marginal effects obtained from a multinomial logit regression of long-term expectation patterns on a pre-selected set of background characteristics. Long-term scenario patterns in this figure are based on the transition between scenario choice for 2022 in April 2020 and scenario choice for 2022 in April 2022. See Section 3.3.3 for details. The marginal effects show the increase in the probability that a person chooses the respective outcome level if the variable in question increases by one unit. See Section 3.A.1 for a description of the scale of each variable.



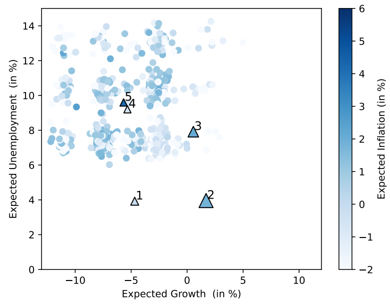
(a) Scenario 1



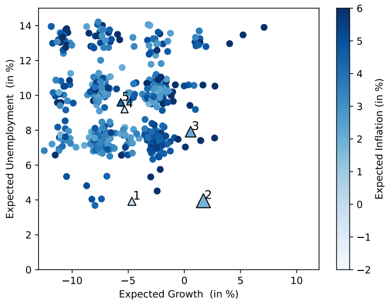
(b) Scenario 2



(c) Scenario 3



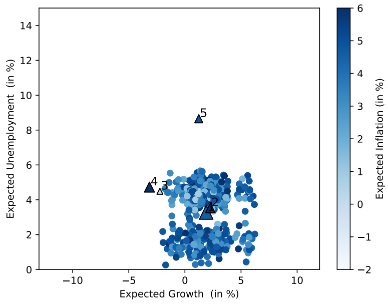
(d) Scenario 4



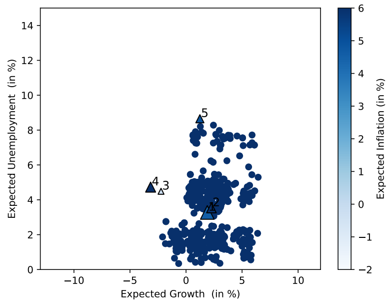
(e) Scenario 5

Note: This figure summarizes identified belief scenarios along with the corresponding observations. The figure shows the result of using a k-means clustering algorithm with five groups on the set of expected scenarios between February and December 2020 for expectation horizons 2020, 2021, and 2022. The y-axis of each panel represents the expected unemployment rate, the x-axis represents the expected growth rate, and the color of each point represents the expected inflation rate. In each panel, all four clusters are indicated as triangles. Each triangle is scaled according to the size of the cluster. Each panel also contains a random sample of the respective group. The random samples are slightly perturbed to improve the visualization.

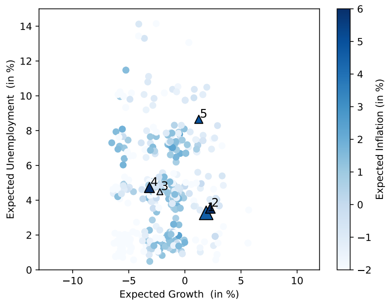
Figure 3.A.1. Alternative Scenarios using five groups.



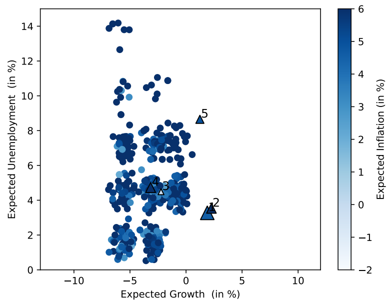
(a) Scenario 1



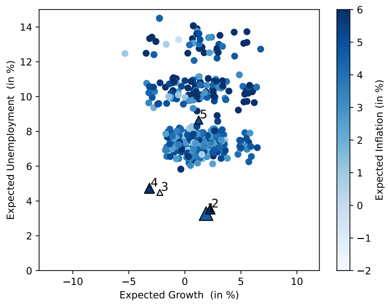
(b) Scenario 2



(c) Scenario 3



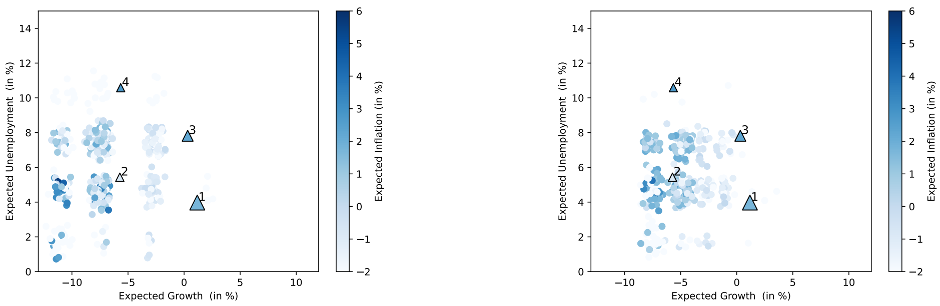
(d) Scenario 4



(e) Scenario 5

Note: This figure summarizes identified belief scenarios along with the corresponding observations. The figure shows the result of using a k-means clustering algorithm with five groups on the set of expected scenarios in April 2022 for expectation horizons 2022, 2023, and 2024. The y-axis of each panel represents the expected unemployment rate, the x-axis represents the expected growth rate, and the color of each point represents the expected inflation rate. In each panel, all four clusters are indicated as triangles. Each triangle is scaled according to the size of the cluster. Each panel also contains a random sample of the respective group. The random samples are slightly perturbed to improve the visualization.

Figure 3.A.2. Alternative Scenarios 2022 using five groups.



(a) Scenario 2: April 2020 for 2020

(b) Scenario 2: December 2020 for 2020

Note: This figure shows 2020 scenarios assigned to scenario 2 in April 2020 and December 2020. See Figure 3.3 for a summary of all the cluster. The y-axis of each panel represents the expected unemployment rate, the x-axis represents the expected growth rate, and the color of each point represents the expected inflation rate. In each panel, all four clusters are indicated as triangles. Each triangle is scaled according to the size of the cluster. Each panel also contains a random sample of the respective group. The random samples are slightly perturbed to improve the visualization.

Figure 3.A.3. Alternative Scenarios 2022 using five groups.

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