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BELIEFS AND PREFERENCES IN COMMUNITY COLLEGE

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Beliefs and Preferences in Community College

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Abstract

Despite high labor market returns and low effective tuition, the majority of community college students never earn a two-year degree and only a fraction transfer to four-year programs. I collect novel survey data on the expected choices of community college students, and on their beliefs about earnings, tuition costs, and dropout risks. Beliefs appear to deviate from rational expectations: respondents underestimate four-year dropout risks but overestimate four-year tuition costs, to ambiguous net effect. An information experiment demonstrates that students are responsive to new information, suggesting the potential for correcting biases. In part to quantify the importance of such corrections, I use the data to estimate a dynamic model of community college student choices. The results show that students' plans are most sensitive to the four-year dropout risk and largely inelastic with respect to expected tuition costs; as a result, counterfactual policy experiments suggest that policymakers can more effectively encourage transfer by decreasing the riskiness of four-year school rather than through tuition subsidies. An exercise in correcting beliefs shifts individuals away from transfer and generates substantial positive welfare effects. Finally, I use the model to examine why students' planned outcomes may differ from the high rates of dropout and low rates of transfer that characterize the community college landscape. This ex-post accounting exercise suggests that learning about four-year dropout risk may play a meaningful role, but is insufficient to close the gap. I demonstrate that "academic mismatch," where students discover they are a worse match for higher education than they believe at the start, is a plausible mechanism for these phenomena.

Keywords: Subjective Expectations, Beliefs, Community College, Higher Education

JEL classification: I23, D84, D83, I21, I26

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1 Introduction

Community colleges are a critical component of the US higher education system. They enroll almost 9 million people each year, comprising 40% of all undergraduate students (Community College Research Center 2025); in one survey, an astonishing 52% of workers who earned a BA between 2008 and 2017 had previous community college experience (Foley et al. 2021). Community colleges are low cost, locally available, and open enrollment, and as a result provide an accessible entry point to higher education for a much more diverse group of students than four-year schools typically serve: per the Community College Research Center, community college students are more likely to be low-income, under-represented minorities, and older. Graduates can receive substantial wage benefits from the two-year degrees which are community colleges' primary offering, and community colleges serve as a stepping stone for transfer into four-year programs (Belfield and Bailey 2017, Velasco et al. 2024).[1]

However, the community college landscape is marked by two persistent phenomena. The first is a high rate of dropout: only about 30% of incoming first-time community college students will complete a two-year degree within 150% of the expected time, about half the rate of four-year programs (National Center for Education Statistics 2022).[2] The second is a low rate of transfer, with only about one in three progressing from community college to a four-year program; furthermore, only about 50% of those who transfer actually complete a four-year degree (Velasco et al. 2024). This is in stark contrast to the oft-cited statistic that 80% of incoming students have a BA as their goal (Horn and Skomsvold 2011). This raises the question of whether community colleges are succeeding in their mission and serving their students well.

It is possible that students enter community college understanding that there is a low probability of completion. They may even select into community college precisely because it is a low-cost environment in which to experiment with higher education, either because they know they have a high risk of non-completion (as in DeLuca et al. (2021)) or in order to learn about their match with higher education (as college enables students to do in Arcidiacono et al. (2025)). They may also only intend to take a few classes, rather than earn a credential. In this case, high community college dropout and low transfer may reflect a feature rather than a bug, and community colleges should not be evaluated negatively based on those metrics. By providing an environment in which students can experiment and learn, and through which some will earn a credential, they may be fulfilling their mission. This would call for a realignment of the priorities and evaluation of the community college system and a redefinition of "success."

[1] I use "AA" degrees to refer to all two-year Associate's degrees.

[2] Community colleges also compare unfavorably to four-year programs when considering receipt of any degree: only about 44% of students earn any credential within 6 years, compared to about 72% at four-year schools (Berg et al. 2025).

It is also possible that students do not know how likely it is that they will complete a two-year degree or transfer. Instead of a redefinition of success, this would suggest the need to understand how community college students are making their decisions, why they are not achieving their goals, and how different policies may affect dropout and transfer. Absent information on students' higher education plans, we cannot distinguish between these two possibilities. Without information on which factors community college students weigh (and how they do so) as they go through higher education, we cannot form policy to encourage persistence and transfer.

This is the gap I aim to fill in this paper. I examine community college students' planned paths through higher education, and then explore the role of uncertainty about four-year tuition costs, earnings, and four-year dropout risks in community college dropout and transfer. There is reason to think that beliefs about each of these factors are important in community college students' decisions, but also that they may suffer from information frictions and biases.[3] For this reason, I work in a framework of subjective expectations which relaxes the full-information rational expectations (FIRE) assumption and allows for individuals' beliefs to be misaligned with the true distributions. Under FIRE, observed dropout and transfer decisions are assumed to be ex-ante optimal; if individuals' subjective beliefs in fact differ from the objective distributions, then biases and limited information may drive students to make correctable mistakes.

Expectations are typically not identified by observational data (Manski 2004). To address this, and because little is known about community college students' beliefs in general, I build on previous work such as Arcidiacono et al. (2012b) and Baker et al. (2018) and collect novel survey data on the subjective expectations of community college students at a large and diverse Maryland system. Survey respondents report the probability that their community college enrollment ends in each of four mutually exclusive outcomes: exit from community college with no degree (dropout), receipt of a terminal AA, and transfer to a four-year program with or without a two-year degree. It is these expected outcome probabilities, or "path probabilities," that form the key set of dependent variables in my analysis. They also contain the first stylized fact: survey respondents do not expect the high dropout and low transfer which characterize the community college system. Instead, they assign a high probability to transfer (on average, 70.5%) and a low probability to community college dropout (on average 3.7%).

I also elicit beliefs about various outcomes along each path, most importantly earnings, four-year tuition costs, and four-year dropout risks. For each variable, I elicit beliefs for oneself ("own" outcomes) as well as for a typical student ("population" outcomes). The baseline population beliefs provide suggestive evidence against FIRE. Respondents are generally *optimistic* about four-year

[3] See Giustinelli (2022) for a review on expectations in education, Dynarski et al. (2022) and Levine et al. (2022) for discussion of four-year costs and the information barriers applicants face, and Hussey and Swinton (2011) and Athreya and Eberly (2021) for discussion on the importance of dropout risk.

graduation rates: while BA attainment for Maryland transfer students is no higher than 61%, the mean population (own) belief is 68.7% (82.7%). On the other hand, they are *pessimistic* about tuition costs at four-year schools. Among the 87.5% of respondents who reported expected tuition at in-state public schools, 72.7% (67.1%) report a population (own) belief above the maximum cost in the University of Maryland system. Beliefs about earnings are mixed, with pessimism about HS earnings, but are overall better calibrated.

To isolate the causal effect of beliefs about tuition, four-year dropout risk, and earnings on students' plans, I conduct an information experiment. Students are randomized to receive population-level information about each key source of uncertainty, following a similar design to Wiswall and Zafar (2015a). Respondents update their population-level beliefs in the direction of the signal they receive, showing that despite (or because of) their biases they are willing to revise when presented with new information. The experimental data allow me to look at how population-level beliefs relate to own-beliefs while controlling for unobserved heterogeneity. In the cases of earnings and tuition, shifting population-level beliefs causes students to revise their own-expectations as well, with imprecise effects for the expected dropout risk. Interventions using population information should thus be effective at shifting students' own beliefs, as in Wiswall and Zafar (2015b).

The experimental data also allow me to look at the impact of beliefs on students' plans, again controlling for unobserved heterogeneity. Using log-odds regressions of plans on beliefs, I show that students assign higher probabilities to paths with higher earnings, and lower probabilities to transfer paths when the four-year dropout risk is high. The effect of tuition is small and imprecisely estimated. I also show that student fixed effects, which I interpret as tastes for (or non-pecuniary returns to) schooling, play a large role in their expected choices.

The log-odds regressions fail to capture the dynamics inherent in investment in higher education, which brings uncertain costs and benefits in the future. To capture these and to separate out the roles of beliefs and preferences, I develop and estimate a dynamic model of education choice tailored to the community college setting. Community college students make period-by-period enrollment and work decisions, solving their problem using their individual-specific subjective belief distributions. The model is estimated by matching reported path probabilities to their model-implied counterparts using a simulated maximum-likelihood methodology which allows for measurement error in the path probabilities. Elicited expectations allow me to avoid the FIRE assumption, and the information experiment allows me to incorporate unobserved heterogeneity in tastes for school.

With the estimated model in hand, I first examine how responsive individuals' plans are to each belief by showing how the path probabilities change in response to one standard deviation changes in each belief. Path probabilities are most elastic with respect to dropout risk in four-year school: a one-standard-deviation increase in that risk changes transfer by -8.7%, increases AA receipt by

2.2%, and increases dropout by 21.8%. Choice probabilities are somewhat elastic with respect to earnings with an AA and BA, but inelastic with respect to four-year tuition costs.

While the model is estimated to match the elicited path probabilities, the main outcomes of interest for policy-makers are the ex-post outcomes *simulated* from the model, where individuals make decisions using their subjective beliefs but realize outcomes based on the true distributions over the uncertain outcomes. For each outcome, I estimate a "benchmark" distribution from appropriate data on realized outcomes; this can be viewed as approximating the FIRE distribution. I simulate outcomes from the model using these distributions, replacing individuals' subjective beliefs with the benchmark beliefs one-by-one to gauge the impact of aligning subjective beliefs with the model's true distribution. The cumulative effect of replacing subjective beliefs with the benchmark distributions is to move transfer by -4.8% and AA receipt by -0.3%, with most of the impact caused by correcting individuals' optimism about four-year dropout risk. Correcting beliefs also has a meaningfully positive welfare effect, increasing average utility by the equivalent of $3,965 in consumption annually over 30 years.

I then test several counterfactual policies. Community college administrators, reacting to the pressures they are under to encourage completion and transfer and recognizing the importance of positive encouragement (as in Papageorge et al. (2018)), may be understandably hesitant to tell their students that transfer is riskier than the students previously thought. Instead, I test two policies which incentivize community college students to insure themselves against the four-year dropout risk by earning a two-year degree prior to transfer. A full tuition subsidy for students transferring *with* a two-year degree has small effects, increasing transfer by just 0.8%; a lower-cost version of this policy which provides full financing rather than a full subsidy obtains about half the effects. I lastly test an alternative policy which decreases the four-year dropout risk directly, mimicking the ACE program from the City University of New York System (Scott-Clayton et al. (2025)). This is much more effective at encouraging transfer than the subsidy policy on its own: the ACE-style policy increases transfer by 5.2%. These experiments suggest that policymakers should focus fewer resources on the blunt instrument of tuition subsidies and more on comprehensive services which can help transfer students remain enrolled in four-year school after transfer.

The survey data show that students do not appear to be intentionally using community college to experiment with higher education: instead, they have a high intention to earn their AA and transfer, demonstrating a significant gap between expectations and the outcomes we expect this cohort to ultimately exhibit. While the cause of this divergence cannot be identified without further data (collection of which is ongoing), the model can be used to test whether learning about earnings, tuition costs, and dropout risks could cause dropout and transfer in my sample to more closely align with Maryland's aggregate outcomes. I show it is implausible for learning about earnings and tuition to play a large role: beliefs about earnings are well-calibrated, and correcting beliefs

about tuition costs generally moves students towards, rather than away from, transfer. Learning about four-year dropout risk may drive students away from transfer, but this can only close about a quarter of the transfer gap.

The model can also evaluate the plausibility of additional explanations besides mistaken beliefs. Because of the high lifecycle returns to education, and significant positive utility for enrollment, idiosyncratic consumption shocks (in line with DeLuca et al. (2021)) are largely ineffective at changing choices. Students learning that they are a worse match for schooling than they believe ex-ante, a phenomenon I term *academic mismatch* (in line with Arcidiacono et al. (2025)), is the most plausible of the tested explanations but requires large ex-ante mistakes in the match.

Related Literature. I will briefly review my contributions to the literatures on education choice and community college, discrete choice models, and subjective expectations.

Education choice and community college. Economists have documented a significant wage premium of four-year over high school degrees (Carneiro et al. 2011, Heckman et al. 2018), with estimates typically falling in the range of 20-50% (Webber 2014).[4] Estimates for the causal effect of a two-year degree are smaller but still substantial, typically on the order of 10-20%, with heterogeneity based on individual characteristics and program of study (see Belfield and Bailey (2017), Marcotte (2019), and Mountjoy (2022)).[5] Researchers have also looked at employment rates (Marcotte 2019) and non-pecuniary returns (Oreopoulos and Salvanes 2011) as further benefits to higher education.

Dynarski et al. (2022) provide a thorough overview on tuition and the financial aid system, which has created a sizable wedge between the nominal *sticker* prices schools charge and the actual out-of-pocket costs students pay. Several papers, including Bettinger et al. (2012) and Hoxby and Turner (2015), provide evidence that limited information about aid may discourage prospective students from applying to and attending college. Community colleges may be attractive in the face of this complicated system, since they are low cost and often functionally free after federal and state-based aid such as Maryland's "Promise" program (Miller-Adams and Iriti 2026).[6]

Dropout from higher education means that the ex-ante expected value of attending college may be much smaller than the ex-post value of earning a degree (Hussey and Swinton 2011, Athreya and Eberly 2021). While economists have historically focused on the latter, the former is the primary object of interest for prospective students. I build on DeLuca et al. (2021), who suggest that uncertain completion may be a particularly important factor for community college students,

[4] Bengali et al. (2025) document a raw earnings gap of around 75%, and Hendricks and Leukhina (2018) estimate that about 59% of this gap is due to selection on ability, leaving a premium around 31%.

[5] Stevens et al. (2019) find a premium as large as 45%.

[6] The average community college student receives grants and aid which exceed tuition and fees, meaning they receive a subsidy to attend (Ma et al. 2025)

and study the joint role this factor plays along with earnings premium and tuition costs in dropout and transfer decisions, offering direct evidence on community college students' beliefs about each.

Discrete choice models. Going back to Keane and Wolpin (1997), a long literature has sought to embed the costs, benefits, and (at times) risks of college attendance into dynamic discrete choice models. I build on models such as Keane and Wolpin (2001), Johnson (2013), and Todd and Zhang (2020) with two principal contributions. First, community college is often omitted entirely, as in the first and last of these papers. When it is included, it is often with significant abstractions, for example ignoring the premium to a two-year degree as in Johnson (2013). Second, these models generally assume full-information rational expectations (FIRE). If prospective students deviate from FIRE, this misspecification will lead to biased estimates of the model parameters and skew downstream analysis (a point illustrated by DeLuca et al. (2021)).

Subjective expectations. The 2022 *Handbook of Economic Expectations* (Bachmann et al. 2022) reviews the large literature that has developed studying subjective expectations. I first contribute to the study of subjective expectations in education, a particularly fruitful area for this research agenda (and reviewed by Giustinelli 2022). Dominitz and Manski (1996) began this literature by studying the beliefs of high school students, work continued by Kaufmann (2014), Delavande and Zafar (2019), Moschini et al. (2026) and others.[7] Economists have also studied education expectations of students' parents (Agte et al. 2024, Giustinelli 2016) and several papers have looked at beliefs about major choice in four-year programs (Zafar 2011, Arcidiacono et al. 2012b, Wiswall and Zafar 2015a). In a unique research program, Ralph and Todd Stinebrickner (with co-authors) have written a number of papers on the beliefs and choices of students at Berea College (Stinebrickner and Stinebrickner 2008, Gong et al. 2019). Since Berea college is tuition-free, serves a low-income population, and exhibits a relatively high dropout rate, their studies are closely related to my work. Baker et al. (2018), to my knowledge the only previous paper to systematically measure the expectations of community college students, study beliefs around different two-year degrees. They do not examine transfer-related outcomes.

A smaller literature, reviewed by Koşar and O'Dea (2022), embeds subjective expectations data into structural models. This includes several of the above papers, as well as Delavande (2008), Wang (2014), and others. Most similar to my approach is the methodology developed by Wiswall and Zafar (2015a), who collect data on the expected returns to majors for four-year students and use an information experiment to identify and estimate a fixed effects model. This paper, and much of the other structural work, involves estimating a logit model which rationalizes a reported

[7] Work in this literature often uses novel survey data, as my current paper does. However, several large-scale surveys have included expectations questions, and Moschini et al. (2026) leverage these from the NLSY97. There are also several public surveys, such as the Survey of Consumer Expectations from the Federal Reserve Bank of New York, which provide expectations data to researchers.

(subjective) choice probability by constructing an expected payoff from respondent beliefs.

I propose two changes to this approach. First, I collect subjective *outcome* probabilities, or the probability of arriving at some future state, rather than the probabilities of a single discrete choice. While this complicates estimation, such an approach is more feasible when we are interested in studying the outcome of sequential, period-by-period decisions.[8] Second, I allow for measurement error in the elicited path probabilities, using a maximum likelihood estimator similar in spirit to that used in Imai and Keane (2004) and reviewed in Keane et al. (2011).

Outline. The rest of the paper proceeds as follows. In Section 2, I detail the survey methodology and discuss my sample. In Section 3, I present evidence from the information experiment, document the relationship between own and population beliefs, and then examine how beliefs relate to choices in a static framework. Section 4 develops the dynamic model of education choice. In Section 5, I discuss the identification and estimation of the model using the elicited beliefs data. Section 6 presents the parameter estimates, calculates elasticities, and shows the results of several counterfactual exercises. Finally, Section 7 concludes.

2 Data

2.1 Survey Administration

Data were collected at one of the largest community college systems in Maryland, hereafter referred to as the "community college partner" (CCP). While there is significant heterogeneity across Maryland, which includes both urban and rural areas and significant income variation, the CCP is relatively typical for the Maryland community college (CC) system across metrics including race, income, and student outcomes.

The survey was administered online via Qualtrics to students between ages 18 and 32 who were pursuing a 2-year degree.[9] Dual-enrollment (high school) students were excluded, but no restriction was placed on accumulated CC experience, so the survey included continuing students (rather than focusing narrowly on first-time students). Respondents were recruited via announcements on Canvas, the school's learning management system, and compensated with an Amazon gift card for successful completion, with bonus payments possible for students who passed attention checks. Additional details can be found in Appendix B.1.

I collected data in November 2024 and 2025. I followed up with the initial 2024 respondents in 2025, receiving responses from about 30% of the original sample. I also recruited a "refresher"

[8] For example, we may be interested in retirement decisions. Since it is not feasible to ask about the probability of choosing to retire at each age, we estimate the probability of *being retired* at a certain point.

[9] Students seeking certificates and enrolled in other training programs were excluded.

sample whose respondents participated in an information experiment. I will draw on different parts of the sample as appropriate in the following analysis. "Baseline data" contains the 2024 observations and the pre-treatment 2025 refresher observations; the "experimental sample" contains the 2025 refresher only.

2.2 Instrument

The basic survey instrument collected information on student background, expected path probabilities, and expected outcomes conditional on different paths. The wording of key questions is provided for reference in Appendix A, and the full instruments are available upon request.

I first collected a set of observable characteristics, including fixed demographics (such as race, ethnicity, and gender), family background (such as parental income and education), and prior academic experiences (such as previous grades and SAT scores). These factors allow me to check the representativeness of the sample and control for some observable characteristics.

Second, I elicited the subjective probability of each possible outcome to the student's community college enrollment. Since expectations questions can be difficult, participants first went through a short refresher module on how probabilities worked. I elicited probability-based questions as a "percentage chance" which was required to lie on $[0, 100]$ and to sum to 100 across mutually-exclusive categories. Sliders were used to elicit the percentage chances so that respondents would have an intuitive visual representation of their answer.

In this question, respondents reported "the percent chance of four possible ways you may end your enrollment at [the CCP]." They assigned probabilities to:

1. Dropping out with no degree
2. Earning a terminal AA
3. Transferring to a four-year school without a 2-year degree
4. Transferring to a four-year school after earning a 2-year degree

These outcome probabilities form the main dependent variable in the ensuing analysis.

The third component consisted of expectations about outcome variables related to each path; these serve as the main explanatory variables. While I collected data on a wide array of expectations, I will focus here on the key variables used in the analysis: earnings, tuition costs, and four-year dropout risks.[10]

[10]For example, respondents also reported expected labor supply conditional on each educational attainment. Since this is not directly used in the analysis, I do not include the results.

Earnings. Respondents reported earnings conditional on highest degree, which could be high school (HS), 2-year (AA), or four-year (BA).[11] Respondents were instructed to answer in pre-tax real terms and to condition on full-time work, which is defined as "about 40 hours per week." The first earnings question was the following:

> *We will now ask about your income. Here, and in all future questions about earnings, we would like you to answer using* ***today's dollars only****. That is, please do not account for inflation or increasing prices. Do not consider taxes and report the expected* ***pre-tax salary****.*
>
> *Consider the case where you are working full-time with a high school degree or equivalent as your highest degree. What annual salary do you expect to earn* ***5 years from now****? That is, what is the most likely salary?*

Respondents entered a point estimate. They then indicated the probability that earnings would actually fall into each of 5 intervals centered around their response.[12]

The mass in each interval allows me to measure uncertainty and to identify the distribution of income. Armantier et al. (2017) suggest that economists avoid using point expectations, since individuals may respond differently when asked to report what economists think of as a mean: some respond with the expectation, but others may provide a median, a mode, or some other statistic. Building on Blass et al. (2010), these authors recommend fitting parametric distributions to elicited PDFs (such as the ones I collect) and to use the moments implied by those distributions. This is similar to the approach that Wiswall and Zafar (2015a) adopt with their earnings distributions, albeit for different reasons: in Wiswall and Zafar (2015a), an earnings distribution is fit to three elicited earnings points in order to interpolate earnings across the whole lifecycle. I unify the two approaches, adopting the flexible Beta distribution specification of Armantier et al. (2017) and the Mincer-style earnings function of Wiswall and Zafar (2015a). In addition, I propose a two-step procedure to "rescue" the information contained in the point expectations (which Armantier et al. (2017) advocate discarding). Details can be found in Appendix C, but through the remainder of the paper, it should be understood that analysis is conducted using these fitted distributions and their moments rather than directly using the elicited beliefs.

Four-year tuition. Respondents were asked to report their expected four-year tuition cost conditional on transfer to a four-year program. The type of institution was specified as the one they self-reported that they were most likely to attend, which could be in-state public (87.5%), out-of-state public (7.5%), or private (5%). It was also made clear that respondents should focus on tuition only:

[11] Since earnings are elicited conditional on highest degree rather than on the 4 paths, this embeds the assumption that earnings with an AA *and* a BA are the same as earnings with a BA only.

[12] Denoting by $\mu_{i,s,D}$ the expected earnings for individual i at age s with degree D, these intervals were: $< 0.4\mu_{i,s,D}$, $[0.4\mu_{i,s,D}, 0.8\mu_{i,s,D})$, $[0.8\mu_{i,s,D}, 1.2\mu_{i,s,D})$, $[1.2\mu_{i,s,D}, 1.6\mu_{i,s,D})$ and $\geq 1.6\mu_{i,s,D}$.

Above, you reported it was most likely that you would attend a [in-state public/out-of-state public/private university] if you transferred to a four-year program. What do you expect your annual tuition cost to be at this type of school? Please do not consider room, board, and other living costs, and just focus on tuition.

Respondents reported a point estimate and then provided a PDF in the same manner as with earnings. I again fit a parametric distribution to these measurements and work with this for the remainder of the paper.

Graduation probabilities. Conditional on transfer to a four-year program, respondents were asked about the probability of successfully earning their BA:

As with 2-year programs, many students who transfer to a four-year program may leave without earning a degree.

*If you were to transfer from [the CCP] to a four-year program, what is the percent chance that **you** will earn a four-year degree?*

This question gives $P(\text{earn BA}|\text{transfer}) = 1 - P(\text{dropout}|\text{transfer})$.

Population- and own-beliefs. Crucially, a subset of each of these questions was repeated both for the respondent's *own* outcomes as well as their beliefs about the outcomes for a *typical* student at the CCP (population beliefs). This will be helpful in examining bias. While own-beliefs may depend on private information unknown to the econometrician, the population-beliefs measure an observable variable about which the survey respondent and the econometrician may, at least in theory, access similar information. As one example, respondents answered questions of the following kind:

We would now like you to consider a typical, 25-year old former [CCP] student who left with no degree and is working full time with a high school degree or equivalent.

What annual salary do you expect them to earn?

2.3 Information treatment

The 2025 refresher sample participated in an information experiment, which consisted of reading a few provided paragraphs. Participants were divided into 4 groups. Three of these groups involved an active treatment on earnings, four-year tuition costs, or the transfer and graduation rates of CC students. The 4^{th} group was a control, who received placebo information on the history of the University of Maryland.

For example, students assigned to the earnings group read through the following:

Economic research suggests that higher education brings significant increases

to earnings throughout one's career, sometimes called the "college premium." In general, 2-year degrees are associated with about 20% higher earnings than a high school degree diploma alone, and four-year degrees are associated with about 40% higher earnings than a high school diploma alone. The data also suggest that the premium increases as workers get older. While the BA premium is about 27% at age 25, it grows to about 60% by age 55.

Many factors go into determining how much money someone makes, but it can be helpful to look at the population averages. In recent years, the average 32-year-old Maryland worker working full time made about $43,000 with a HS degree, about $55,000 with a 2-year degree, and about $72,000 with a four-year degree (figures calculated from the Maryland Current Population Survey).

The full set of treatments may be found in Appendix A.2. In each case, the goal was to provide relevant information which would affect the individual's beliefs about one of the relevant sources of uncertainty. The full set of outcome probability and expectation questions were repeated before and after the treatment, forming what Wiswall and Zafar (2015a) call "pseudo-panel data," which contain two measurements for each individual with only the information set changing between elicitations. Table 1 shows balance of the treatment assignment using a multinomial logit regressing the treatment group onto a set of observable characteristics (with the control group serving as the omitted category). While the small sample size in each group means we see finite sample differences, the regressors are statistically indistinguishable from zero except for the indicator for White race in columns (1) and (3).

2.4 Sample

The data were cleaned using the explicit attention checks as well as additional filters for meaningful responses, the details of which can be found in Appendix B.2. The following discussion uses the cleaned baseline dataset, but inclusion of the excluded respondents does not significantly alter the composition of the sample.

The baseline data contain responses from $N = 630$ unique individuals. The original sample consisted of 356 respondents who took the survey in 2024; of these, 91 responded to the follow-up in 2025. The refresher sample consisted of 298 respondents: 66 in the control group, 68 in the tuition cost group, 78 in the graduation and transfer rates group, and 86 in the earnings group.[13]

Table 3 presents selected statistics for the baseline sample. The "Population" column shows statistics provided by the community college administrator for the relevant student body, which

[13] 23 students who signed up for the refresher were in the original sample, and 1 individual participated in the 2024 survey, the 2025 followup, and the 2025 experiment. This creates a small group for which I have both longitudinal data and the pseudo-panel data generated by the information experiment, and it means I have longitudinal data for 114 of the original respondents.

allows me to make a direct comparison to my sample.[14] Relative to the population, my sample is slightly older and slightly more female. Both GPA and full-time enrollment are significantly higher than the population; however, both of these variables may be more subject to reporting bias than demographic characteristics. I match race and major fairly closely, shown in tables 4 and 5 respectively. A complete set of observable characteristics is discussed in Appendix B.3.

A joint test for differences between my sample and the population, using the statistics for which I have population information, rejects the null of no differences. I take this as evidence for some selection into the survey, which appears to occur in expected ways. First, since the survey was distributed via Canvas, it is unsurprising that students who spend more time on their Canvas accounts would be more likely to take the survey; this would include more diligent students (higher GPA) as well as students taking a heavier courseload (more likely to be full-time). Second, the survey is relatively long, which may skew the sample towards non-workers and non-caregivers who have more free time. Finally, the gift card incentive may skew the sample towards lower income students who value the gift card more than their peers. Such bias (or worse) would be likely to exist if the survey were distributed via school email addresses (which would suffer from many of the same issues) or self-selected school survey recruitment lists.[15]

Finally, I test for selection of the original 2024 participants into the 2025 follow-up. Participants were required to provide their school email address in order to receive their compensation. They were also prompted to provide a non-school address for future contact, which a majority opted to do. The follow-up survey contacted each respondent at all email addresses in order to reach those students who were no longer in the community college. Table 2 shows the results of a probit model predicting selection into the follow-up. I find little evidence for selection on observables, with only the coefficient on female gender being statistically significant. However, the follow-up sample leans significantly towards continuing CC students and contains no dropouts, raising a concern for selection on the outcome. For this reason, the second wave of the longitudinal data will not be used in the core analysis, but will serve as an out-of-sample validation test of the model.

3 Empirical evidence

I now present evidence from the data. I first show patterns for each key variable, including a few suggestive tests for rationality. I then examine the relationship between own- and population-beliefs; I show a robust relationship between the two, which in general holds up when I leverage the experimental data to allow for unobserved heterogeneity. Next, I show the efficacy of the information intervention: treated individuals revise their population-beliefs in response to new

[14] These are for the 2024-25 school year.

[15] While not available at the CCP, this approach has been used in similar projects.

information. As a sanity check, I verify there is also a direct effect on own-beliefs.

All of this may be of limited interest if own-beliefs do not have a meaningful impact on one's choices, and so I lastly show the relationship between own-beliefs and the subjective path probabilities using log-odds regressions. Results show that the path probabilities are positively related to expected earnings and negatively related to the four-year dropout risk; the relationship between expected outcomes and tuition costs appears close to zero.

3.1 Data patterns

I first present summary statistics and patterns in the elicited beliefs using the baseline dataset. For each key variable, I present suggestive evidence against FIRE by showing how the distribution of population-expectations compares to observational data benchmarks and administrative statistics. As discussed in Section 2, drawing conclusions about rationality using individuals' own-expectations is challenging; by focusing on the population expectations, about which we have some idea of the true outcomes, I am able to draw stronger conclusions. Additional details on the tests can be found in Appendix B.5.

Path probabilities. Figure 1 illustrates the expected outcomes, or path probabilities, by showing the mean of each belief as well as the fraction of the sample which ranks each path as their most likely outcome. Both paint the same picture: respondents overwhelmingly expect to earn a 2-year degree, on average assigning an 86.5% chance to this outcome. Respondents also report a high expectation of transfer, with a 70.5% chance, but a sizable minority of 24% rate a terminal AA as their most likely outcome. Perhaps unsurprisingly for a group of students who are investing in their education, respondents assign a very low probability to dropout from CC; on average a 3.7% chance, with just 1.2% rating this as the most likely outcome.

It must be emphasized that *there is no trace of the community college puzzle* in these expected choice probabilities. This is illustrated in Figure 2, which compares the mean outcome probabilities against the overall figures for MD. On the one hand, expected dropout is very small, and respondents assign a very high probability to earning their AA. Intended transfer is also very high, and skews towards transfer with a 2-year degree. The overall MD totals, on the other hand, suggest that respondents will ultimately show a much higher rate of dropout and a much lower rate of transfer. Of course, this could be skewed by differences between my sample and the population, and in Section 6 we will take a closer look at exactly this.

Earnings. Table 6 details mean expected own-earnings at ages 25, 30, and 40 and population-earnings at ages 25 and 40. As a simple benchmark, I provide mean earnings for full-time workers from the CPS, averaged from 2015-2024, adjusted to 2024 USD, and weighted by the gender ratio in the survey sample; further details are provided in Appendix F.2. Figure 3 shows own-beliefs and

the CPS means graphically, with circles representing the survey means and crosses the medians, adjusted for the sample size at each point (for example, there are relatively few people reporting an observation at age 50, which is the +20 horizon for the oldest students in the sample). The dashed lines show CPS means. Note that we do not necessarily expect individuals' own-beliefs to coincide with their population beliefs or with the CPS means; the latter reflect selection into each highest degree, while subjective own-expectations provide the treatment effect for each degree.

Expected earnings show strong growth over time for each degree, with significant premia to both two- and four-year degrees. Population beliefs about earnings with a HS degree are low compared to the CPS benchmark; beliefs about earnings with two- and four-year degrees are somewhat high at age 25, and then somewhat low at age 40, indicating an age-earnings profile slightly flatter than that seen in the data. Own expected earnings are similar to the CPS benchmark at age 25, but otherwise appear high. In the case of age-40 earnings, the gap is significant.

To measure the average expected premium, I run the following regression:

$$\log(Y_{isd}) = \alpha_d + \beta' X_i + \epsilon_{isd} \tag{1}$$

Where Y_{isd} is the expectation of individual i for their full-time earnings at age s with highest degree d. X_i is a vector of observable covariates, including s and s^2, race, gender, (log) high school GPA, and parental education. α_d are level premia to 2- and four-year degrees, with high school serving as the reference category. Following Candia et al. (2023), I estimate this equation (and all following regression models) using both standard OLS and Huber-robust regression. The Huber regressions control the influence of outliers, a desirable feature when working with highly heterogeneous (and potentially noisy) beliefs data, and I discuss these estimates as my preferred specification.[16]

On average, individuals expect a 22.7% premium to a 2-year degree and a 57.5% premium to a four-year degree. These are shown graphically in Figure 4, with reference to the approximate literature estimates discussed in Section 1.[17] We see that individuals are somewhat optimistic about the four-year premium; their response appears more in line with the observed population gap in earnings than with causal estimates of the premium. In the context of their level expectations, this appears to be largely driven by their *pessimism* about earnings with a high school degree rather than optimism about BA earnings. The two-year premium is also slightly above the standard range suggested in the literature but appears more well calibrated.

In order to gauge rationality, I test the null hypothesis that the mean expectation of mean

[16] Standard errors are always clustered at the respondent level in cases where individuals contribute multiple observations. I use the analytical formulation where possible and a bootstrap for the more complex specifications.

[17] I use the midpoint of CC range, and the four-year premium calculated from the Bengali et al. (2025) and Hendricks and Leukhina (2018) results.

earnings for full-time workers with degree D is equal to the CPS value. I conduct this test jointly for expectations at ages 25 and 40. I reject the null of rational expectations with $p \leq 0.01$ in each case.

Completion. The means for the expected four-year success rates (the probability of earning a BA conditional on transfer) along with the latest available statistic from MD are shown in Table 7 and illustrated in Figure 5. Per Office of Research and Policy Analysis (2022), 61% of the 2015-16 cohort of MD CC transfer students had completed a BA degree by the 2019-20 academic year. It is worth noting that this is somewhat larger than the statistics normally cited. Velasco et al. (2024) report that for MD community college transfers from the 2015-16 cohort, just 50% earned a BA by the 2021-22 school year. This uses a 6-year horizon from the start of CC; this is common in the literature but is less generous than the Office of Research and Policy Analysis (2022), which gives their cohort 4 years after the point of entry to the four-year program itself.[18] Since my survey question placed no such restriction on the time horizon, this latter statistic would seem to be the more appropriate comparison, but I view this as an approximate upper bound.

On average, survey respondents report an 82.7% chance that they will successfully earn a BA after transfer. This is much higher than the 68.7% chance they report for the population, which is in turn higher than the 61% benchmark. The means do not tell the whole story: 83.6% (65%) of the sample reports an own-probability (population-probability) above the MD benchmark.

I test for rationality in expected graduation rates by comparing the mean subjective belief about the graduation probability for the typical transfer student to the data counterpart of 61%. I reject the null with p <0.01.

Four-year tuition. Table 8 shows the mean of expected own- and population-tuition, along with the maximum annual sticker price for the University of Maryland system of $11.5 thousand; Figure 6 shows the same information graphically with fitted densities. 67.1% of respondents have beliefs above the upper bound. While the distribution of own-tuition expectations appears similar to that of the population tuition expectations, the mean individual difference is $-1.17 thousand and I reject the null of no difference with $p \leq 0.01$.

Finally, I run a conservative test for rationality using the maximum sticker price at the University of Maryland College Park, which is the flagship of the University of Maryland system. In 2024, nominal tuition and fees before aid were approximately $11.5 thousand. I test whether the mean expectation for the "typical" transfer student's tuition exceeds these upper bounds, and reject the null with p <0.01.

Summary. Taken together, the above data show sensible patterns in the elicited beliefs, but provide suggestive evidence against FIRE. Students are pessimistic about expected earnings with a HS

[18] This would capture a student attending consistently part-time, who might require 8 years to earn a four-year degree.

degree. For earnings with 2- and four-year degrees, they are optimistic about earnings at age 25 and pessimistic about earnings at age 40. Respondents are *optimistic* about the probability of successfully completing a four-year degree after transfer, but *pessimistic* about tuition costs at four-year schools, with beliefs biased-upwards in each case.

While these tests are conducted using the population-level beliefs rather than own-beliefs, in the following subsection I present evidence on the close relationship between population- and own-beliefs, and then on the efficacy of the information treatment at shifting both sets of beliefs. This suggests that own-beliefs may suffer from biases as well.

3.2 Own- and population-beliefs

The treatments provided individuals with statistics about population level outcomes. For this reason, I examine the relationship between own- and population-beliefs. In this section I use the experimental data, where the pre- and post-treatment data will allow me to examine the sensitivity of estimates to unobserved heterogeneity.

Let $Y_{i\ell k}$ be the belief of individual i for variable ℓ, which includes earnings at a specific age and education, four-year tuition costs, and four-year graduation rates. I let k index own (k =0) vs. population (k =1) beliefs. I run the following regression:

$$\log\left(Y_{i\ell 0}\right) = \beta_0 + \beta_{1\ell}\log\left(Y_{i\ell 1}\right) + \boldsymbol{\beta'_{2\ell}} X_i + \epsilon_{i\ell} \tag{2}$$

Where X_i is a vector of observable characteristics. For earnings expectations, I restrict $\beta_{1\ell}$ to be constant for each degree across each horizon.

Taking the logarithm means that $\beta_{1\ell}$ can be interpreted as an elasticity of own-beliefs with respect to population-beliefs.[19] I also include a specification which imposes $\boldsymbol{\beta'_{2\ell}} = 0$ to see how the coefficient changes when observable characteristics are included. Results are shown in tables 9 - 10. We see for each variable a large and significant value for β_1, which is attenuated only slightly with the inclusion of observable characteristics.

We might be concerned about the presence of individual-specific unobservable factors affecting both own- and population-beliefs. This would make eq. (2):

$$\log\left(Y_{i\ell 0}\right) = \beta_0 + \beta_{1\ell}\log\left(Y_{i\ell 1}\right) + \boldsymbol{\beta'_{2\ell}} X_i + \alpha_{i\ell} + \epsilon_{i\ell} \tag{3}$$

I address this by leveraging the experimental data. Denote with a $'$ the post-treatment measure-

[19] In order to ensure the log is well-defined everywhere, I limit all success probabilities to be interior to (0,1) by rounding the 0% reports up to 0.1% and the 100% down to 99.9%. This will be continued through the regressions in this section. However, this ad-hoc adjustment will **not** be required when I estimate the structural model.

ment, and define the log-revision as:

$$r_{i\ell k} = \log\left(\frac{Y'_{i\ell k}}{Y_{i\ell k}}\right) \tag{4}$$

By differencing the pre- and post-versions of (3), we can eliminate the $\alpha_{i\ell}$ fixed effects:

$$r_{i\ell 0} = \beta_{1\ell} r_{i\ell 1} + u_{i\ell} \tag{5}$$

Wiswall and Zafar (2015a) note that because the pre- and post-beliefs are elicited in the same survey session, separated only by the information treatment, we do not even need to impose that $\alpha_{i\ell}$ is time invariant; we only need to assume that it is invariant to the *treatment*, which gives information about the population outcomes for the beliefs.

Table 12 shows results for these regressions, and Figure 7 graphs the coefficients for each variable. $\beta_{1\ell}$ remain positive and significant for earnings and tuition, and the coefficient for graduation loses significance. These results suggest that unobserved variables may indeed play a role in the formation of own beliefs, for graduation from four-year school in particular, but that population-level information is quite important.[20] However, we also expect the first-difference to create some attenuation bias if beliefs are measured with error.

3.3 Information experiment and belief updating

The identification of the structural model relies in part on the "pseudo-panel" data generated by the information experiment. To be useful, the treatment must meaningfully shift beliefs.

Let $j \in \{0, 1, 2, 3\}$ index the treatment arms (which correspond to the control, earnings, tuition, and graduation), ℓ continue to index a type of belief (which may be related to earnings, tuition, or four-year completion probabilities), and k to index type of belief, which may be own or population. Let $D_{i\ell}$ indicate that individual i was exposed to a treatment which is thought to affect belief ℓ. For example, the treatment about earnings should affect expected earnings with each highest degree and at each age (9 own-beliefs and 6 population-beliefs), but will not affect expected tuition.

I test if the treatment causes population beliefs to change in the direction of the information signal. Define Y^*_ℓ as the signal relevant to belief ℓ.[21] The (log) pre-treatment difference is $e^*_{i\ell k} = \log\left(Y_{i\ell k}/Y^*_\ell\right)$. I estimate the following regression:

$$r_{i\ell 1} = \alpha_{\ell 1} + \gamma_{\ell 1} D_{i\ell} e^*_{i\ell 1} + \epsilon_{i\ell 1} \tag{6}$$

[20] For example, some families may place greater value on education than others, independent of the included controls for income and parental education, in a way which influences both own- and population-beliefs.

[21] In the case of earnings, this is an age-32 statistic which is relevant for population expectations at ages 25 and 40 even if not a statistic for those specific ages.

$\alpha_{\ell 1}$ allows for baseline drift specific to each target belief, but unrelated to the treatment. The coefficients $\gamma_{\ell 1}$ measure the amount that each belief updates in the direction indicated by the signal, which we expect to be negative, since a large value of $e^*_{i\ell k}$ indicates that the pre-treatment belief was above the signal and individuals should revise down (and vice-versa).

The results from eq. (6) are shown in Table 13. For all targeted beliefs, the pre-treatment difference is negatively and significantly associated with the post-treatment revision, meaning beliefs which initially are lower than the signal are revised upward. This shows that population-beliefs update towards the population-level signal. Above, we also showed that population-beliefs affect own-beliefs, which provides evidence that the treatment should also shift own-beliefs in the direction of the signal. We can verify this directly by running a slightly-modified own-beliefs counterpart to eq. (6):

$$r_{i\ell 0} = \alpha_{\ell 0} + \gamma_{\ell 0} D_{i\ell} e^*_{i\ell 0} + \delta_{\text{earn}} D_{i\,\text{earn}} e^*_{i\,\text{earn}\,0} \,|a_{i\,\text{earn}} - 32| + \epsilon_{i\ell 0} \tag{7}$$

I impose the restriction that $\gamma_{\ell 0}$ is constant across ages within each highest degree, so there is one value for HS earnings, AA earnings, and BA earnings. The final term makes an age adjustment for the earnings belief, allowing directional updating to vary with the distance between the expected earnings age, given by $a_{i\ell}$, and age 32, the age referenced by the earnings information signal.[22] Results from this regression are shown in Table 14, and confirm that the treatment also significantly impacts own-earnings beliefs. Coefficients for graduation and tuition beliefs are negative but are imprecisely estimated in the Huber specification.

3.4 Path-probabilities and expected outcomes

Finally, I ask how the subjective path probabilities depend on beliefs about earnings, tuition, and four-year dropout using the experimental data.

Let Y_{ik} be expected earnings 10-years in the future with highest degree k, and let $Z_{i\rho}$ be expected earnings 10-years in the future associated with path ρ.[23] Denote by $\mathcal{Z}_{i\rho} = \log\left(Z_{i\rho}/Z_{i1}\right)$ the expected premium for path $\rho \in \{2, 3, 4\}$ relative to dropout. Similarly, let $Tu_{i\rho}$ be expected annual four-year tuition and $T_{i\rho}$ the expected tuition for path ρ; this is \$0 for dropout and for a terminal 2-year degree, is $3 \times Tu_{i\rho}$ for transfer without an AA, and is $2 \times Tu_{i\rho}$ for transfer with an AA.[24] I denote by $\tilde{p}_i$ the four-year dropout probability, and by $\tilde{p}_{i\rho}$ the dropout risk associated with path ρ. Finally, X_i is a vector of observable characteristics capturing grades, age, and SES.

[22] Own-beliefs are elicited based on a fixed horizon. The adjustment makes elicitations comparable across individuals of different ages.

[23] Results are similar if the +5 or +20 horizons are used as reference points instead.

[24] Extra time spent in community college is less time in four-year school.

Let $\pi_{i\rho}$ be the elicited subjective probability of realizing path ρ, and define the log-odds of path ρ relative to dropout as $\boldsymbol{\pi}_{i\rho} \equiv \log\left(\pi_{i\rho}/\pi_{i1}\right)$.[25] I estimate the following regression on the pre-treatment observations:

$$\boldsymbol{\pi}_{i\rho} = \beta_{0\rho} + \beta_1 \mathcal{Z}_{i\rho} + \beta_2 T_{i\rho} + \beta_3 \tilde{p}_{i\rho} + \boldsymbol{\Gamma}'_{\boldsymbol{\rho}} X_i + \epsilon_{i\rho} \tag{8}$$

so that β_j for $j = 1, \ldots, 3$ show how the log-odds for the expected probability of choosing path ρ change with a change in expected earnings, tuition costs, and dropout risk. We expected that $\beta_1 > 0$, $\beta_2 < 0$, and $\beta_3 < 0$.

I estimate eq. (8) on pre-treatment observations. The results are given in specifications (1) and (2) of Table 15, where (1) does not include $\boldsymbol{\Gamma}'_{\boldsymbol{\rho}} X_i$ (and each specification provides Huber and OLS estimates). The earnings premium is positively correlated with choice probabilities and statistically significant at the 5% level; four-year dropout risk is negatively related to the log-odds (and significant at the 1% level). The coefficient on tuition is significant, but small and of the wrong sign.

As in the belief regressions, we may worry that unobserved factors, such as a non-pecuniary taste for schooling, are associated with both the reported beliefs and subjective path probabilities; this could lead, for example, to the positive coefficient seen on expected tuition. I assume that unobserved factors are associated with CC attendance (α_i^{CC}) and with four-year attendance (α_i^{4Y}). Eq. (8) becomes:

$$\begin{aligned}
\boldsymbol{\pi}_{i2} &= \beta_1 \mathcal{Z}_{i2} + \beta_2 T_{i2} + \beta_3 \tilde{p}_{i2} + \alpha_i^{CC} + \boldsymbol{\Gamma}'_{\mathbf{2}} X_i + \epsilon_{i2} \\
\boldsymbol{\pi}_{i3} &= \beta_1 \mathcal{Z}_{i3} + \beta_2 T_{i3} + \beta_3 \tilde{p}_{i3} + 0.5\alpha_i^{CC} + 1.5\alpha_i^{4Y} + \boldsymbol{\Gamma}'_{\mathbf{3}} X_i + \epsilon_{i3} \\
\boldsymbol{\pi}_{i4} &= \beta_1 \mathcal{Z}_{i4} + \beta_2 T_{i4} + \beta_3 \tilde{p}_{i4} + \alpha_i^{CC} + \alpha_i^{4Y} + \boldsymbol{\Gamma}'_{\mathbf{4}} X_i + \epsilon_{i4}
\end{aligned} \tag{9}$$

Where α_i^{CC} and α_i^{4Y} are weighted for paths 2-4 based on duration spent in each type of school.[26] By exploiting the pre- and post-treatment log odds for the treated groups only (and dropping the control), I can estimate:

$$\boldsymbol{\pi}'_{i\rho} - \boldsymbol{\pi}_{i\rho} = \beta_1 \left(\mathcal{Z}'_{i\rho} - \mathcal{Z}_{i\rho}\right) + \beta_2 \left(T'_{i\rho} - T_{i\rho}\right) + \beta_3 \left(\tilde{p}'_{i\rho} - \tilde{p}_{i\rho}\right) + u_{i\rho} \tag{10}$$

I estimate this using pre- and post-observations for the treated individuals, with standard errors clustered on the individual level. As shown in Column (5) of Table 15, the coefficients on expected

[25] Probabilities are bound to $\left[10^{-3}, 1 - 10^{-3}\right]$ so that this is well defined, but results are robust to $\left[10^{-4}, 1 - 10^{-4}\right]$ and $\left[10^{-2}, 1 - 10^{-2}\right]$.

[26] A weight of 1 represents two years, so I assume that path 2 represents two years in CC, path 3 captures one year in CC and three years in four-year, path 4 captures two years in CC and 2 years in four-year.

earnings and dropout risk retain both their direction and are significant at the 10% level, though the drop coefficient attenuates towards zero. The coefficient on expected tuition attenuates dramatically and has a wide confidence interval which includes zero.

This demonstrates sensible relationships between beliefs and expected paths, but points to the importance of non-pecuniary factors; while expected returns matter, unobserved individual tastes (α_i^{CC} and α_i^{4Y}) play an important role in determining outcome probabilities. The results also show larger standard errors, which may reflect measurement error being exacerbated by the first difference. Overall, I take this as evidence of the significant role both beliefs and non-pecuniary tastes play in determining the subjective path probabilities.

3.5 Full model

The results from Section 3.4 provide reassurance that the path probabilities relate to expected outcomes in sensible ways (albeit with some noise) in a straightforward linear regression. However, several factors point to the need for a more complete model.

First, although this approach appears at first glance to be relatively atheoretical, it in fact embeds a few important assumptions and approximations. As discussed, extreme probabilities must be rounded away from 0 and 1; although the results are not overly sensitive to the choice of cutoff, this is an arbitrary decision. Similarly, I use dropout as the default category, as is standard in the education choice literature, since a HS degree is each individual's no-investment default. But the results are somewhat sensitive to this choice. Finally, even the construction of the right-hand side variables may be disputed; for example, we can imagine interacting the dropout risk with the premium, since in the event of a dropout event, the individual will at the very least not receive the full four-year earnings boost. A more robust estimation strategy would avoid these judgement calls, and a richer model will naturally address the last complaint.[27]

At a higher level, education decisions are inherently dynamic, and the static log-odds model cannot fully capture the option value of continued enrollment, earnings growth across the lifecycle, or the evolution of uncertainty. In addition, the elicited probabilities are *cumulative* probabilities over a series of period-by-period decisions while enrolled in CC. Finally, a richer model can leverage additional information elicited in the survey, such as parental transfers and the probabilities of attending four-year school with PT and FT intensity. This model will also allow for policy experimentation: evaluating the impact of changing beliefs, implementing new financial aid policies, and isolating the impact of each factor in driving the transfer and dropout phenomena which motivate this work. I now turn to the formulation and estimation of a dynamic structural model of community college choices.

[27] In appendix B.6, I present a half-way version of this, regressing the log-odds on a semi-structural "expected premium" constructed from the three beliefs variables.

4 Dynamic model

4.1 Overview

In this section, I will present the dynamic discrete choice model. It is a model of education choice in the vein of Keane and Wolpin (2001) or Johnson (2013), but focused on community college students. Agents make choices to attend 2- and four-year programs (CC and four-year) or to participate in the labor force. *Transfer* occurs when an agent chooses to attend four-year school, either before obtaining a 2-year degree (transfer without an AA) or after receiving a 2-year degree (transfer with an AA). Dropout occurs when an agent exits CC to enter the labor force before earning a two-year degree.

Investing in education is costly via the opportunity cost of foregone earnings and through tuition costs, which may be partially financed through student loans and parental transfers. Further, it carries a non-pecuniary utility impact, which may be positive or negative. Attaining a degree then influences earnings throughout the remainder of the life cycle. Transfer is risky: agents face dropout risk from four-year school, which means their investment may not pay off. Community college students choose enrollment in each period to maximize their expected lifetime utility, integrating out uncertainty over future earnings, dropout risk, and tuition costs at four-year schools. Formally, community college students will make a choice which solves:

$$V_t(X_{it}) = \max_{d_{it}} \{\mathbb{E}_i \left[u(d_{it}) + \beta V_{t+1}(X_{it+1})\right]\} \tag{11}$$

In (11), X_{it} represents the state variables for individual i in period t, d_{it} is their discrete enrollment choice, and β an (annual) discount factor. The subscript in the expectations operator, $\mathbb{E}_i$, reflects the fact that individuals take the expectation using their individual-specific expected beliefs about the future state, $F_i(\cdot|X_{it})$. This is provided by the data (about earnings, four-year tuition, and dropout risk) and is expanded on below. Flow utility is inside of the expectations operator because students only realize their tuition costs after choosing enrollment.[28] Agents are hand-to-mouth in the sense that they do not make an optimal consumption choice; however, they do have access to student loans which are drawn automatically based on their enrollment decisions and realized income. As a result, d_{it}, X_{it}, and the tuition draw will determine their consumption following a budget constraint specified below.

My principal departure from the prior literature, beyond modeling the choices of community college students in more detail than is standard, is to use the survey-based elicitations of $F_i(\cdot|X_{it})$ and of the path-probabilities to estimate the model. In Section 5, I will discuss how the expectations data map to each element.

[28] This is a modeling choice which I discuss in Appendix D.3.

4.2 State

In each period agents make a discrete enrollment choice d_{it}, defined in detail below. They will make this decision based on their state X_{it}, which consists of:

1. Prior period enrollment choice, d_{it-1}
2. Age s_{it}
3. CC intensity type $\mathbf{a}_i^{CC} \in \{PT, FT\}$
4. A probability $P_i^a(\mathbf{a}_i^{4Y})$ for attending four-year school with PT, FT, or mixed status, conditional on transfer
5. Accumulated credits K_{it}
6. Highest degree $D_{it} \in \{HS, AA, BA\}$, representing high school, 2-year, and 4-year
7. Annual four-year tuition, Tu_{it}^*, for continuing four-year students
8. Student loan balance B_{it}
9. Student loan payments b_i^0
10. Earnings Y_{it}
11. Parental transfers, Pt_i
12. A beliefs distribution over future earnings, tuition, and dropout risk, F_i
13. Latent type $\varphi_i = k$

Agents begin the model with the full range of enrollment options (equivalent to $d_{it_1-1} = CC$, defined below). Highest degree begins at $D_{it_1} = HS$ for all, but initial credits and student loan balances are heterogeneous, as are age, earnings, parental transfers and beliefs. Tuition is known at the time of the decision for continuing four-year students but not for community college students.

4.3 Timing

Within-period. The model is in discrete time with each period representing one year.[29] An overview of the per-period timing is given by Figure 8. Agents enter period t and draw their earnings, which then complete state X_{it}. They then draw the discrete choice taste shocks and make their choices. Agents who choose to enroll in four-year school for the first time then draw their tuition; for already-enrolled four-year students, this is carried over from the prior period. Similarly, four-year students draw their attendance intensity, and then draw a dropout shock and find out if that period's enrollment was successful. Flow utility is then realized, and then the state updates

[29]The model could be extended to semesters, as in Keane and Wolpin (2001) or Arcidiacono et al. (2025).

according to choices, loan payments and accumulation, and the enrollment shock. Details on each shock and component of the decision are provided below.

Life cycle stages. Agents enter the model as community college students at age s_{i0} in period t_1 and face a finite-horizon ending at $t = T^*$ (and with mortality risk in the final years of life). The life cycle can be divided into an education stage, a working stage, and retirement. Within the education stage, students who exit from CC enter the workforce and students who transfer to 4-year school enter a 4-year stage, with no choices modeled in either. These stages are given by:

1. In $t \in [t_1, \ldots, T_1 - 1]$ community college students make enrollment decisions.
2. In $t \in [T_1, \ldots, T_2 - 1]$ all agents work full time.
3. At $t = T_2$ agents retire.
4. At $t = T_3$ agents begin facing an exogenous risk of death, which increases to 100% by T^*.

While each stage is modeled, agents only make active choices in the first stage, and only while they are enrolled in CC or have just completed a 2-year degree.

4.4 Choices

Let d_{it} represent an agent's enrollment or work status in period t. In $t \in [t_1, \ldots, T_1 - 1]$, agents who remain in community college choose:

$$d_{it} \in \{0, CC, 4Y\} \equiv \mathcal{D}$$

where 0 represents exit from schooling and entering the workforce, CC is persistence in community college, and 4Y is transfer to a four-year program without an AA.

If an agent has just earned their 2-year degree, that is, if $d_{i,t-1} = CC$ and $D_{i,t} = AA$, they may choose to work or transfer to a four-year program with an AA:

$$d_{it} \in \{0, 4Y\}$$

Enrollment may occur with part-time or full-time intensity. In community college this is a fixed characteristic $\mathbf{a}_i^{CC}$ (determined from the survey). When transferring to four-year school, students draw whether they will attend with PT, FT, or "mixed" intensity, $\mathbf{a}_i^{4Y}$, which remains fixed thereafter. The probability of each is a characteristic captured by $P_i^a(\mathbf{a}_i^{4Y})$, $\mathbf{a}_i^{4Y} \in \{PT, FT, mixed\}$. Realized intensity in each period is $a_{it} = \mathbf{a}_i^j$, where j gives CC and $4Y$ based on d_{it}. The exception is when $\mathbf{a}_i^{4Y} = mixed$ and $d_{it} = 4Y$, in which case $a_{it} = PT$ and FT each with probability 0.5. Realized

intensity affects flow utility, credit accumulation, degree progression, tuition, and four-year dropout risk. Further details on the mapping from the survey to intensity are given in Section 5.

Exit from CC, either into the workforce or into four-year school, is absorbing. After exit, no further decisions are made. Agents who have transferred to four-year programs remain enrolled until they complete their degree or are hit by a dropout shock; that is, $d_{it} = 4Y$. At $t = T_1$, agents can no longer enroll in school, and highest degree remains constant at D_{i,T_1} for the remainder of the lifecycle. Agents who enter the workforce supply exogenous labor in $t = T_1, \ldots, T_2 - 1$, indicated by $d_{it} = 0$; students also supply an exogenous amount of labor which may represent 0, PT, or FT work. Agents are retired from T_2 until death.

4.5 Flow utility

Utility depends on log consumption and the discrete enrollment choice. Since agents are hand-to-mouth, this simplifies to a function of the enrollment choice, a tuition draw, and the state:

$$u(d_{it}; X_{it}) = \alpha \log(c_{it}) + \psi(d_{it}, X_{it}) + \kappa\omega_{it} + \nu_{it}(d_{it}) \tag{12}$$

Where c_{it} is an implicit function of the choice d_{it}, the state X_{it}, and tuition Tu_{it} based on a set of budget constraint rules presented below. $\nu_{it}(d_{it})$ is an i.i.d. taste shock following the type-1 extreme value (T1EV) distribution, normalized to have a scale parameter $\sigma = 1$ and mean of 0.

$\psi(d_{it}, X_{i,t})$ represents the non-pecuniary flow utility from enrollment, which may be thought of as a taste for schooling. These shifters depend on a latent unobserved type $\varphi_i = k$, $k = 1, \ldots, K$, where agents are of type k with probability w_k. Types are randomly distributed throughout the population and uncorrelated with observable characteristics. The non-pecuniary school effects are therefore:

$$\psi(d_{it}, X_{it}) = \sum_{k=1}^{K} \sum_{g \in \{CC, 4Y\}} \sum_{a \in \{PT, FT\}} \psi_{kga} \mathbb{I}[\varphi_i = k] \mathbb{I}[d_{it} = g] \mathbb{I}\left[a_{it}^{g} = a\right] \tag{13}$$

$\psi(0, X_{i,t})$ is normalized to 0. κ is a transition cost four-year students pay when they are hit by a dropout shock, which makes it so that flow utility from a period ending in dropout is different from utility during a successful period.

4.6 Degree progression

Agents' progress in school is indexed by their stock of credits, K_{it}, which are normalized so that 1 unit represents 1 year of full-time equivalent (FTE) enrollment. Credits accumulate deterministically based on enrollment intensity.

The agent's highest degree is captured by $D_{it} \in \{HS, AA, BA\}$. An AA requires two FTE years of enrollment *in community college*, that is, $K_{it} \geq 2$ does not automatically imply that $D_{it} = AA$, since the agent may transfer to a four-year program before earning their degree.[30] A BA requires four FTE years of enrollment, but may be obtained from any combination of credits earned in CC and four-year school. I assume that CC credits are perfectly transferable to four-year school.[31] Both credit and degree progression are presented in further detail in Appendix D.4.

As discussed in Section 4.4, the success of enrollment in four-year school is uncertain. With probability $p_i^{4Y}(a_{it}^{4Y}, K_{it})$ an agent suffers an exogenous dropout shock, $\omega_{it} = 1$, and is unable to continue their education in $t+1$. $p_i^{4Y}(\cdot,\cdot)$ is a function of a_{it}^{4Y} since the dropout probability may be different for PT and FT students, and of K_{it} since the probability may change as agents get closer to graduation.

$\omega_{it} = 1$ is realized at the *end* of period t. This means that the agent spends the period enrolled and incurs the costs of attendance, but if $\omega_{it} = 1$ cannot update their degree or continue enrollment and is forced to work in $t+1$. The highest degree is updated based on enrollment, accumulated credits, and the completion shock, with the specific rules provided in Appendix D.4.

4.7 Earnings

Let Y_{it} be full-time earnings and let $y_{it} = \log(Y_{it})$. Log earnings y_{it} follows a four-parameter Beta distribution $F_y(y; s, D, \theta_y)$, which depends on age s_{it}, highest degree D_{it}, and parameters θ_y. The distribution is bounded on the left by log full-time earnings at the minimum wage, and on the right by a parameter r_y. The distribution is fully characterized by these bounds and by a mean μ_y and a precision ϕ_y. r_y, μ_y, and ϕ_y all follow degree-specific Mincer-style functions in age; see Appendix D.1 for further details.

In each period, agents receive a draw from $F_y(y; s, D, \theta_y)$. Realized earnings then depend on exogenous labor supply $h_{it} \in \{0, 0.5, 1\}$, representing no work, PT work, and FT work, so that agents receive labor income $h_{it}Y_{it}$. If $d_{it} = 0$ then $h_{it} = 1$, while students may have any value of h_{it}.

4.7.1 Retirement income

Retired workers receive a constant benefit Y_i^r from T_2 until death. The retirement benefit is set at 50% of the mean earnings during $[T_1, \ldots, T_2 - 1]$. Since all agents supply $h_{it} = 1$ in those years, this is:

$$Y_i^r = 0.5 \times \frac{1}{T_2 - T_1} \sum_{\tau=T_1}^{T_2-1} Y_{i\tau} \tag{14}$$

[30] This distinction adds an extra state variable, since K_{it} is now insufficient for knowing D_{it}. But this allows for the well-known sheepskin effect.

[31] This is not always the case, and is an interesting direction for future study.

This means that the benefit is deterministic at retirement in $t = T_2$, but is stochastic from the point of view of a young worker who does not know what their earnings will be later in life.

4.8 College costs and financing

4.8.1 Tuition costs

Community college is tuition-free. Four-year school comes at an annual full-time tuition cost of Tu^*_{it}, which similarly follows a Beta distribution which is bounded to the left at 0, to the right at r_T, and is characterized by mean μ_T and precision ϕ_T.

Tuition is only seen at the time of transfer: if $d_{it} = 4Y$ and $d_{it-1} \neq 4Y$, then the agent draws an i.i.d. value of Tu^*_{it}. Tuition remains constant after beginning enrollment. Part-time students only pay half of this cost, so realized tuition costs are:

$$Tu_{it} = Tu^*_{it} - \mathbb{I}\left[a^{4Y}_{it} = PT\right] \times 0.5 \times Tu^*_{it} \tag{15}$$

Enrolled students receive parental transfers of Pt_i in each period. These are deterministic, fixed at the time of entry, and known to agents.

4.8.2 Student loans

While enrolled. Disposable income (di_{it}) for students is the amount by which labor earnings $h_{it}Y_{it}$ and parental transfers Pt_i exceed a student consumption floor $\underline{c}_s$:

$$di_{it} = \max\left\{0, h_{it}Y_{it} + Pt_i - \underline{c}_s\right\} \tag{16}$$

Students pay 50% of disposable income towards tuition costs, mirroring the federal expected family contribution formula, so student tuition payments are given by:

$$tu_{it} = \min\left\{Tu_{it}, 0.5 \times di_{it}\right\} \tag{17}$$

Students finance any unpaid tuition costs via federally subsidized student loans which do not accumulate interest while in school. The stock of loans at which agents enter period t is given by B_{it}, so the law of motion for students is:

$$B_{it+1} = B_{it} + (Tu_{it} - tu_{it}) + \max\left\{0, \underline{c}_s - h_{it}Y_{it} - Pt_i\right\} \tag{18}$$

While working. Agents who are working and not in school ($d_{it} = 0$) must make payments on their student loans. At the point of exit from education, workers determine their annual student

loan payments, which occur at a rate so that payments for τ_B periods will pay off the loan. In the first period that the agent works they determine:

$$b_i^0 = B_{it} \frac{r_B(1+r_B)^{\tau_B}}{(1+r_B)^{\tau_B} - 1} \tag{19}$$

where r_B is the real interest rate student borrowers face. Workers are automatically enrolled in an income-based repayment scheme which caps loan payments at 20% of income above the consumption minimum for non-students, $\underline{c}_{ns}$. Thus, each period's payment is:

$$b_{it} = \min\left\{b_i^0, 0.2 \times \max\left(0, Y_{it} - \underline{c}_{ns}\right)\right\} \tag{20}$$

The student loan balance accumulates interest and is credited by the amount of the payment:

$$B_{it+1} = (1+r_B)B_{it} - b_{it} \tag{21}$$

Payments cease once the loan is repaid and are capped at the outstanding balance (including accrued interest). Consistent with the IBR scheme, any remaining balance is forgiven after the τ_B periods of repayment.

4.9 Budget constraint and consumption

We are now ready to specify the budget constraint. Total resources available for consumption in each period are given by:

$$M_{it} = h_{it}Y_{it} - b_{it} \times \mathbb{I}\left[d_{it} = 0\right] + (Pt_i - tu_{it}) \times \mathbb{I}\left[d_{it} \neq 0\right] \tag{22}$$

Student loan repayment is always complete by retirement at T_2, so that $M_{it} = Y_i^r$ for retirees.

Agents are hand-to-mouth and consume their available resources, subject to the consumption floors introduced in Section 4.8.2. Market resources depend on labor earnings, parental transfers, tuition costs, and student loans, where the latter decreases consumption for non-students who have to pay down their balance and increases consumption for students who automatically borrow to reach a consumption floor. Total consumption is given by:

$$c_{it} = \begin{cases} \max\left\{\underline{c}_s, M_{it}\right\} & \text{if } d_{it} \neq 0 \\ \max\left\{\underline{c}_{ns}, M_{it}\right\} & \text{if } d_{it} = 0 \end{cases} \tag{23}$$

4.10 Uncertainty and the agent's problem

Agents face uncertainty about their earnings, as shown in Section 4.7, and tuition, shown in Section 4.8.1. Agents also face an exogenous dropout risk, described in Section 4.6. Finally, there is the T1EV shock to utility associated with each discrete choice, $\nu_{it}(d_{it})$.

Denote by $F(X_{it+s}|X_{it})$ the distribution over future state X_{it+s} given current state X_{it}, where the uncertain elements include tuition, degree status (dropout), and earnings. $F_i(X_{it+s}|X_{it})$ is the individual-specific distribution of individual i. $F_i(X_{it+s}|X_{it}) = F(X_{it+s}|X_{it})$ represents the special FIRE case (all agents at the same state hold the same belief), but this is not an assumption of the model. My setup does not allow for learning, in large part due to data restrictions, but this possible extension is discussed in Appendix D.6.

Agents are defined by a state X_{it}, which most importantly contains prior enrollment, accumulated credits, highest degree, student loan balance, latent type, and a beliefs distribution over uncertain future outcomes. The choice of d_{it} affects utility in period t through consumption via tuition costs and labor earnings, through the non-pecuniary impacts of ψ_k and $\nu_{it}(d_{it})$, and through the exogenous dropout risk. It affects future utility through the accumulation of debt that will need to be repaid, thus lowering consumption, and through progress towards a two- or four-year degree, which can yield increased earnings.[32] Community college students take all of this into account when choosing d_{it}, discounting future utility at a rate of β. Agents also account for uncertainty by taking the expectation over their future outcomes using their beliefs distribution F_i.

Formally, after observing their period t state, earnings, and taste shocks, they choose d_{it} to maximize their expected discounted lifetime utility. This yields the Bellman equation shown in eq. (11), which can be written to explicitly show the beliefs distributions:

$$\begin{aligned} V_t(X_{it}) &= \max_{d_{it}} \left\{ \mathbb{E}_i \left[u(d_{it}) + \beta V_{t+1}(X_{it+1}) \right] \right\} \\ &= \max_{d_{it}} \left\{ \int_{\mathbf{X}_{it+1}} \left(u(d_{it}) + \beta \int_{\nu} V_{t+1}(x)\, dF_\nu(\nu) \right) dF_i(x|X_{it}) \right\} \end{aligned} \tag{24}$$

Where $u(\cdot)$ is inside the expectations operator because four-year tuition is not known at the time of the choice. The terminal value function is shown in eqs. (47) and (48) in Appendix D.5.

The T1EV assumption for the shocks gives the per-period probability of each discrete choice the familiar logit form, a feature which I take advantage of in estimation. Details of that representation and the specific way it relates to the survey timing and subjective beliefs can be found in Appendix D.5.1.

[32] Some agents may expect lower earnings with higher degrees, though this is very rare in the data.

5 Estimation and Identification

I estimate the model on the survey data using a simulated maximum likelihood procedure and an EM algorithm. In the spirit of the measurement error maximum likelihood approach described in Keane et al. (2011), the likelihood function is derived under the assumption of measurement error in the elicited path probabilities.[33] The estimation targets respondents' subjective outcome probabilities, while beliefs about earnings, tuition, four-year completion, enrollment intensity and labor supply enter as *inputs* to the model rather than as estimation targets.

The intuition behind the estimation procedure parallels the standard approach using data on realized choices with a slight modification. In typical discrete choice models, the econometrician finds the set of parameters most likely to have generated a set of observed choices. In this paper, which follows others in this literature, I find the set of parameters such that the model-implied probabilities of each path match the *expected choices* of survey respondents. This answers the question: *if the respondent filled out the survey with this model in mind, what would they have said?* Put another way: *what set of preferences must they hold, such that I would have observed these responses from this model?*

5.1 Data inputs and restrictions

Initial conditions are taken directly from the data. This consists of previously accumulated college credits, age, outstanding student debt, parental transfers, and enrollment intensity. I assume that parental transfers are constant while students are enrolled, and that students remain in their current intensity during CC, determining $\mathbf{a}_i^{CC}$.[34] For four-year intensity, I elicit the probability of attending four-year school with PT, FT, and "mixed" intensity (conditional on transfer occurring), so that I have direct counterparts for $P_i^a(\mathbf{a}_i^{4Y})$. These probabilities are used directly when simulating four-year spells for transfers.

I assume full-time labor supply for non-students. For students, the labor supply is taken from the survey. For community college enrollment, I hold labor supply fixed at the observed level. During four-year enrollment, I use elicited probabilities of working part-time, full-time, or not at all conditional on four-year enrollment. To simplify computation, I calculate expected hours and input these directly:

$$h_i^{4Y} = 0.5Pr_i(h = PT \mid 4Y) + Pr_i(h = FT \mid 4Y)$$

Because expected labor supply was not elicited conditional on the intensive margin of enrollment, I assume the two are independent. Finally, tuition and earnings distributions are fit to the

[33] I assume no measurement error in the right-hand side expected outcomes, as is standard in the literature. However, this is an area for future work.

[34] I did not elicit an intensive margin probability while enrolled in CC as I did for 4Y school.

survey data in the way described in Section 2 and Appendix C, and then directly used as individual beliefs.

Dropout risk in four-year schools, $p_{it}^{4Y}(\cdot,\cdot)$, is similarly taken directly from the survey data. As described in Section 2, respondents report the probability that they will earn a BA conditional on transfer. I take one minus this belief as the dropout risk. This is a belief about cumulative dropout over an entire four-year spell, and so needs to be distributed across periods. I do so using data on realized enrollment spells (from the NLSY97). The data disciplines how dropout risk evolves with accumulated credits K_{it} and intensity while respecting the individual-specific beliefs about the total dropout risk while enrolled. Further details can be found in Appendix F.3.

5.2 Calibration

Calibrated parameters, environmental details, and institutional specifics are listed in table 16. Panel A specifies key ages in the timing of the lifecycle. Panel B gives details of the student loan and tuition cost landscape; these are simplified representations of the system, taken in most cases from institutional rules. Panel C contains two calibrated model elements: the number of discrete types, which is set to 5 based on a k-means cluster of the fixed effects from eq. (9), and the discount rate β, which is calibrated to 0.9. While lower than a typical macro value of 0.95 or 0.98, this value is well within the literature range for young people, in particular for students (Belzil et al. (2021), Todd and Zhang (2020)). Further discussion of the calibration can be found in Appendix E.1.

5.3 Estimation

I estimate the model by pooling the initial 2024 observations, the pre-treatment observations for the experimental control group, and pre- and post-observations for the treated groups. I leave out the follow-up observations from the original sample and the post-treatment observations from the control group, which will serve in an out-of-sample validation exercise.

There are 22 non-calibrated model parameters to estimate, collected in the vector θ:

- α (consumption coefficient)
- ψ_k (tastes for schooling; 4 parameters (CC and 4Y for PT and FT attendance) and 5 types)
- κ (four-year dropout cost)

I also estimate four discrete type probabilities, w_k, $k \in \{1,\ldots,5\}$ (where w_5 is determined by $w_1,\ldots,w_4$). Finally, I estimate a parameter for the precision of the reporting distributions, detailed below and denoted by ϕ, for a total of 27 estimated parameters collected into vector Θ.

The simulated maximum-likelihood (SML) approach is based on the elicited outcome probabilities. These are denoted $\tilde{\pi}_{ij}$ for $j \in \{1,2,3,4\}$, where j indexes dropout, terminal AA receipt,

transfer without an AA, and transfer with an AA respectively. $\tilde{\boldsymbol{\pi}}_i$ collects the vector of probabilities. They are mutually exclusive and exhaustive of outcomes to CC enrollment.

Note that these are *cumulative* outcome probabilities. These can also be understood as the probability of being at a certain *state* at some point in the future.[35] This is in contrast to previous discrete choice models estimated with elicited probabilities (such as Wiswall and Zafar (2015a) and Delavande and Zafar (2019)). This approach may be useful in other contexts where we are interested in outcomes which depend on multiple period-by-period choices, and it is not feasible to elicit probabilities of each period's choice.

For a given value of θ, I can calculate the model-implied counterparts for each probability, for each person, by accumulating probabilities from eq. (52) (detailed in Appendix D.5.1). See Appendix E.2 for further details on the mapping to the survey probabilities.

5.4 Likelihood

I draw on maximum-likelihood methods which incorporate measurement error, such as that used in Imai and Keane (2004) and reviewed in Keane et al. (2011). I assume that the reported path probabilities follow a Dirichlet-Multinomial (DM) distribution. This is in contrast to Wiswall and Zafar (2015a), who use non-linear least squares.[36] Another alternative would be a multinomial quasi-likelihood approach as suggested by Papke and Wooldridge (1996).[37]

My approach allows for elicited probabilities to be noisy measurements of the true latent beliefs and for heaping at focal points (such as 0% and 100%). It also incorporates respondent-specific tendencies to report at given intervals (such as increments of 10%) often observed in elicited probabilities. This phenomenon, and the issue of measurement error in elicited probabilities, are both discussed in Blass et al. (2010) and known in the literature. I present here the essential details of the method, with additional context, including motivation from a measurement model, provided in Appendix E.4.

Elicited probabilities are still denoted by $\tilde{\boldsymbol{\pi}}_i$. The model-implied counterparts are $\pi_{ij}(\theta)$, with $\boldsymbol{\pi}_i(\theta)$ the vector. The probabilities were elicited in the survey as percentage chances, so I let $\mathbf{R}_i = 100\tilde{\boldsymbol{\pi}}_i$ be the vector of elicited percentages. I assume reported percentages are a noisy measurement for the true latent subjective belief, which is denoted by the probability vector $\boldsymbol{\pi}_i^*$;

[35] The model has been laid out to avoid having to track credits from CC and 4Y school separately, but if instead of K_{it} we tracked K_{it}^{CC} and K_{it}^{4Y}, then these probabilities would correspond to the probability that at T_1 one will hold $K_{it}^{CC} < 2$ and $K_{it}^{4Y} = 0$ (dropout); $K_{it}^{CC} \geq 2$ and $K_{it}^{4Y} = 0$ (terminal AA); $K_{it}^{CC} < 2$ and $K_{it}^{4Y} > 0$ (transfer without AA); and $K_{it}^{CC} \geq 2$ and $K_{it}^{4Y} > 0$ (transfer with AA).

[36] As the authors point out, NLLS is less sensitive to severe mismatches between the predicted and reported probabilities than maximum likelihood.

[37] Those authors study fractional response rates; in their case 401(K) plan participation, but this is easily extended to an elicited probability vector.

put another way, $\mathbf{R}_i$ is a noisy measurement of $100\boldsymbol{\pi}_i^*$.

Each individual is assumed to report percentages according to a reporting scale G_i, meaning they consider percentages in increments of $100/G_i$. For example, if $G_i = 2$, then their reports fall in $\{0, 50, 100\}$; if $G_i = 20$, then their reports fall in $\{0, 5, \ldots, 95, 100\}$; and if $G_i = 100$, the most granular level allowed on the survey (since responses were restricted to integers), then reports may be any integer on $\{0, 1, \ldots, 100\}$. I classify G_i by considering a set of 15 probability-based questions on the survey. Details of the classification, including the percentage of respondents at each value of G_i, are also provided in Appendix E.3.

Finally, denote by $\boldsymbol{C}_i = G_i\tilde{\boldsymbol{\pi}}_i$ the count vector. The result is that:

$$\mathbf{C}_i|\boldsymbol{\pi}_i^*, G_i, \phi \sim \text{DirMult}\left(G_i, \phi\boldsymbol{\pi}_i^*\right) \tag{25}$$

Where ϕ is a "precision" parameter (see Appendix E.4 for details). This means that:

$$\mathbb{E}\left[\mathbf{C}_i \mid G_i, \boldsymbol{\pi}_i^*\right] = G_i\frac{\phi\boldsymbol{\pi}_i^*}{\phi} = G_i\boldsymbol{\pi}_i^* \tag{26}$$

So that $\mathbb{E}\left[\tilde{\boldsymbol{\pi}}_i \mid G_i, \boldsymbol{\pi}_i^*\right] = \boldsymbol{\pi}_i^*$. Define by $r \in \mathscr{R}_i$ an index for pre- and post-measurements, where $\mathscr{R}_i = \{0, 1\}$ for individuals who receive treatments in the information experiment and $\mathscr{R}_i = \{0\}$ otherwise. The likelihood contribution for person i and report r is:

$$\mathscr{L}\left(\phi, \boldsymbol{\pi}_{ir}^* \mid \boldsymbol{C}_{ir}, G_i\right) = \text{DM}\left(\boldsymbol{C}_{ir} \mid G_i, \phi\boldsymbol{\pi}_{ir}^*\right) \tag{27}$$

Where $\text{DM}(\cdot)$ is the PMF for the Dirichlet-Multinomial. This formulation assumes that conditional on G_i and latent beliefs, errors are independent across the survey rounds.

To estimate the model, I plug the model-implied probabilities into eq. (27). Since type φ_i is not observed, we have to consider the possibility that type $\varphi_i = k, \forall k = 1, \ldots, K$. Denote by θ_k the vector collecting common model parameters with type-specific parameters for type k. I rewrite eq. (27) as a type-specific contribution:

$$\mathscr{L}_{irk} \equiv \mathscr{L}\left(\phi, \theta_k \mid \boldsymbol{C}_{ir}, G_i\right) = \text{DM}\left(\boldsymbol{C}_{ir} \mid G_i, \phi\ \boldsymbol{\pi}_{ir}(\theta_k)\right) \tag{28}$$

Denote by $\{w_k\}_{k=1}^K$ the population type shares. The observed-data likelihood is:

$$\mathcal{L}(\phi, \boldsymbol{\theta}, \boldsymbol{w}) = \prod_{i=1}^{N}\left[\sum_{k=1}^{K} w_k \prod_{r\in\mathscr{R}_i}\mathscr{L}_{irk}\right] \tag{29}$$

Further details on the likelihood function can be found in Appendix E.4.

I jointly estimate $\phi, \boldsymbol{w}, \boldsymbol{\theta}$ by maximizing eq. (29) in an EM algorithm. The application of the algorithm is straightforward, with one exception. After the ℓ^{th} E-step, I calculate respondents' posterior type probabilities, $P^{(\ell)}(\varphi_i = k|\boldsymbol{C}_i, G_i; \hat{\Theta}^{(\ell)})$. For the experimental sample, I have pre- and post-measurements. Since an individual may only be of one type, I utilize both reports in estimating their type. I calculate standard errors from the Hessian of the observed-data log likelihood in eq. (29), evaluated at the converged estimates. Further details on the type probabilities, the EM loop, and standard errors can be found in Appendix E.5.

5.5 Identification

Here, I briefly discuss the variation in the data used to identify each parameter. Table 17 provides an abbreviated version of the discussion.

Identification of the consumption coefficient α is given by the degree to which the subjective path probabilities depend on degree-specific earnings and tuition costs. α, along with all of the other utility parameters, is only identified relative to the scale of the shock $\nu(d_{it})$, which is normalized to 1.

Identification of the ψ tastes for schooling depends on propensity to choose community college and four-year school. Distinction between PT and FT utility for CC is given by students observed attendance choices. Distinguishing between PT and FT utility for four-year school depends on the $P_i^a(\mathbf{a}_i^{4Y})$ probabilities of attending PT, FT, and "mixed" conditional on transfer. The subjective four-year dropout probabilities help pin down the four-year exit cost, based on the variation between propensity to transfer (with and without a 2-year degree) and expected dropout risk. Individuals of the same type with similar beliefs about tuition and earnings, but different expected dropout risks, will make different decisions. This is identified conditional on the assumption of how such risk evolves during a four-year spell, which is calibrated from the NLSY97 (described above).

The population type shares, w_k, are identified by common patterns in reported probabilities. Individuals with similar type probabilities will tend to display similar patterns, for example, a high propensity of attending a certain type of school combined with a low probability of dropout, despite different beliefs. The share w_k is then identified by the average posterior probability most consistent with the probabilities generated by θ_k.

The distribution of types is identified *cross-sectionally* by the logit assumption on $\nu(\cdot)$, similar to the major-choice model in Arcidiacono et al. (2012a). It is non-parametrically identified thanks to the pseudo-panel data generated by the information experiment similar to the fixed effects model of Wiswall and Zafar (2015a). Intuitively, the response of $\boldsymbol{\pi}_i$ to the experiment-induced change in beliefs (which is orthogonal to the type) will differ based on ψ, which in turn depends on φ_i.

Finally, the reporting-concentration parameter ϕ is pinned down by the dispersion of reported

percentage chances around the model-implied values, with larger ϕ implying less dispersion. This is identified jointly with the rest of the parameters and is conditional on the reporting grid G_i.

6 Results

6.1 Estimates

Parameter estimates and type shares are presented in Table 18 with standard errors in parentheses. The utility-shifters, ψ_k and κ, are presented in multiples of the annual consumption utility at \$64K, the rounded observed median earnings of age-40 AA full-time workers in the CPS. That is, they are divided by $\alpha \log(64)$, with consumption measured in thousands of dollars. Non-pecuniary utility effects are very important, with most of the tastes several multiples of this benchmark annual consumption utility.[38] In general, respondents have positive tastes for schooling, with these effects being generally larger in two-year than four-year programs. The second feature is substantial heterogeneity across the types, who have different preferences for education and for CC vs. four-year programs.

The model fits the aggregate moments targeted in the likelihood function well, as shown in Table 19 and in Figure 9. The individual-level fit is shown in Figure 10. The model estimated with 5 types captures substantial individual-level variation, though sizable differences between predicted and reported probabilities remain.

As discussed in Section 5, not all the data was used in estimation. I use the post-treatment observations for the experimental control group, and the follow-up reports for the longitudinal data, as an out-of-sample validation test. The fit on the aggregate moments in this out-of-sample data is shown in Figure 11. The fit deteriorates somewhat, with the RMSE increasing from 0.14 to 0.21, but the aggregate moments match well. The deterioration in fit is mostly from the second round elicitations from the longitudinal sample; the RMSE for the post-treatment beliefs of the control group is essentially unchanged from the in-sample value, at 0.14. Given the challenging nature of fitting elicitations from a year later (while holding the type probabilities fixed from the original elicitations), I view this as confirmation of satisfactory model fit.

6.2 Elasticities of path probabilities with respect to beliefs

I first evaluate the relative sensitivity of expected outcomes to each of the uncertain variables: earnings (with HS, AA, and BA), four-year tuition, and (annualized) four-year dropout risk. To do so, I calculate changes in the ex-ante outcome probabilities given a one standard deviation

[38] While quite large, the prominent role assigned to non-pecuniary factors in education decisions is comparable to that found in similar models such as Wiswall and Zafar (2015a) and Delavande and Zafar (2019).

increase in each of the core belief variables. For tuition and earnings, I use the s.d. from each individual-specific distribution. For dropout risk, I use the s.d. across population beliefs. The intention behind this exercise is to reflect the relevant uncertainty that individuals face with respect to each belief (acknowledging that for four-year dropout risk, variation across the population is used as a proxy).

Results are shown in Figure 12, in both percentage points and percentages. Outcome probabilities are most sensitive to the dropout risk: an increase of 6.6 p.p. changes transfer by -6.1 p.p. (-8.7%) and changes CC dropout by 0.8 p.p. (21.8%). Outcomes are somewhat responsive to earnings; for example, a 1 s.d. increase in expected AA earnings (on average, $22,651) changes AA receipt by 0.9 p.p. (1.1%), while a 1 s.d. increase in expected BA earnings (on average, $29,118) changes transfer by 1.6 p.p. (2.3%). Expected choices are more inelastic with respect to HS earnings, and are essentially unresponsive to expected tuition: increasing tuition by 1 s.d. (on average, $5,456) only changes transfer by -0.1 p.p. (-0.2%).

Alternatively, we can perform the same exercise using semi-elasticities; this is shown in Figure 13. Here, I increase mean earnings and tuition by $1K, and increase the four-year dropout risk by 1 p.p. These results mirror those found from looking at the s.d. changes: dropout risk in four-year programs appears most important, followed by AA and BA earnings, with outcomes relatively inelastic to HS earnings and tuition costs.

The small elasticity of expected outcomes with respect to expected tuition costs may be surprising, in particular because several experiments have found that prospective four-year students are responsive to information which lowers their expected tuition costs (Bettinger et al. (2012), Hoxby and Turner (2015)). Rather than contradicting this prior work, I view my results as pointing to several important differences in the sample and context. The literature cited here focuses on high school students who have not yet made a first step on their higher education journey, while my sample is of community college students who have already made an initial investment. It is possible that the CC students, most of whom are receiving state or federal aid to attend, have already overcome the kind of information barrier that the high-achieving low income students in Hoxby and Turner (2015) suffer from. Conditional on having taken that first step, CC students appear inelastic to tuition costs.[39]

Moreover, the small elasticity in the structural model mirrors the result from the log-odds regressions. Any model of how intended transfer behavior varies with expected tuition costs must

[39]It is also true that the student loan environment, which has been calibrated to match institutional details, serves to mute the impact of a change in tuition. Holding the parameter estimates fixed and making the student loan rules harsher (for example, decreasing the consumption floor) increases sensitivity towards tuition. However, we would also need to re-estimate the model. In such tests, harsher rules lead to a *lower* estimate for α, since we must explain why young people desire to go to school despite the low consumption while enrolled. So the impact of changing the student loan calibration on the results is ambiguous.

rationalize the fact that the data shows individuals have both high intentions to transfer and high tuition expectations, and that correcting tuition expectations does not have a large effect on the intention to transfer.

Non-pecuniary tastes. Finally, I corroborate the important role for the non-pecuniary tastes for enrollment. I do so first by calculating the type-specific standard deviation of ψ across the four kinds of schooling, and increase tastes by this amount. As is shown with the other standard deviation elasticities in Figure 12, this has a much larger effect on outcomes than any of the other beliefs.

I then set the ψ_k parameters to 0: this means that the motivations for investing in education, and choosing CC over four-year school, are the financial returns, consumption while enrolled, and the risk of dropout (which affects both non-pecuniary flow utility and future pecuniary utility). With these non-pecuniary enrollment effects zeroed out, transfer changes by -27.8 p.p. (-39.5%) and AA receipt by -46.1 p.p (-53.9%).

Lastly, I evaluate the ex-ante probabilities when the entire sample is assigned to each latent type, which equalizes non-pecuniary tastes for enrollment ψ_k. Figure 14 shows the results. Choice probabilities change dramatically with type, by much more than they do in the elasticity exercises. Since type 1 is the dominant type, with a 42.5% share, this is relatively close to the population level. The other types display distinct patterns: for example, type 4 is relatively unlikely to earn an AA, and type 5 is relatively unlikely to transfer. Outcomes are largely determined by these type-specific tastes.

Non-pecuniary tastes for schooling thus play a large role in expected outcomes, in particular incentivizing attainment of an AA, driven by a relatively large utility of CC attendance, compared to smaller or negative utility to four-year attendance. Non-pecuniary tastes also generate a large wedge between types.

6.3 Aligning beliefs

I now shift to the metric most relevant to the policy-maker: simulated ex-post outcomes. While individuals make decisions based on their individual-specific subjective beliefs, outcomes will be realized based on the "true" distributions. When evaluating the impact of policies, whether those aimed at providing information, or more "active" policies such as tuition subsidies, it is these outcomes which matter rather than ex-ante subjective probabilities.

This is not straightforward. As discussed above, the *true* distributions are not known because outcomes have not been fully realized (or observed) for the sample. As a result, I introduce a set of "benchmark" distributions, which are meant to give the best estimate for expected outcomes. These may be seen as approximations for the FIRE distributions.

I estimate benchmark distributions for earnings conditional on each highest degree, four-year tuition costs, and dropout risk at four-year programs. For each outcome variable, I use public data with observed outcomes and estimate a model conditional on a common set of observables available in both the observational data and in the survey data set. I then plug the observable characteristics from my sample into the benchmark models to find the benchmark distribution individuals face. I estimate earnings distributions from the CPS, tuition distributions from the HSLS, and dropout risk from the NLSY97. Further details are provided in Appendix F.

I then explore the impact of "correcting" beliefs, or aligning individuals' beliefs with the benchmark distributions used to simulate the model, on these ex-post simulated outcomes. For each distribution (earnings, tuition, and four-year dropout), I give agents the benchmark belief, *for that variable only*, and observe how outcomes change (using the benchmark distributions to simulate outcomes).[40] I also explore the total effect of aligning all beliefs simultaneously.

Results are shown in figure 15. Correcting tuition beliefs has small effects on choices or welfare, given the established low elasticity. Correcting earnings beliefs has moderate effects, causing people to shift away from earning an AA and towards both transfer and exit from CC. Updating dropout beliefs, has the most significant impact, changing CC dropout by 0.8 p.p. (22.8%) and overall transfer by -6.8 p.p. (-9.7%). Note that updating dropout beliefs and earnings beliefs work at cross purposes with respect to AA receipt and transfer, leading to relatively muted effects when both sets of beliefs are corrected simultaneously.

Aggregate movements may mask individual changes, as individuals can sort more efficiently between paths without a significant change to overall outcomes. This is indeed the case, in particular with respect to earnings, where individuals are on average relatively accurate but may individually exhibit large mistakes. For each person, I calculate their *churn* as the total distance between outcome probabilities at baseline (π_{ij}^{base}) and those with the benchmark beliefs (π_{ij}^{cf}):

$$churn_i = \frac{1}{2} \sum_{j=1}^{4} \mid \pi_{ij}^{cf} - \pi_{ij}^{base} \mid$$

The mean churn is 7.9 p.p. (median 6.6 p.p.). Furthermore, there are significant utility benefits to updating beliefs, as shown in Figure 16. At the median, correcting beliefs increases utility by about \$1,615 (in annual consumption equivalent terms) over 30 years. The largest winners experience much larger gains: at the 90$^{\text{th}}$ percentile, \$8,197.

However, Figure 16 also illustrates how correcting just *one* belief does not necessarily lead to an increase in utility. In particular, we see that when correcting earnings beliefs only, individuals

[40]Note that correcting all the beliefs must lead to improvements in utility, but correcting one belief while leaving others unchanged need not improve outcomes. This is the case here; correcting tuition beliefs only encourages people to transfer but leads to lower utility because they are optimistic about the four-year dropout rates.

are on average (and at the median) worse off. This is because they shift towards transfer, which is for many a mistake because they underestimate the four-year dropout risk.

Welfare effects of the experiment. To demonstrate this, I perform an exploratory exercise in partially correcting beliefs based on the own-belief pass-through coefficients from the information experiment (shown in Table 14).[41] I assume that agents are told that someone "like them" would draw from the benchmark distributions; they then update their subjective distribution towards the benchmark distribution based on the pass-through coefficients.[42]

As Table 14 shows, individuals react less to the four-year dropout risk than to earnings and tuition, indicating a possible resistance to new information which works against their biases. For this reason, the information treatment operates primarily through tuition and earnings. This is reflected in the net welfare effects shown in Figure 17 (with the "Full" correction shown for comparison to the "Partial" updates from the pass-through coefficients). The changes are necessarily smaller than in the full-correction exercise since the pass-through coefficients are less than 1. In this simulation, the net welfare effect of the information treatment is close to $0 at the median and is in fact negative at the 10^{th} percentile. This is for the same reason that correcting earnings or tuition on their own in the full-update exercise can be welfare negative: individuals update beliefs based on the earnings and tuition information by much more than they do for the dropout risk. This encourages them to transfer when it is not optimal to do so, e.g. it encourages them to make a mistake.

Both the full and partial correction exercises thus highlight the importance of providing individuals with a full set of information, since correcting one bias while leaving another need not improve welfare. It also highlights nonlinearity in the welfare gains: correcting multiple biases may combine to leave individuals better off than one would think by looking at each on their own.

6.4 Encouraging transfer

I next conduct several exercises aimed at encouraging transfer from CC to four-year school – the stated goal of most CC systems, and the intended outcome for students.

Subsidizing tuition. The survey data provide evidence that individuals under-estimate the risk of dropout in four-year school: they believe that transfer will be less risky than the population data suggests. While the obvious (and optimal) solution may simply be to correct individual beliefs and let CC students make optimal decisions, this may be infeasible for two reasons. First, beliefs may not be sufficiently responsive to information provision, as seen by imperfect pass-through in the

[41] I use the point estimates, though it should be noted that some are estimated imprecisely.

[42] There are other ways to examine this; in particular, because the benchmark distributions reflect a wider set of individual-specific characteristics, we might think that individuals will update by more than the estimates in Table 14 imply. However, the core idea that partial updating, with different magnitudes for different beliefs, will have ambiguous welfare effects survives such an exercise.

information experiment. Second, given the central importance of four-year transfer to the mission (and evaluation) of community colleges, CC administrators would likely be hesitant to undertake any campaign which would have the effect of discouraging transfer, even if such a policy may benefit their students. There may also be positive spillovers for optimistic individuals investing in their education, and a social planner would like to incentivize them to continue doing so.

To address these restrictions, I instead implement an alternative policy which offers free four-year tuition to students who transfer *with* an AA, but not to those who transfer without. This is intended to incentivize students to insure themselves against the risk of non-completion in four-year school by first earning their 2-year degree.

The impacts seen are modest, reflective of the low elasticity of outcomes with respect to tuition established above, and can be seen as "Free tuition" in Figure 18. Relative to the common baseline of subjective decisions without the subsidy, the subsidy alone increases transfer with an AA by 0.8 p.p. and AA attainment by 0.3 p.p. The policy disproportionately draws from students who would otherwise earn an AA and enter the workforce, rather than from students who would otherwise transfer without an AA. This is a targeting problem: the administrator would like to offer the subsidy only to those who otherwise transfer without an AA, but cannot distinguish them from students who would otherwise earn a terminal AA.

I then implement a lower-cost version of this policy. Rather than offering a tuition subsidy to AA transfer students, I offer full financing of tuition costs, allowing four-year students to fully defer payment on tuition until after they have exited four-year school. This is shown as "Full financing" in Figure 18. The impacts are strictly smaller, reflecting that this policy is strictly less generous than the full subsidy. However, extended financing accomplishes about half of the effect of the subsidy, simply through extending more credit. In the model, this is because the increase in consumption while enrolled has a large impact on students' wellbeing relative to the decreased consumption later in the lifecycle when repaying the loans. This result mirrors the findings in Stinebrickner and Stinebrickner (2008), who find that many four-year students who do not face credit constraints in covering schooling costs would nevertheless like to borrow more for consumption.

Decreasing risk. We have seen from Section 6.2 that students are relatively inelastic with respect to tuition. Recognizing that the four-year risk is a more salient factor, I next implement a policy inspired by the City University of New York's "Accelerate, Complete, Engage" (ACE) program. ACE offered free tuition, comprehensive advising services, and other support to students (Scott-Clayton et al. (2025)). Per City University of New York (2025), this program had the effect of increasing the four-year completion rate among transfers by about 100% (or 35-percentage-points). Inspired by this prorgam, I both make four-year school free and lower each individual's subjective expected dropout risk by 50%. Results are shown as "ACE" in Figure 18. As we would expect, the effects are substantially larger than those seen from the tuition subsidy: transfer increases by 3.6

p.p. (5.2%) and exit from CC changes by -0.5 p.p. (-14%), impacts several times larger than those from the targeted tuition subsidy.

However, this comparison also points to a shortcoming of the model which merits caution: four-year dropout risk is taken as an exogenous hazard, rather than an endogenous choice. To the extent that dropout from four-year programs is driven by tuition costs or credit constraints (a disputed idea which is also spoken to by Stinebrickner and Stinebrickner (2008)), the tuition subsidy may have a secondary impact operating through reduced four-year dropout risk, and my result may underestimate its impacts. Put another way, it is possible that the decrease in dropout risk seen in the ACE study flows from the tuition subsidies, rather than the counseling and support services; further data and study will be needed to provide a more satisfying decomposition.

Discussion. Since the ACE policy combines a tuition subsidy with a decrease in the four-year dropout risk, we cannot make a perfect comparison to the tuition subsidy on its own. However, these results suggest that policies which target the four-year dropout risk through the kind of counseling services and supports contained in the ACE program are much more effective at encouraging transfer than tuition subsidies will be.

However, much of the policy discussion around community college transfer (and four-year attendance in general) focuses on affordability and costs rather than risks. In part, the centrality of affordability may be because ACE-style policies tend to be implemented and funded at local and school-specific levels, while funding for tuition subsidies often flows from the state or federal levels. Tuition subsidies are also easier to implement and require less knowledge of local conditions and context. Still, my data and model suggest that the focus on tuition may be misguided and that policies such as the ACE program may be significantly more effective not just at increasing completion for students who transfer but also at encouraging CC students to take that step in the first place. In their analysis of the ACE program, Scott-Clayton et al. (2025) conclude that the public benefits well outweigh the costs of the program; while their analysis was not restricted to CC transfer students, it offers further encouragement for the idea that wraparound services to decrease dropout risk may be worthwhile in a cost-benefit sense.

6.5 Examining additional explanations for low transfer

Finally, I return to the "gap" illustrated in Figure 2 and discussed in Section 3: while policy makers are concerned about low transfer and high CC dropout, CC students *do not expect these phenomena*. In fact, they assign a high probability to transfer, and a low probability to dropout. One may be concerned that this reflects reporting bias or measurement error; the evidence laid out in Section 3 is intended to show that the data obey sensible patterns, and that students' self-reported expected outcomes should be taken seriously. Moreover, my result mirrors that from Horn and Skomsvold

(2011) (based on a larger survey) that 80% of incoming CC students intend to transfer. There is thus significant evidence that this gap represents a meaningful divergence between students' intentions, or expected outcomes, and what the data suggests they will experience. This last qualification is important since, for my sample, the vast majority are still pursuing their educational paths and thus their outcomes have not yet been decided. It is thus possible that their ex-ante expectations will align with their ultimate outcomes, even if these diverge from the overall MD statistics.

In order to get a more realistic picture for the sample's expected outcomes than that provided by overall MD statistics, I use the NLSY97 (the same sample used for the benchmark four-year dropout model and described in Appendix F) to reweight based on gender, race, age, and HS grades. This keeps the overall MD statistics as the target, but assumes that the *gradient* from the NLSY97 (which reflects a previous period) is transferrable to the current sample. The results are shown in Figure 19. Reweighting with the NLSY97 somewhat lowers the expected rate of CC dropout and increases expected terminal AA receipt and transfer with an AA, but large gaps remain: expected dropout from the survey is 25 p.p. lower than that based on the reweighted data, and expected transfer is 24 p.p. too high, with a large gap between transfer with and without an AA.

What truly causes this divergence *is not identified by my data*. As mentioned, it is not even possible to rule out the possibility that the sample outcomes will ultimately align with their expectations. To accomplish both, more years of data collection are necessary.

However, the model may be used to evaluate the *plausibility* of possible explanations for why the ex-ante expected outcomes reported by individuals may diverge from the "objective" expected outcomes. This is of first-order interest, because if we can identify what is causing the gap between ex-ante expected outcomes and realized outcomes, we will have identified the cause of the motivating "puzzle" and potential paths for addressing high dropout and low transfer.

First, the exercise from Section 6.3 in aligning individuals' expectations with the benchmark distributions already demonstrates the extent to which learning about earnings, tuition, and four-year dropout risk may explain the gap:

- **Tuition**: not plausible. Individuals are not very responsive to a change in expected tuition; moreover, for most individuals, the difference between subjective and benchmark beliefs goes in the opposite direction, encouraging transfer.
- **Earnings**: also not plausible, since individuals are, overall, relatively accurate about their expected earnings.
- **Four-year dropout risk**: plausible, but not of sufficiently large magnitude. Updating dropout risk beliefs does shift individuals away from transfer, closing about a quarter of the gap, but leaving a significant residual. Moreover, individuals largely move into the terminal AA pathway rather than into CC dropout, which only increases by about 1 p.p.

It should be noted that the exercise provides an upper bound for the possible impact of learning, since it assumes individuals fully converge to the benchmark distributions. Of course, the exercise rests on the assumption that the benchmark distributions used in the exercise are accurate, and that individuals converge *towards* them (they do not become less accurate over time). It cannot test an alternative story, such as people becoming more pessimistic about tuition costs, or that they end up over-estimating the four-year dropout risk. Overall, I conclude that learning about dropout risks could contribute to lower transfer rates, but that this cannot resolve a majority of the gap. Learning about tuition costs and earnings do not appear to be significant drivers of the two "puzzle" phenomena.

I next examine whether idiosyncratic consumption shocks could play a role. These could capture events such as job loss or a health shock of oneself or a close family member, in line with the events that DeLuca et al. (2021) suggest may drive individuals to choose community college over a four-year program in the first place. Let $Z_{it} \sim Bernoulli(p_z)$ be an indicator for being hit by a consumption shock of magnitude ς. Denote by c^*_{it} consumption in the absence of a shock; if $Z_{it} = 1$, then realized consumption is $c_{it} = \max\{\underline{c}, c^*_{it} - \varsigma\}$, with $\underline{c}$ the consumption floor. I calibrate p_z and ς to minimize the discrepancy between the aggregate model outcomes and the reweighted MD outcomes from Figure 19, but am unable to find values which close the gap by any meaningful amount.

This failure persists in two extensions of the exercise. First, I add persistence to the shock by having its effects decay over two subsequent periods. Second, I make the shock enrollment-specific, so that individuals can avoid it by choosing dropout; this would capture, for example, a sudden loss of financial aid. Neither extension is able to generate significant convergence, even when minimum consumption is allowed to fall to very low levels ($1,000 annually). This is both because of the decisive role for non-pecuniary tastes and because the lifecycle returns to education, accumulating over many years, can outweigh the impact of a temporary shock.

Finally, I test whether individuals may be incorrect about their tastes for schooling (the ψ_k parameters), a phenomenon I term *academic mismatch*. This would not threaten the identification and estimation of the model so long as respondents answered the survey consistent with their beliefs about ψ_k. However, it would mean that as my sample progresses through their education they may come to find that schooling provides different utility than they originally thought.

I assume that in the period after responding to the survey, individuals have a 50% probability of discovering that their tastes for CC are lower by Ψ^{CC}, a 50% probability of discovering that their tastes for four-year are lower by Ψ^{4Y}, and a Υ% probability of discovering that both are lower by these amounts at the same time. I calibrate Ψ^{CC}, Ψ^{4Y}, and Υ to best match the four aggregate outcome probabilities. This can be thought of as a stylized (and extreme) version of the kind of learning explored by Stinebrickner and Stinebrickner (2013) and Arcidiacono et al. (2025).

As shown in Figure 20, this exercise is relatively successful at closing the gap, although only with a large amount of mismatch.[43] Using the 50% marginal probabilities and the calibrated values (shown in Table 20), significant portions of students shift away from transfer and towards dropout. Using a larger marginal probability of 75% brings the match closer still.

I interpret this as evidence for the plausibility of a story of academic mismatch, or learning about one's match with schooling, as a primary factor in driving dropout and transfer decisions. At the same time, I cannot rule out other explanations, and it is likely that a combination of factors may be at play simultaneously.

7 Conclusion

In this paper I have presented novel survey data on the beliefs of community college students; to my knowledge, this is the first survey to offer evidence on community college students' beliefs over transfer outcomes. Students overwhelmingly intend to transfer to four-year programs and expect significant wage premia to 2- and four-year degrees. However, there is evidence that beliefs about tuition costs and graduation probabilities deviate from rational expectations. Expectations about own-outcomes are tightly linked to population level expectations. When exposed to new information on population-outcomes, individuals update their beliefs in sensible ways, which in turn affects own-beliefs. Own beliefs are then closely related to expected outcomes in a static framework.

Results from the dynamic discrete choice model suggest that student plans are most elastic with respect to exogenous dropout risk, moderately responsive to expected earnings with two- and four-year degrees, and relatively unresponsive to expected HS earnings and tuition costs. Correcting beliefs has moderate impacts on simulated outcomes, but leads to meaningful increases in welfare. Implementing a tuition subsidy for students transferring with a two-year degree, as opposed to without, successfully encourages transfer with an AA but mostly pulls from those who previously earned an AA and entered the workforce. Results indicate that policies focused on lowering dropout risk in four-year programs may be more effective at encouraging transfer than tuition subsidies, despite the policy conversation's focus on the latter.

Students' ex-ante plans reflect a high intention to transfer and low intention to drop out of community college; in other words, students do not expect the low transfer and high dropout rates which characterize the "puzzle" laid out in Section 1. While the precise cause of this gap is not identified by my dataset, I show that learning about earnings and tuition costs is unlikely to be a significant driver of the two phenomena. While learning about four-year dropout risks

[43] The estimated $\widehat{\psi}^{CC}$ should be interpreted with caution. At a certain point, all of those hit by the shock drop out, and it grows without effect on the outcomes.

may discourage students from transferring, I demonstrate that students learning about academic mismatch, in the vein of Arcidiacono et al. (2025), is the most plausible explanation.

Future work will be able to incorporate data on the realized outcomes of the sample, as students continue to progress through their education and determine which of the four outcomes they will ultimately arrive at. This will provide more conclusive evidence on the rationality of own-beliefs and on the ultimate explanations for high dropout and low transfer.

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Tables

Table 1: Treatment balance table

	Treatment group		
	earnings	graduation	tuition
	(1)	(2)	(3)
Female	−0.043 (0.366)	−0.146 (0.368)	−0.239 (0.380)
Age	−0.012 (0.042)	−0.051 (0.045)	−0.064 (0.048)
White	0.666* (0.368)	0.504 (0.376)	0.868** (0.398)
Black	0.002 (0.531)	0.179 (0.537)	0.186 (0.589)
FARM	0.278 (0.384)	−0.068 (0.392)	−0.001 (0.407)
Parent BA	0.195 (0.376)	0.337 (0.379)	0.057 (0.394)
HS GPA	−0.248 (0.308)	−0.181 (0.323)	0.015 (0.344)
STEM+	0.003 (0.388)	−0.238 (0.387)	0.277 (0.424)
Constant	0.813 (1.546)	1.761 (1.629)	0.802 (1.734)
Akaike Inf. Crit.	860.027	860.027	860.027
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 2: Selection into followup

	Dependent variable:
	Completed follow-up
Age	−0.005 (0.020)
Female	0.305* (0.185)
Non-binary	−0.056 (0.395)
White	−0.001 (0.352)
Black	−0.120 (0.376)
Hispanic	−0.213 (0.385)
Asian	0.318 (0.429)
Part-time student	−0.031 (0.150)
HS GPA	0.018 (0.124)
Parent BA	0.139 (0.153)
Work	0.051 (0.161)
Arts and Humanities	−0.070 (0.272)
Business and Economics	−0.330 (0.278)
Medicine and Health	−0.246 (0.229)
STEM	0.095 (0.238)
Social Sciences	−0.054 (0.341)
Constant	−0.585 (0.729)
Observations	356
Log Likelihood	−217.687
Akaike Inf. Crit.	469.374
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 3: Selected Demographics

Variable	Overall	Population
N	630	6,888
Age	21.83 (0.16)	21.49
Female	0.69 (0.02)	0.60
White	0.54 (0.02)	0.49
Parent BA	0.45 (0.02)	
Employed	0.70 (0.02)	
Has children	0.11 (0.01)	
Part-time student	0.45 (0.02)	0.62
HS GPA	3.24 (0.02)	
Mean GPA	3.33 (0.03)	
STEM+	0.75 (0.02)	

Table 4: Race

Variable	Overall	Population
N	630	6,888
White	0.54 (0.02)	0.49
Black	0.17 (0.01)	0.20
Hispanic	0.17 (0.02)	0.17
Asian	0.08 (0.01)	0.05
Other	0.02 (0.01)	0.01
Multi-race	0.02 (0.01)	0.08

Table 5: Major

Variable	Overall	Population
N	630	6,888
Arts and Humanities	0.11 (0.01)	0.14
Business and Economics	0.13 (0.01)	0.12
Medicine and Health	0.30 (0.02)	0.23
STEM	0.25 (0.02)	0.22
Social Sciences	0.07 (0.01)	0.08
Transfer Studies	0.15 (0.01)	0.20
STEM+	0.75 (0.02)	
Humanities and SS	0.25 (0.02)	

Table 6: Mean expected earnings

	HS			AA			BA		
Age	Own	Pop.	CPS	Own	Pop.	CPS	Own	Pop.	CPS
25	48 (1.0)	42 (0.8)**	48 (0.7)	57 (0.9)	57 (0.8)	55 (1.6)	72 (1.2)*	73 (1.1)**	68 (1.0)
30	60 (1.4)**	-	55 (0.3)	70 (1.5)**	-	65 (0.5)	89 (1.7)**	-	82 (0.4)
40	76 (2.0)**	55 (1.0)**	64 (1.0)	87 (1.9)**	72 (1.1)$^{\cdot}$	76 (2.1)	112 (2.2)**	96 (1.9)	99 (1.4)

Thousands 2024 USD; standard errors in parentheses. $^{\cdot}$ indicates $p < 0.1$, * $p < 0.05$, ** $p < 0.01$.

Table 7: Completion rates after transfer

	Mean	S.D.
Own-success	0.83	0.21
Population-success	0.69	0.18
Maryland	0.61	-

Table 8: Mean expected tuition (thousands USD)

Tuition belief	Mean	S.D.
Own	20.7	17.5
Population	21.9	16.8
Maximum sticker price	11.5	-

Table 9: Own–population earnings belief elasticities

Dependent variable	Log own belief			
Observable controls	No		Yes	
Model	(1)		(2)	
Estimator	Huber	OLS	Huber	OLS
	(1)	(2)	(3)	(4)
Variables				
Earnings (HS)	0.854**	0.722**	0.850**	0.719**
	(0.055)	(0.069)	(0.057)	(0.070)
Earnings (AA)	0.886**	0.837**	0.880**	0.835**
	(0.035)	(0.050)	(0.036)	(0.051)
Earnings (BA)	0.850**	0.778**	0.853**	0.776**
	(0.046)	(0.058)	(0.049)	(0.057)
Earnings target fixed effects	Yes	Yes	Yes	Yes
SE method	Sandwich	Sandwich	Sandwich	Sandwich
Fit statistics				
Observations	2,681	2,681	2,681	2,681
R^2	0.726	0.587	0.729	0.594

All SEs are clustered by respondent. Huber R2 uses final residual weights.
$^{\cdot}$ indicates $p < 0.10$, * indicates $p < 0.05$, ** indicates $p < 0.01$.

Table 10: Own–population tuition belief elasticities

Dependent variable	Log own belief			
Observable controls	No		Yes	
Model	(1)		(2)	
Estimator	Huber	OLS	Huber	OLS
	(1)	(2)	(3)	(4)
Variables				
Log population belief	0.880**	0.955**	0.876**	0.940**
	(0.058)	(0.083)	(0.058)	(0.077)
SE method	Sandwich	Sandwich	Sandwich	Sandwich
Fit statistics				
Observations	293	293	293	293
R^2	0.613	0.173	0.632	0.249

All SEs are clustered by respondent. Huber R2 uses final residual weights.
· indicates $p < 0.10$, * indicates $p < 0.05$, ** indicates $p < 0.01$.

Table 11: Own–population graduation belief elasticities

Dependent variable	Log own belief			
Observable controls	No		Yes	
Model	(1)		(2)	
Estimator	Huber	OLS	Huber	OLS
	(1)	(2)	(3)	(4)
Variables				
Log population belief	0.287**	0.235*	0.276**	0.239**
	(0.088)	(0.100)	(0.080)	(0.088)
SE method	Sandwich	Sandwich	Sandwich	Sandwich
Fit statistics				
Observations	298	298	298	298
R^2	0.101	0.014	0.137	0.037

All SEs are clustered by respondent. Huber R2 uses final residual weights.
· indicates $p < 0.10$, * indicates $p < 0.05$, ** indicates $p < 0.01$.

Table 12: Pass-through in own- and population-belief revisions

Dependent variable	Log own-belief revision	
Estimator	Huber	OLS
	(1)	(2)
Variables		
Earnings (HS)	0.288**	0.260**
	(0.063)	(0.073)
Earnings (AA)	0.416**	0.398**
	(0.058)	(0.073)
Earnings (BA)	0.305**	0.218·
	(0.047)	(0.123)
Tuition	0.410**	0.492**
	(0.121)	(0.108)
Graduation	0.053	-0.341
	(0.047)	(0.404)
Fixed-effects		
SE method	Sandwich	Sandwich
Fit statistics		
Observations	3,272	3,272
R^2	0.164	0.048

All SEs are clustered by respondent. Huber R2 uses final residual weights.
· indicates $p < 0.10$, * indicates $p < 0.05$, ** indicates $p < 0.01$.

Table 13: Directional updating of population beliefs

Dependent variable	Log population-belief revision	
Estimator	Huber	OLS
	(1)	(2)
Variables		
Earnings (HS), age 25	-0.383**	-0.431**
	(0.104)	(0.110)
Earnings (HS), age 40	-0.365**	-0.473**
	(0.086)	(0.108)
Earnings (AA), age 25	-0.405**	-0.398**
	(0.048)	(0.050)
Earnings (AA), age 40	-0.315**	-0.333**
	(0.040)	(0.045)
Earnings (BA), age 25	-0.338**	-0.348**
	(0.066)	(0.060)
Earnings (BA), age 40	-0.366**	-0.328**
	(0.071)	(0.071)
Tuition	-0.299*	-0.480**
	(0.139)	(0.114)
Graduation	-0.145**	-0.281**
	(0.051)	(0.082)
Fixed-effects	Yes	Yes
SE method	Sandwich	Sandwich
Fit statistics		
Observations	2,384	2,384
R^2	0.119	0.098

All SEs are clustered by respondent. Huber R2 uses final residual weights.
· indicates $p < 0.10$, * indicates $p < 0.05$, ** indicates $p < 0.01$.

Table 14: Directional updating of own beliefs

Dependent variable	Log own-belief revision	
Estimator	Huber	OLS
	(1)	(2)
Variables		
Earnings (HS)	-0.424**	-0.476**
	(0.075)	(0.088)
Earnings (AA)	-0.452**	-0.545**
	(0.090)	(0.098)
Earnings (BA)	-0.377**	-0.469**
	(0.086)	(0.127)
Tuition	-0.598	-0.806**
	(0.842)	(0.136)
Graduation	-0.111	-0.739**
	(0.075)	(0.234)
Earnings: |Expected age − 32|	0.013*	0.015*
	(0.006)	(0.007)
Fixed-effects	Yes	Yes
SE method	Sandwich	Sandwich
Fit statistics		
Observations	3,272	3,272
R^2	0.228	0.566

All SEs are clustered by respondent. Huber R2 uses final residual weights.
· indicates $p < 0.10$, * indicates $p < 0.05$, ** indicates $p < 0.01$.

Table 15: Expected outcomes and subjective path odds

Dependent variable	Log path odds relative to HS/dropout					
Sample	Cross-section				Fixed effects	
Model	(1)		(2)		(3)	
Estimator	Huber	OLS	Huber	OLS	Huber	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Log 10-year earnings premium	0.622*	0.602*	0.589*	0.551·	0.601·	0.462
	(0.297)	(0.292)	(0.292)	(0.297)	(0.329)	(0.482)
Total tuition cost (thousands USD)	0.008**	0.008**	0.008**	0.007**	0.001	-0.0002
	(0.003)	(0.003)	(0.002)	(0.003)	(0.005)	(0.007)
4-year dropout probability	-4.61**	-4.45**	-4.49**	-4.29**	-2.78·	-1.95
	(0.626)	(0.649)	(0.654)	(0.668)	(1.44)	(1.66)
Observable controls	No	No	Path-specific	Path-specific	No	No
Path fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
School tastes	No	No	No	No	Yes	Yes
SE method	Sandwich	Sandwich	Sandwich	Sandwich	Bootstrap	Sandwich
Fit statistics						
Observations	894	894	894	894	1,788	1,788
R^2	0.351	0.302	0.379	0.327	0.761	0.694

All SEs are clustered by respondent. Huber R2 uses final residual weights.
· indicates $p < 0.10$, * indicates $p < 0.05$, ** indicates $p < 0.01$.

Table 16: Calibrated parameters

Parameter	Description	Value	Source
Panel A: Lifecycle environment			
T_1	Post-enrollment	age 41	
T_2	Retirement begins	age 66	Social security eligibility
T_3	Mortality risk begins	age 75	
T^*	End of life	age 96	
$P^d(s)$	Mortality hazard	varying	SSA 2022 actuarial table
T_r	Retirement averaging window	25	Post-enrollment career
	Pension replacement rate	50%	Simplified Social Security
Panel B: College costs and financing			
	CC tuition	\$0	MD Promise Scholarship
$\underline{c}_s$	Student consumption floor	\$11,170	Federal aid IPA, 2024 dollars
	Tuition share of disposable income	50%	Federal EFC formula
r_B	Student loan interest rate	8%	Blend of federal and private rates
τ_B	Repayment horizon	20 yrs	Typical realized term; IBR forgiveness
	IBR payment cap	20%	Income-contingent repayment rules
$\underline{c}_{ns}$	Worker consumption floor	\$7,530	50% of 2024 poverty line
Panel C: Preferences and heterogeneity			
β	Discount factor	0.9	Todd and Zhang (2020), Belzil et al. (2021)
K	Number of latent types	5	k-means, see Section 5

Notes: Ages refer to the calibrated mapping of model periods; t_1 varies by respondent and is taken from the survey. Panel B values are stated in 2024 dollars. See text for discussion.

Table 17: Identifying variation

Parameter	Variation
α	How outcome probabilities vary with expected consumption (through expected earnings and tuition).
κ	How transfer probabilities vary with expected four-year dropout risk beyond the financial consequences.
ψ_k	Propensities to remain in CC or transfer to four-year school, conditional on beliefs and initial conditions.
w_k	Prevalence of the response patterns associated with each preference type, in particular responses to information experiment.
ϕ	Dispersion of reported probabilities around type-specific model predictions (conditional on reporting granularity).

Notes: Utility coefficients are identified relative to the normalized scale of the $\nu(\cdot)$ choice shocks.

Table 18: Parameter estimates

Parameter	**All Types**	**Type 1**	**Type 2**	**Type 3**	**Type 4**	**Type 5**
Consumption coefficient (α)	0.07	–	–	–	–	–
	(0.02)					
Path reporting precision (ϕ)	3.88	–	–	–	–	–
	(0.21)					
Type share % (w_k)	–	42.5	22.8	21.4	4.9	8.4
		(2.9)	(1.9)	(2.7)	(1.0)	(1.5)
CC PT shifter	–	5.08	26.64	13.99	3.96	10.19
		(1.49)	(8.22)	(4.18)	(1.40)	(3.03)
CC FT shifter	–	5.02	29.83	14.76	6.79	7.98
		(1.45)	(8.79)	(4.56)	(2.15)	(2.54)
4Y PT shifter	–	0.47	6.51	0.80	5.23	-2.45
		(0.20)	(2.56)	(0.31)	(1.61)	(0.77)
4Y FT shifter	–	2.40	11.79	2.10	8.14	-2.46
		(0.69)	(4.09)	(0.75)	(2.42)	(0.92)
Four-year dropout cost (κ)	-5.43	–	–	–	–	–
	(1.75)					

Notes: Non-pecuniary parameters are divided by $\alpha \log(64)$, the annual consumption utility at \$64K, the rounded observed age-40 AA full-time earnings median in the CPS. Consumption is measured in thousands of dollars. Hessian-based standard errors are in parentheses; standard errors for rescaled utility parameters use the delta method, including uncertainty in α.

Table 19: Model fit

Outcome	Data (%)	Model (%)	Difference (pp)	Difference (%)
CC dropout	3.63	3.55	-0.08	-2.31
Terminal AA	24.95	26.25	+1.30	+5.22
Transfer without AA	10.07	10.78	+0.70	+6.96
Transfer with AA	61.34	59.42	-1.92	-3.13

Notes: Entries are means of the model-targeted probabilities. Difference is Model minus Data; the final column divides this difference by the data mean. Each row uses observations with finite data and model values.

Table 20: School-mismatch calibration

Calibration quantity	Value
CC revelation probability	50%
Four-year revelation probability	50%
Joint revelation probability	37.4%
CC enrollment-utility penalty	23.50
Four-year enrollment-utility penalty	2.78
Four-path squared-error reduction	89.0%

Notes: At the first CC continuation decision, the exercise fixes the marginal probabilities of a permanent CC and four-year revelation. It estimates their joint probability. Conditional on revelation, the listed penalties are subtracted from the relevant enrollment utility from that decision onward. The squared-error reduction compares the four terminal-path shares with the NLSY–Maryland reweighted target.

Figures

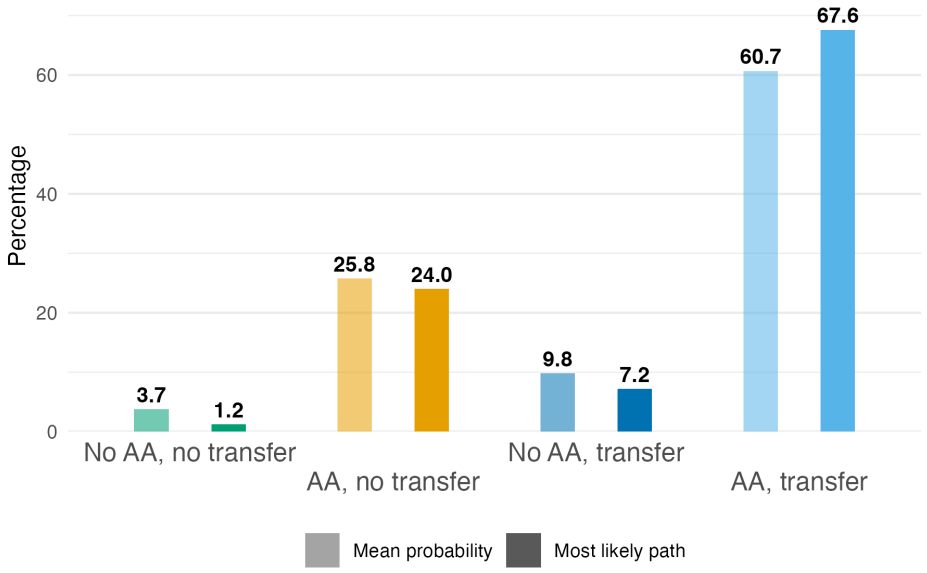


Figure 1: Path probabilities

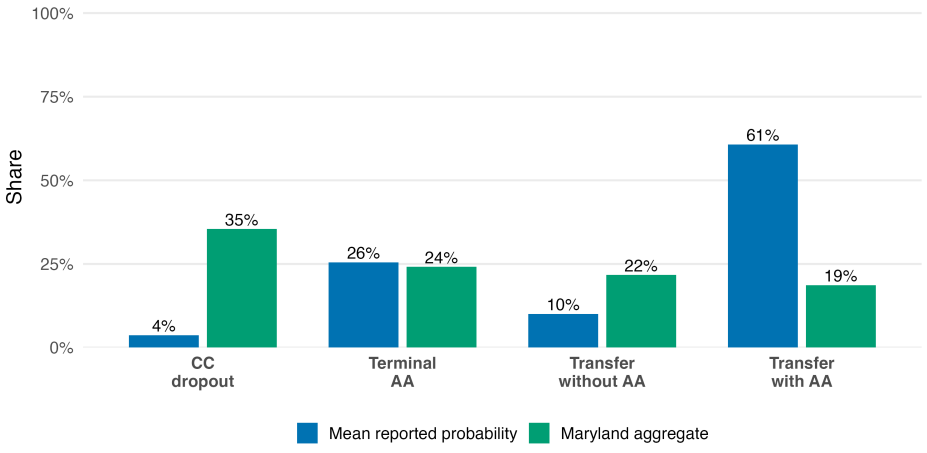


Figure 2: Mean path probabilities with MD comparisons

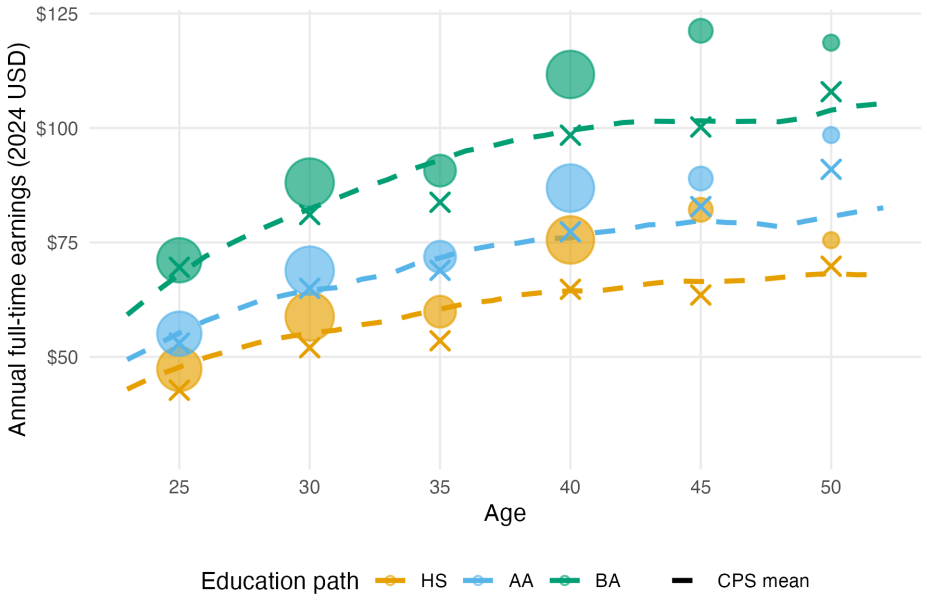


Figure 3: Expected full time earnings

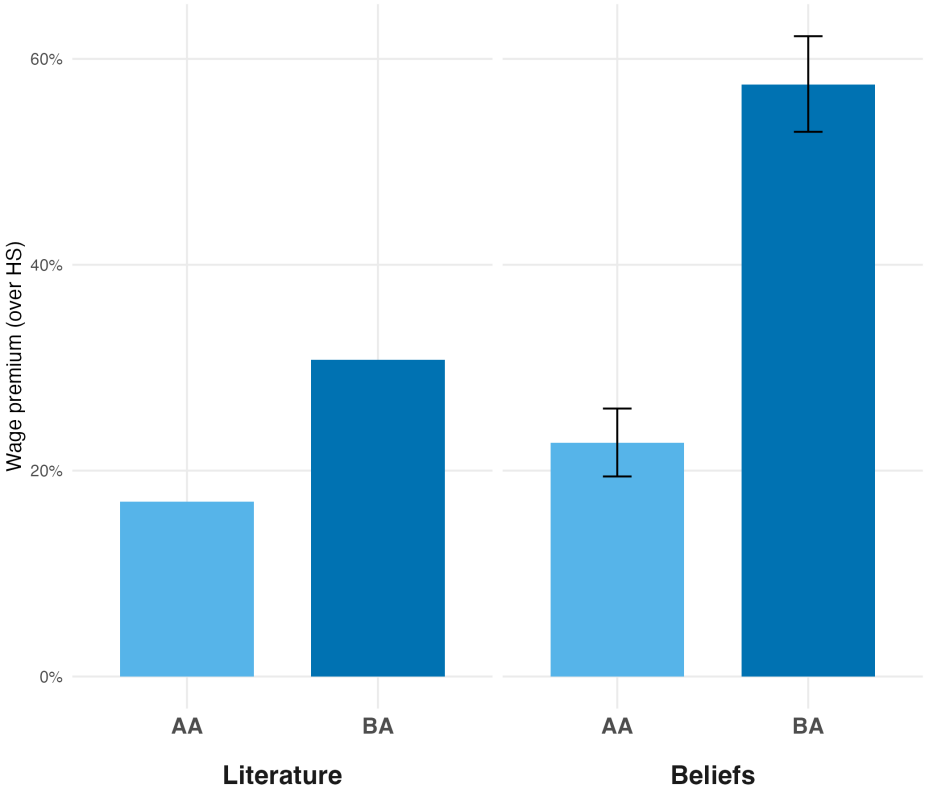


Figure 4: Expected earnings premia

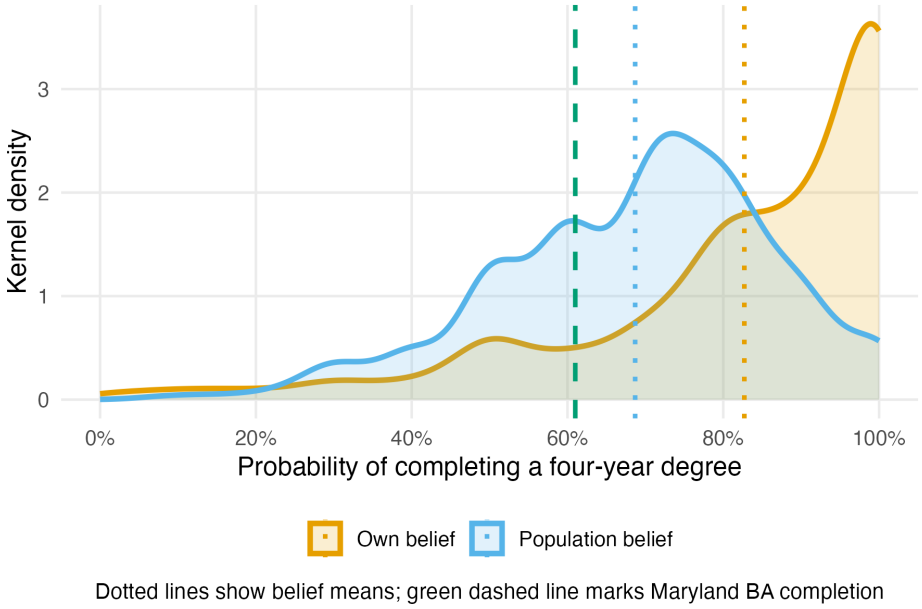


Figure 5: Expected four-year success

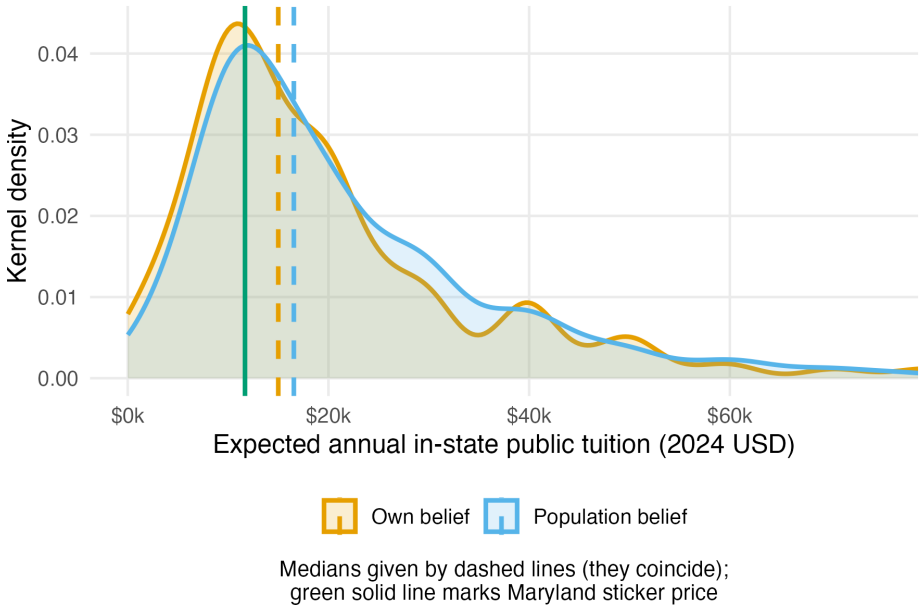


Figure 6: Expected annual tuition

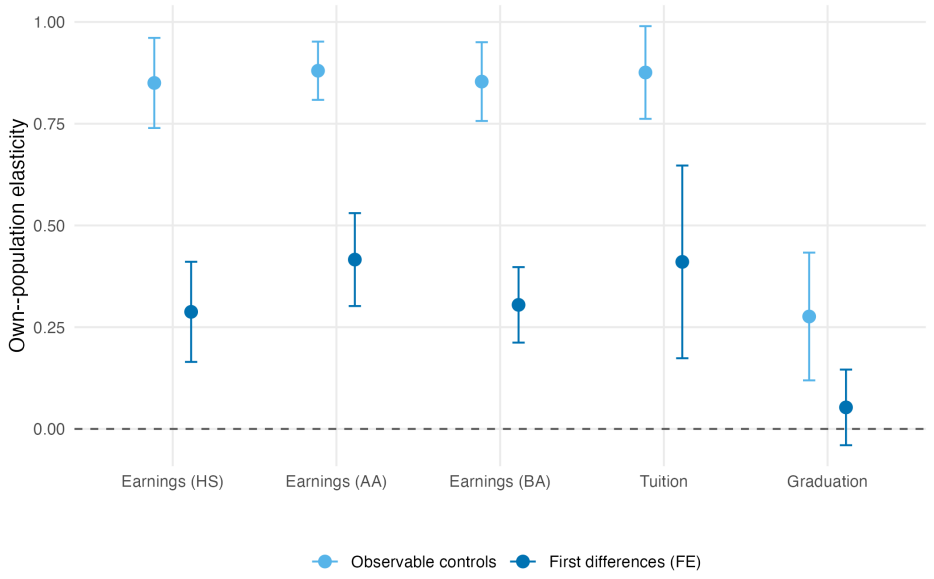


Figure 7: Own–population belief elasticities: cross-section and revisions

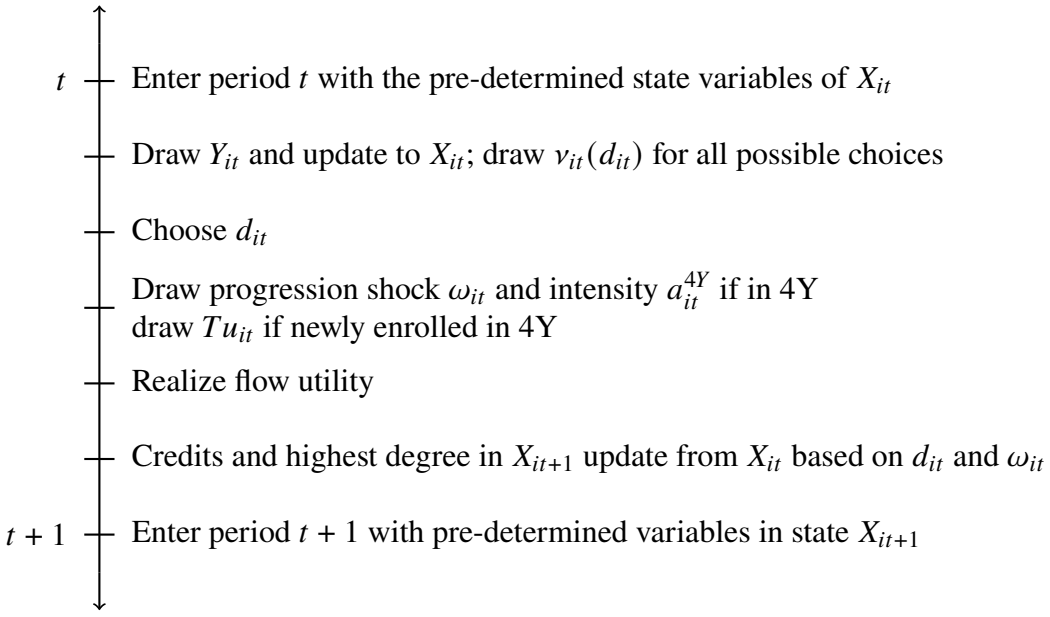


Figure 8: Model timing within a period

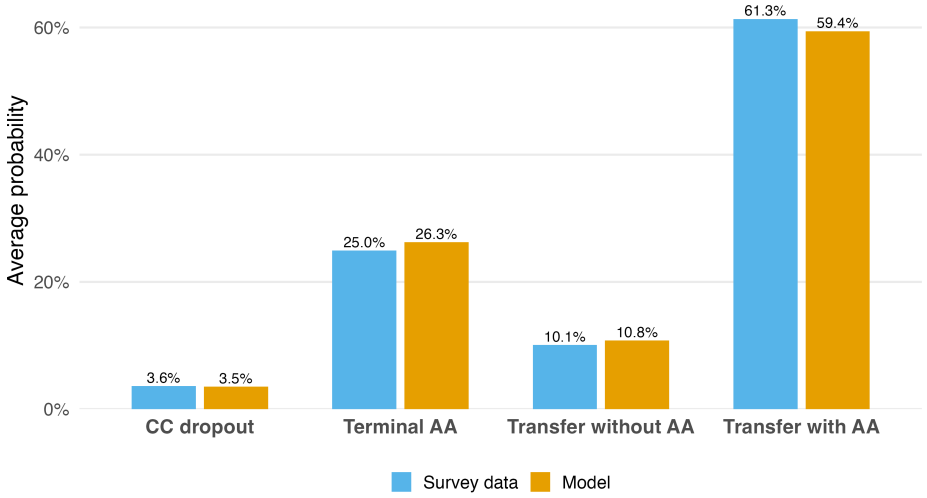


Figure 9: Model fit on path probabilities

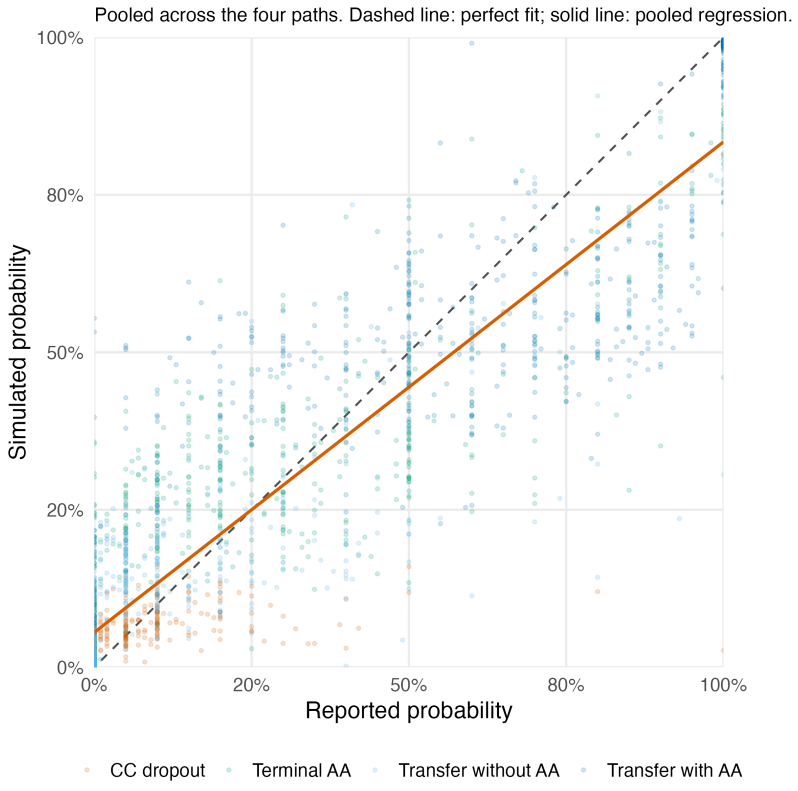


Figure 10: Model fit on individual probabilities

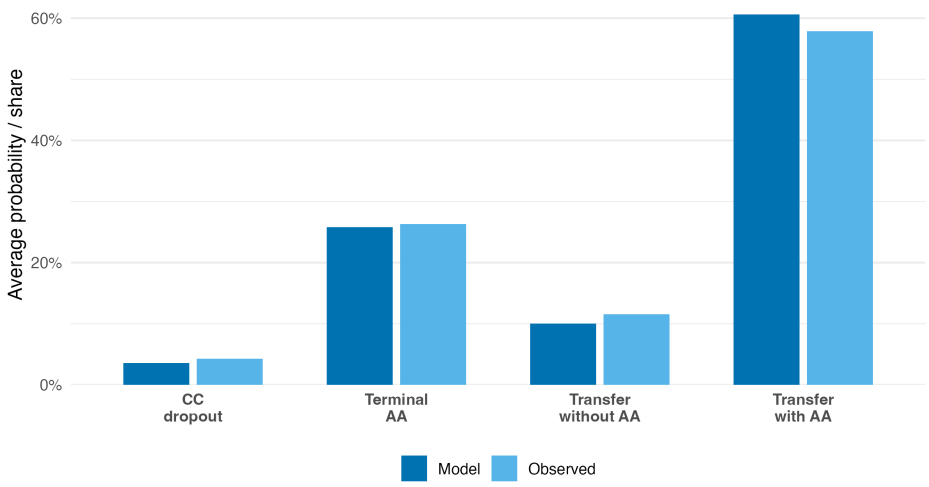


Figure 11: Out-of-sample fit

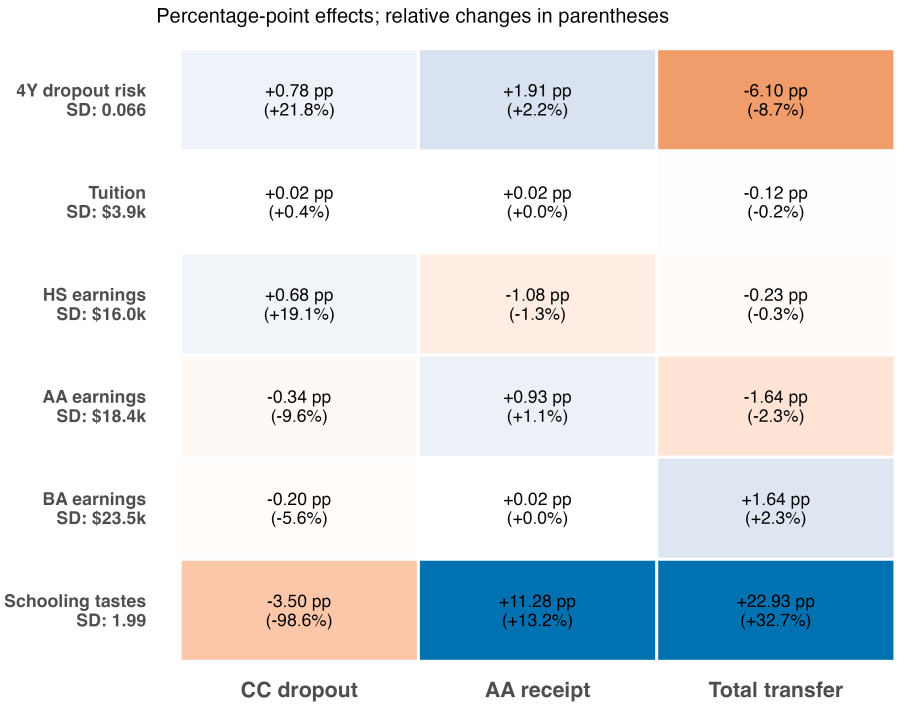


Figure 12: Standard deviation elasticities

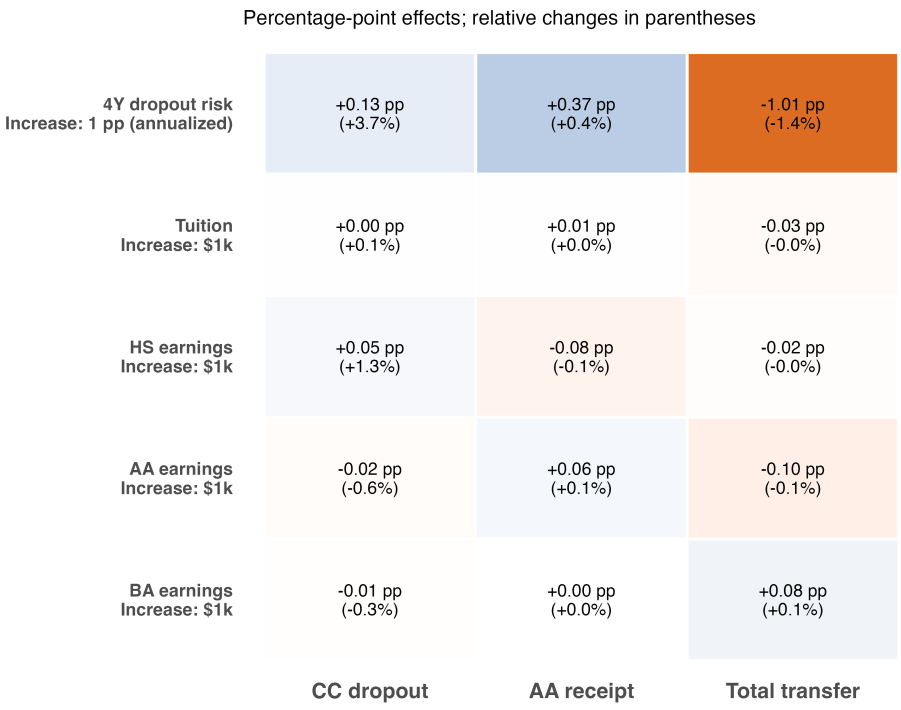


Figure 13: Semi-elasticities

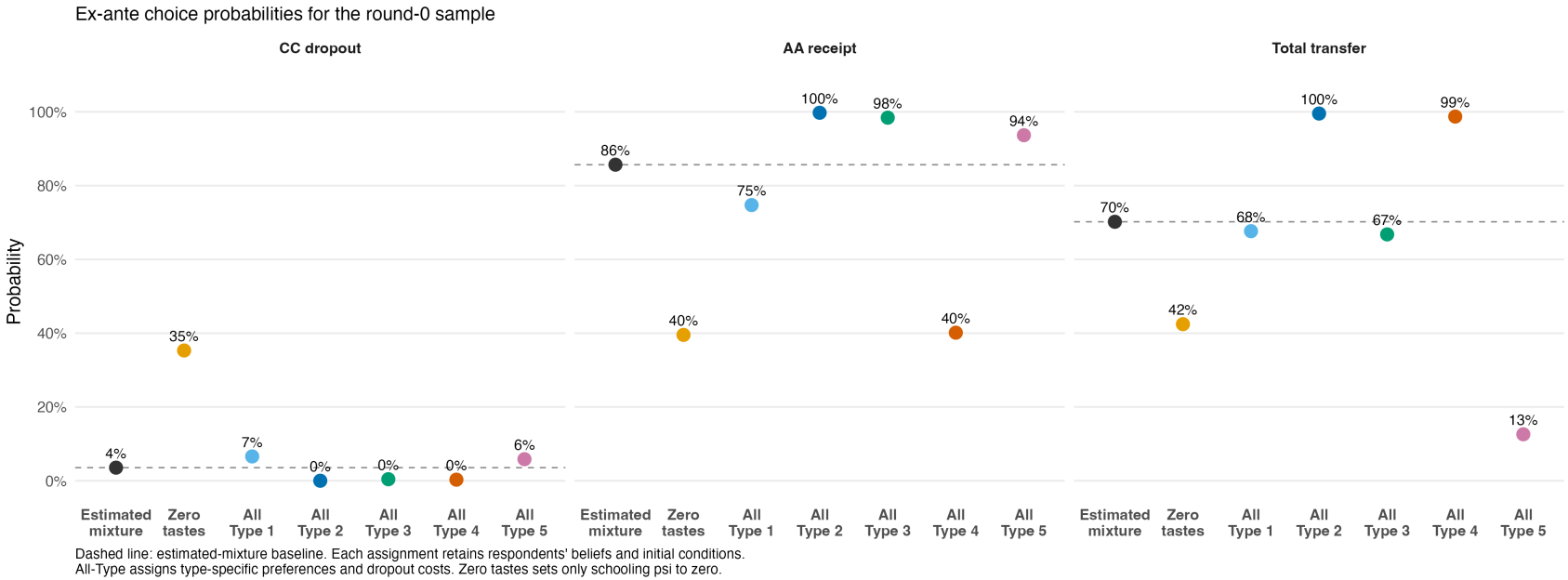


Figure 14: Role of tastes

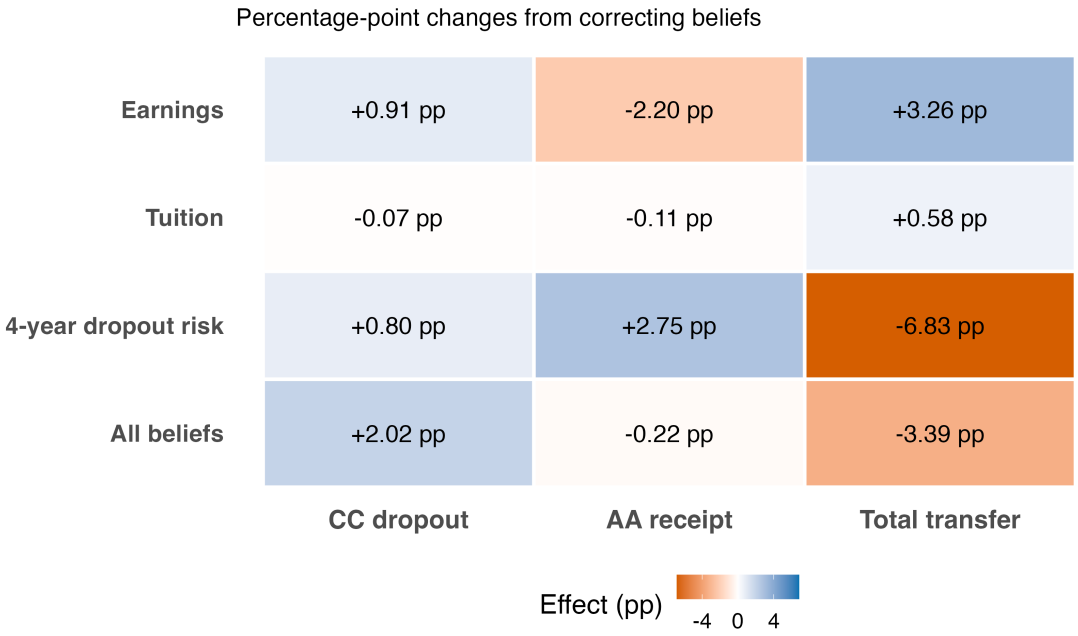


Figure 15: Effects of correcting beliefs on simulated outcomes

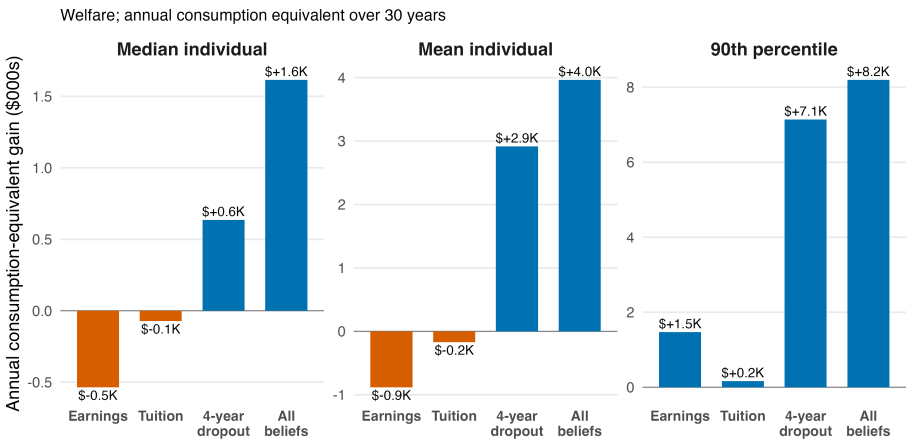


Figure 16: Welfare changes

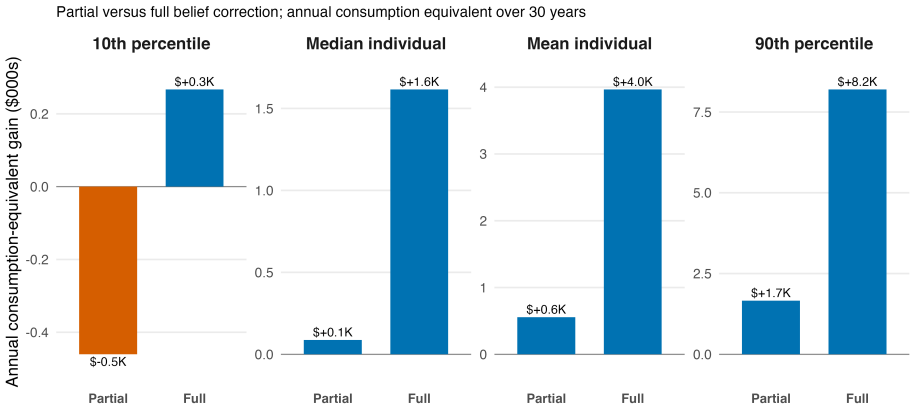


Figure 17: Welfare changes from information experiment

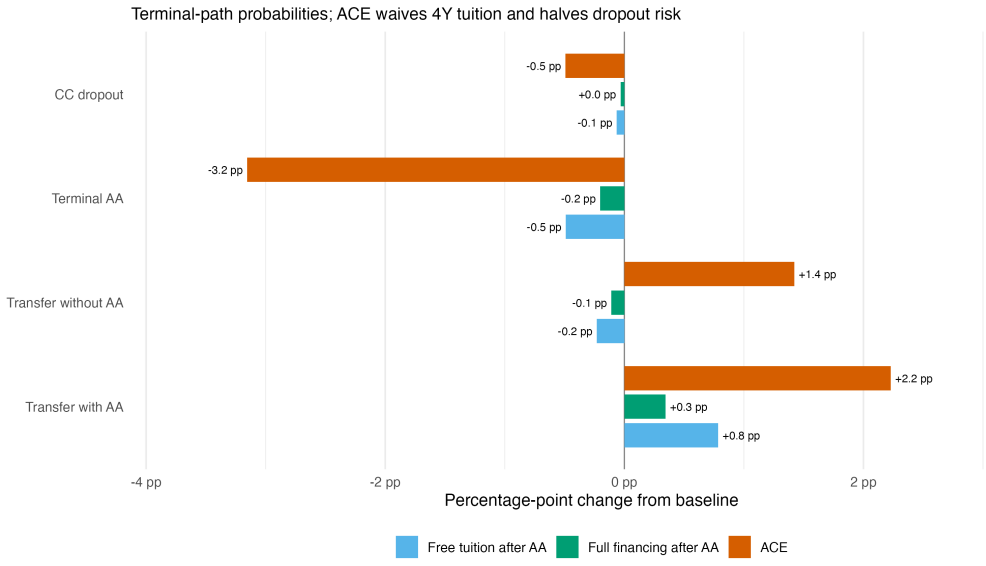


Figure 18: Change from baseline

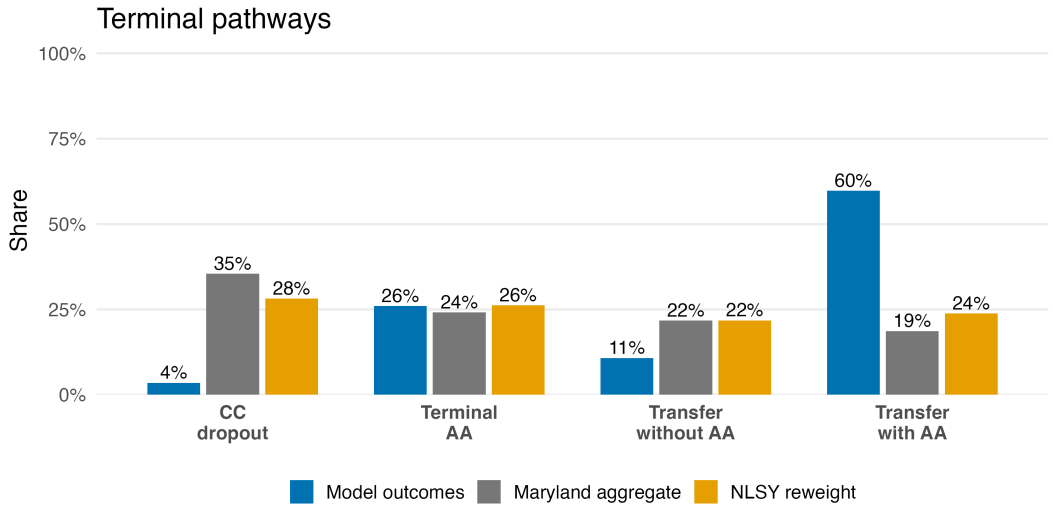


Figure 19: Expected outcomes

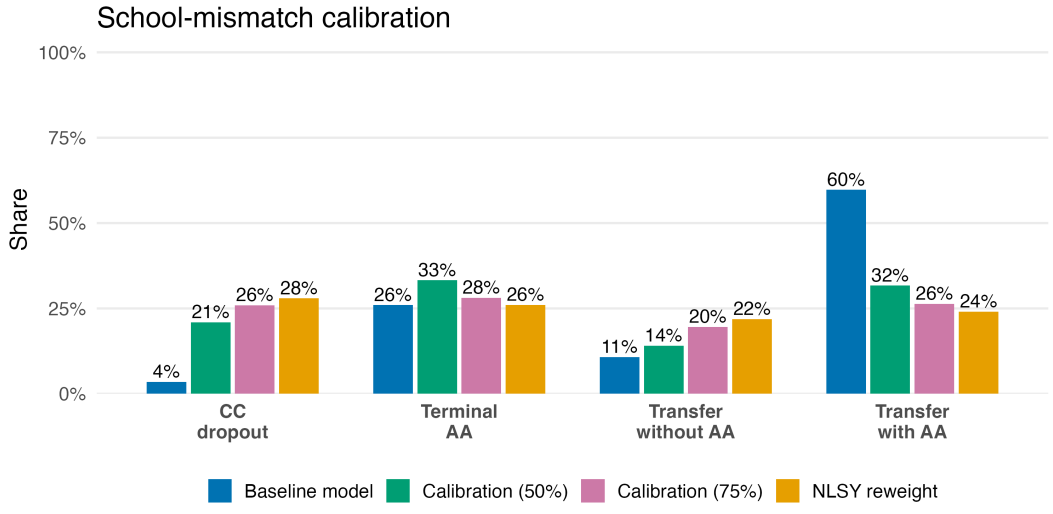


Figure 20: School-mismatch calibration

A Survey instrument

A.1 Select survey questions

Section 2.2 shows survey questions used to elicit expectations about earnings, four-year tuition, and four-year dropout risk. Here I will present a few additional questions; the full survey instrument is available upon request.

The outcome probabilities were elicited with the following question:

> *Community college students take many paths through higher education. Here, we would like you to consider the percent chance of four possible ways you may end your enrollment at [the CCP], each of which involves whether or not to earn a 2-year degree from [the CCP] and whether or not to transfer to a four-year program.*
>
> *These paths are mutually exclusive, so the total across all four choices should sum to 100.*
>
> *What is the percent chance that **you** will choose each of these paths?*
>
> 1. *Leave [the CCP] with no degree and do not transfer to a four-year program*
> 2. *Earn a degree from [the CCP] and do not transfer to a four-year program*
> 3. *Transfer to a four-year program without earning a degree from [the CCP]*
> 4. *Earn a degree from [the CCP] and then transfer to a four-year program*

Respondents dragged a slider between 0 and 100 for each option, with responses constrained to sum to 100.

For the probability of dropout from four-year school, respondents dragged a slider from 0 to 100 to answer:

> *As with 2-year programs, many students who transfer to a four-year program may leave without earning a four-year degree.*
>
> *If you were to transfer from [the CCP] to a four-year program, what is the percent chance that **you will** receive a four-year degree?*

To measure the intensive margin of attendance at four-year school, I asked:

> *If you were to transfer to a four-year program, what is the percent chance that you attend part-time, full-time, or a mixture of both?*
>
> *Part-time attendance is 11 credit hours or less, typically 3 or fewer classes. Full-time attendance is 12 credit hours or more, typically 4 or more classes.*
>
> 1. *Part-time*
> 2. *Full-time*
> 3. *Mixture of part-time and full-time*

A.2 Information treatments

Section 2.3 shows the earnings treatment; here I will show the other two treatments and the placebo received by the control group. Each was split across at least two pages.

The tuition treatment was as follows:[44]

> *Average tuition and fees at Maryland public universities for in-state residents were roughly $11,800 in the 2024-2025 school year. However, many students pay less than this full amount: according to the National Center for Education Statistics, about 72% of undergraduate students received some form of financial aid in the 2019-2020 school year.*
>
> *Because of the prevalence of financial aid, the total cost of four-year school, which also includes room, board, and other expenses, varies significantly according to family income.*
>
> *While the full price with no financial aid at the University of Maryland at College Park is about $32,000 per year, the CollegeBoard reports that total costs after all aid is applied are about:*
>
> 1. *$25,000 per year for students whose families earn more than $110,000 per year*
> 2. *$14,000 for students whose families earn between $48-$75,000 per year*
> 3. *$3,000 for students whose families earn $30,000 or less per year.*
>
> *While these numbers are different at each school, the pattern stays the same: financial aid makes four-year schools much more affordable than their sticker prices suggest, and students from middle class and working class families usually receive a significant amount of aid so that their total cost of attendance is much lower than the "sticker" price.*

The four-year graduation treatment was:

> *According to the most recent "Tracking Transfer" report, about 1 in 3 students who enroll in community college transfer to a four-year program, and about half of those who transfer earn a BA within 6 years. However, Maryland is one of the best states in the country for community college transfer: MD students have a higher-than-average transfer rate and BA completion rate. For example, 39% of MD CC students transfer to four-year programs, compared to 33% for the whole country.*
>
> *The 2015 report "What We Know About Transfer" from the Community College Research Center highlights the value of first earning a 2-year degree. In their analysis and in the work of two other sources, they find that transfer students who earn a certificate or two-year degree before transferring have a*

[44] The treatment mentions $11.8K as the maximum sticker price. The analysis in this paper will use $11.5K, which adjusts the original 2025 number to the 2024 dollars used throughout.

higher likelihood of completing their four-year degree than those who transfer without first earning a degree.

"Tracking Transfer" is an ongoing collaboration between the National Student Clearinghouse Research Center, the Community College Research Center at Columbia University, and the College Excellence Program at the Aspen Institute.

Finally, the placebo treatment, drawn directly from the University of Maryland *Traditions & History* page (Pines (2024)), was:

The University of Maryland traces its history to 1856, when the General Assembly chartered a state agricultural school. The Maryland Agricultural College was established on ancestral land of the Piscataway tribe, which it purchased from a slaveholding farmer and agricultural education advocate, and three years later opened with 34 students.

It eventually grew to encompass new disciplines in engineering, science and the liberal arts, welcomed trailblazing women and people of color, survived the Great Fire of 1912, re-emerged as a public college and boomed following World War II. Today, the university is a national powerhouse in research, academics, the arts and athletics; committed to embracing diversity in its campus community of 50,000; and tackling the grand challenges of our time.

B Data and empirical evidence

B.1 Survey administration

This project was initially approved by the Johns Hopkins University Institutional Review Board (Protocol #HIRB00020175) on November 11, 2024. The project was approved for continuation on November 21, 2025. It was also approved at both points by the IRB of the CCP.

The initial survey was open from November 21 to December 14, 2024. Students received a $10 Amazon gift card for completing an approximately 25 minute survey. Support for the project came from the Hopkins Population Center through a Summer Student Fellowship.

The follow-up survey was fielded via three mass emails to the CCP and personal email addresses provided in the first wave. This was administered approximately one year after the initial survey, from November 12 to December 7, 2025. Respondents were given baseline compensation of a $10 Amazon gift card, with an additional $5 possible for those who passed both attention checks.

The cross-sectional experimental survey was fielded between November 3 and November 16, 2025. Participants received baseline compensation of $15, with an additional $5 possible for those who passed two attention checks. Support for both of the 2025 surveys was provided by a Russell Sage Foundation Dissertation Research Grant.

B.2 Cleaning

The basic data-cleaning procedure is as follows. First, I only retain complete, unique, eligible responses. Second, each survey instrument contained attention checks embedded in the body of the survey. Typically, one of these was a stand alone question of the following kind:

> *This is just an attention check; please set the following slider to 20.*

Other checks were embedded into larger questions.

A shortcoming in survey design was that point estimates were elicited in dollars, without an automatic check for unit errors. This meant that some respondents appear to add or drop 0s, and so I correct a small amount of clear, order-of-magnitude errors using a set of simple heuristics which compare own-to-population beliefs for tuition, and compare across age and degree beliefs for earnings, to detect outliers which would indicate an order of magnitude error. For example, someone may report expected earnings with a HS degree of $60,000, $7,000, and $90,000. I would first detect that there was an outlier decrease from the +5 horizon to the +10 horizon, and then that there was an outlier increase from +10 to +20, indicating the likelihood of a dropped 0. Any individual requiring more than 5 such corrections is dropped as a low-quality response.

After this correction, a final filter is placed for implausible or inconsistent reports, such as

extreme earnings levels or growth. Respondents who report mean earnings below $5,000 (below minimum wage) or above $600,000 are dropped. Similarly, reports with expected earnings growth of -75% or worse, or 300% or better, between horizons, are dropped. Finally, respondents with mean expected tuition greater than $200,000 are dropped.

The results of the cleaning procedure can be found in Table 23. This includes the number of completed responses, the final sample after the preferred cleaning specification is complete, and the percentage of the sample which fails at least one attention check.

B.3 Demographics

Table 24 shows the full set of demographic characteristics for the sample and, where possible, for the student body at large.

I allowed respondents to check all racial categories with which they identify. In order to compare my statistics against those from the CCP, which allow only one category per-person, I use the following procedure:

1. If a respondent only checks one category (83% of the sample), they are simply considered in that category.
2. If a respondent identifies with more than one race and identifies as Hispanic, I assume this is the most salient identity.
3. If a respondent identifies with more than one race and does not identify as Hispanic, I randomly assign them to either "multi-race" or to one of the categories they identified with.

The implicit assumption behind (3) is that if non-Hispanic respondents were forced to choose a most salient identity, they would do so randomly from the list of identities they chose. It should be noted that this procedure is only important for comparisons between the registrar population statistics and my sample; in the regression analyses, there is no problem in using indicator variables for multiple overlapping racial identities, although the interpretation is slightly different than if I had the binary indicator. Table 21 shows the differences in statistics on race before and after this procedure is followed.

Another discrepancy is that I allow respondents to select non-binary as a gender identity, where the registrar only reports statistics for Male and Female students. For comparing gender between my sample and the registrar, I use the portion female conditional on not being non-binary.

B.4 CPS earnings comparison

I extract CPS (ASEC) data from IPUMS. I look at data from 2015-2024 (inclusive), with all dollar figures deflated to 2024 values using the PCE deflator. The sample consists of adults ages 19–65

who are in the labor force and excludes currently enrolled students. In line with the survey language, I filter for full-time workers: I keep only those who work at least 40 weeks in the prior year, and who usually work more than 30 hours per week. The sample is clustered based on highest degree, which may be HS, AA, or BA; I exclude those who do not hold at least a HS degree and those with a graduate degree.

I construct an hourly wage by dividing annual wage and salary income by annual hours worked. I exclude observations above the 99$^{\text{th}}$ percentile of usual weekly hours, and winsorize wages at the 1$^{\text{st}}$ and 99$^{\text{th}}$ percentiles. I then convert the hourly wage to annual full-time earnings by multiplying by $40 \times 52 = 2{,}080$ hours.

The first desired output is a mean wage by age and highest degree for *Maryland* workers; this is because the survey elicited population expectations based on the CCP itself, not workers more broadly. This creates a sample-size problem, since some of the age–degree cells may be sparsely populated for Maryland specifically.

I take two steps to improve the sample size. First, I do not filter based on state. Instead, for each highest degree I calculate the ratio of Maryland earnings to non-Maryland earnings, which yields a Maryland-specific degree adjustment. I use these adjusters to rescale the non-Maryland observations, leaving the Maryland observations unchanged.[45] Second, I use a three-year window when calculating earnings statistics: for each age a, the mean earnings are based on the pooled sample from $a - 1$ to $a + 1$. This also serves to smooth the age-earnings profile in Figure 3, since adjacent ages share overlapping portions of the sample.

B.5 Testing for rational expectations

Earnings

I use the same national CPS sample described above to test for rational expectations for earnings. Specifically, I evaluate whether the mean of population beliefs for full-time earnings with degree d is equal to that in the CPS sample. For each d, I elicit expected population earnings at ages 25 and 40. I perform a Wald test on the joint hypothesis:

$$H_0: \quad \mathbb{E}\left[Y_{i25d}\right] = \bar{Y}_{25d} \quad , \quad \mathbb{E}\left[Y_{i40d}\right] = \bar{Y}_{40d}$$

I obtain the variance-covariance matrix for the CPS statistics by bootstrap to control for uncertainty from the MD adjustment factor. I reject the null hypothesis with $p < 0.01$ for HS; $p < 0.01$ for AA; and $p < 0.01$ for BA.

Table 6 also shows the results from paired t-tests between population (as well as own) beliefs

[45] For this reason, I use a bootstrap procedure to calculate the standard errors for the later RE test.

and the CPS benchmarks. HS beliefs are statistically different from the CPS figures, but this is not true for earnings with an AA. For BA earnings, age-25 beliefs appear different, but age-40 beliefs do not. Overall, earnings beliefs appear fairly well-calibrated relative to tuition and dropout risks.

Tuition

As discussed in Section 3.1, tuition and fees at the University of Maryland College Park were $11.5K in 2024 (and adjusted for inflation, the 2025 cost was unchanged). This forms the maximum possible price for an in-state student and is an easy way to test for rationality. Denoting by Tu_{ik} the expected tuition for individual i, where $k \in \{0, 1\}$ indexes own- and population-beliefs, I test:

$$H_0 : \mathbb{E}\left[Tu_{ik}\right] \leq 11.5$$

I reject the null with p <0.01 for the population-level beliefs, and with p <0.01 for own beliefs.

Four-year completion

Finally, I examine beliefs about the probability of earning a BA conditional on transfer from CC to a four-year program. As discussed in Section 3.1, 61% can be viewed as an upper bound for this figure, and so a rejection at this level provides strong evidence that beliefs do not follow FIRE.

Let $\bar{P}_i$ denote respondent i's belief about the completion probability for a typical transfer student. I test the null hypothesis:

$$H_0 : \quad \mathbb{E}\left[\bar{P}_i\right] = 0.61$$

I reject the null with $p \leq 0.01$.

B.6 Log-odds regressions with expected premia

As discussed in Section 3.4, the linear form may be overly simplistic. Here, I use the three beliefs to construct an earnings premium associated with each path, which is then used to estimate a similar log-odds model.

I ask how the subjective path probabilities depend on beliefs about earnings, tuition, and four-year dropout. Rather than enter these factors separately, I combine them into a path-specific expected payoff. First, I calculate the present-discounted value of lifetime earnings with degree k as:

$$\mathbf{Y}_{ik} = \sum_{t=d_\rho+1}^{65-age_i} \beta^t \mathbb{E}[Y_{ikt}] \tag{30}$$

where $\beta = 0.9$ is a discount factor and d_ρ represents time remaining in education before earnings

begin.[46] Let $T_{i\rho}$ be the expected discounted four-year tuition needed along paths $\rho = 3$ and $\rho = 4$, where $T_{i3} = T_i(1 + \beta + \beta^2)$ and $T_{i4} = T_i(1 + \beta)$. Finally, $\tilde{p}_i$ is the four-year dropout probability. Expected, discounted net-earnings are:

$$
\begin{aligned}
Z_{i1} &= \mathbf{Y}_{i1} && \text{for dropout} \\
Z_{i2} &= \mathbf{Y}_{i2} && \text{for terminal AA} \\
Z_{i3} &= (1 - \tilde{p}_i)\mathbf{Y}_{i3} + \tilde{p}_i\mathbf{Y}_{i1} - T_{i3} && \text{for transfer without AA} \\
Z_{i4} &= (1 - \tilde{p}_i)\mathbf{Y}_{i3} + \tilde{p}_i\mathbf{Y}_{i2} - T_{i4} && \text{for transfer with AA}
\end{aligned}
$$

I then define $\mathcal{Z}_{i\rho} = \log\left(Z_{i\rho}/Z_{i1}\right)$ as the expected premium for path $\rho \in \{2, 3, 4\}$ relative to dropout. Let $p_{i\rho}$ be the elicited subjective probability of realizing path ρ, and define the log-odds of path ρ relative to dropout as $\mathbf{p}_{i\rho} \equiv \log\left(p_{i\rho}/p_{i1}\right)$. I estimate the following regression on the pre-treatment observations:

$$\mathbf{p}_{i\rho} = \beta_{0\rho} + \boldsymbol{\beta}'_{\mathbf{1}\boldsymbol{\rho}} X_i + \gamma \mathcal{Z}_{i\rho} + \epsilon_{i\rho} \tag{31}$$

so that γ has an elasticity interpretation as the change to the log-odds for choosing path ρ given a change in its expected premium.

The result of eq. (31) is given in column (1) of Table 22. The expected premium is positively correlated with choice probabilities and statistically significant at the 5% level.

As in the belief regressions, we may worry that unobserved factors, such as a non-pecuniary taste for schooling, is associated with both the reported beliefs and subjective path probabilities. I assume that unobserved factors are associated with CC attendance (α_i^{CC}) and with four-year attendance (α_i^{4Y}). These will also absorb the fixed characteristics, so that eq. (8) becomes:

$$
\begin{aligned}
\mathbf{p}_{i2} &= \gamma \mathcal{Z}_{i2} + \alpha_i^{CC} + \epsilon_{i2} \\
\mathbf{p}_{i3} &= \gamma \mathcal{Z}_{i3} + 0.5\alpha_i^{CC} + 1.5\alpha_i^{4Y} + \epsilon_{i3} \\
\mathbf{p}_{i4} &= \gamma \mathcal{Z}_{i4} + \alpha_i^{CC} + \alpha_i^{4Y} + \epsilon_{i4}
\end{aligned}
\tag{32}
$$

Where paths 2-4 have a weighted combination of α_i^{CC} and α_i^{4Y} based on duration spent in each type of school. By exploiting the pre- and post-treatment log odds for the treated groups only (and dropping the control), I can estimate:

$$\mathbf{p}'_{i\rho} - \mathbf{p}_{i\rho} = \gamma\left(\mathcal{Z}'_{i\rho} - \mathcal{Z}_{i\rho}\right) + u_{i\rho} \tag{33}$$

As shown in specification (3) of Table 22, the inclusion of individual fixed effects attenuates the

[46] 1 year for the terminal AA and 3 years for the BA. I also assume that during the d_ρ periods of enrollment, individuals work part-time and earn 50% of full-time earnings with a HS degree.

coefficient on the expected premium. It also causes the coefficient to lose statistical significance. Overall, these results mirror those from the original exercise.

C Fitting distributions

C.1 Motivation

Building on Blass et al. (2010), Armantier et al. (2017) suggest that it is better to fit parametric distributions to elicited PDFs and work with the moments implied by that distribution, rather than to use reported expectations directly. However, the econometrician is constrained by the number of bins with positive probability that the individual reports, since they can identify at most one fewer parameters than they have measurements, which in the case of an elicited PDF are probabilities assigned to bins or intervals.

Those authors recommend using different distributions based on the number of measurements: uniform (one measurement), triangular (two measurements), and what they term the "generalized beta" (for 3+ measurements).[47] Recognizing that the beta distribution can approximate the other two distributions as special cases, I will work with the Beta directly. The Beta may be preferable to the log-Normal distribution used in Wiswall and Zafar (2015a) because it is more flexible, and can better capture heterogeneity in the shape of beliefs.

C.2 Earnings function

Log-earnings follow a Beta distribution following the model laid out in Appendix D.1; this should be reviewed before reading this section. I use the elicited expectations, along with the elicited PDFs, to identify individual-specific beliefs for each coefficient in eqs. (40)-(42). Because these are individual-specific, we cannot separately identify the impact of characteristics from the intercept, e.g., we can only estimate the expectation for the combined $\Gamma_D' Z_{it} + \gamma_{0D}$ in eq. (40). Instead, we rewrite the functions as:

$$\mu_i(s_i, d_i) = \gamma_{i0d} + \gamma_{i1d} s_i + \gamma_{i2d} s_i^2 \tag{34a}$$

$$\phi_i(s_i, d_i) = \delta_{i0d} + \delta_{i1d} s_i + \delta_{i2d} s_i^2 \tag{34b}$$

$$r_i(s_i, d_i) = \lambda_{i0d} + \lambda_{i1d} s_i + \lambda_{i2d} s_i^2 \tag{34c}$$

This points to a strength of this approach, since Z_{it} may be viewed as containing variables which are unobserved by the econometrician (so long as they are known to the individual).

For exposition, it will be easiest to work with a normalized value, so I define:

$$x_{isd} \equiv \frac{y_{isd} - \ell}{r_{isd} - \ell}$$

[47] The generalized beta distribution usually refers to a more flexible 5-parameter distribution than the one they use in this paper. For that reason, I will simply refer to this as a Beta distribution.

Where $x_{isd} \sim Beta(\alpha_{isd}^{earn}, \beta_{isd}^{earn})$.

For each highest degree, I find the parameters θ_{id}^{earn} which minimize the loss between the earnings implied by the model and the elicited expectations and PDFs.

C.2.1 Identification

As discussed above, we need to be careful that we have sufficient measurements to identify the desired parameters. Fixing D, there are three coefficients in each equation (34a) – (34c), for a total of 9 parameters. There are always three point expectations for each person, and a minimum of three probability measurements (the case where all probability is assigned to a single bin), for a minimum of 6 measurements.

Most individuals have many more measurements than this. However, for computational convenience and to avoid the under-identifying case, instead of estimating the parameters λ jointly with the earnings function, I impose a simple first step. For each belief, I set $r_{isd} = \log(2 \times \mathcal{Y}_{isd})$, where $\mathcal{Y}_{isd}$ is the elicited point expectation. I then fit the parameters λ to interpolate r_{isd} off of the elicited points. I plug these values $\hat{r}_{isd}$ into the model when estimating $\boldsymbol{\gamma}_{id}$ and $\boldsymbol{\delta}_{id}$.

In addition, I utilize a logit link function for (34a) to ensure it is bounded on (0,1) and an exponential link function for (34b) to ensure it is positive.

C.2.2 Using the probabilities

Take an arbitrary vector of parameters $\boldsymbol{\gamma}_{id}$ and $\boldsymbol{\delta}_{id}$, from (34a) and (34b), and fix d_i' and s_i'. This yields $\mu_i(d_i', s_i')$ and $\phi_i(d_i', s_i')$, which in turn yield $\alpha_i(d_i', s_i')$ and $\beta_i(d_i', s_i')$. The Beta distribution also requires endpoints; these could in principle be estimated, but are naturally bounded by the intervals we set above at ℓ and $r_i(d_i', s_i')$. Dropping the parentheses for conciseness, I match:

$$\begin{aligned} P_i\left(c_{j,isd} \leq Y_{isd} < c_{j+1,isd}\right) &= P_i\left(\frac{\log(c_{j,isd}) - \ell}{r_{isd} - \ell} \leq \frac{\log(Y_{isd}) - \ell}{r_{isd} - \ell} < \frac{\log(c_{j+1,isd}) - \ell}{r_{isd} - \ell}\right) \\ &= \mathcal{I}_{\frac{\log(c_{j+1,isd}) - \ell}{r_{isd} - \ell}}(\alpha_{isd}, \beta_{isd}) - \mathcal{I}_{\frac{\log(c_{j,isd}) - \ell}{r_{isd} - \ell}}(\alpha_{isd}, \beta_{isd}) \end{aligned} \tag{35}$$

Where $\mathcal{I}_x(\alpha_{isd}, \beta_{isd})$ is the incomplete beta function, which is the CDF of the standard Beta distribution.

C.2.3 Using the point expectations

Armantier et al. (2017) suggest discarding the point expectations, as it is not clear which moment or statistic they refer to. Instead, I will estimate $\boldsymbol{\gamma}_i(d), \boldsymbol{\delta}_i(d)$ three times, under the case where the individual's point expectation is a mean, a median, and a mode. I then look across the full set of

an individual's earnings expectations, and classify each person's "response type" based on which statistic leads to the best overall fit. I then assume that they consistently respond to questions using that moment.

Mean. Since $\log(Y_{isd}) \sim Beta(\alpha_{isd}, \beta_{isd})$, $Y_{isd} \sim \exp(Beta(\alpha_{isd}, \beta_{isd}))$. The expectation is then $\mathbb{E}_i[Y_{isd}] = \mathbb{E}_i[\exp(Beta(\alpha_{isd}, \beta_{isd}))]$. This is the moment generating function of the Beta distribution, which is given by Kummer's confluent hypergeometric function (first kind), denoted ${}_1F_1(\alpha_{isd}; \alpha_{isd} + \beta_{isd}; 1)$. However, we must account for the normalization. Thus we match the elicited means to:

$$\mathcal{Y}_{isd} = \mathbb{E}[Y_{isd}] = \exp(\ell)\,{}_1F_1(\alpha_{isd}; \alpha_{isd} + \beta_{isd}; r_{isd} - \ell)$$

Median. The median is very simple; we use the CDF, just as we did for the probabilities. Recalling the normalized variable:

$$x_{isd} = \frac{\log(\mathcal{Y}_{isd}) - \ell}{r_{isd} - \ell}$$

Then we can directly fit the condition:

$$0.5 = \mathcal{I}_{x_{isd}}(\alpha_{isd}, \beta_{isd})$$

Since the median for Y is the exponential of the median of $\log(Y)$.

Mode. The mode is a bit more complicated, and is not always guaranteed to exist; this will place constraints on α_{isd} and β_{isd}. The mode of the log-Beta is the exponential of the root in $(0, 1)$ of the following:

$$x^*_{isd} = \frac{(\alpha_{isd} + \beta_{isd} - 2 + (r_{isd} - \ell)) \pm \sqrt{(\alpha_{isd} + \beta_{isd} - 2 + (r_{isd} - \ell))^2 - 4(r_{isd} - \ell)(\alpha_{isd} - 1)}}{2(r_{isd} - \ell)} \tag{36}$$

That is, the mode of Y_{isd} is $\exp(x^*_{isd}(r_{isd} - \ell) + \ell)$.

C.2.4 Extrapolation

There is no theoretical problem with extrapolating from the functions (34a) – (34c); this needs to be done forward (to provide the distribution for ages from the +20 horizon to retirement) and backward (to provide the distribution prior to the +5 horizon). However, extrapolation with a function fit to three points in time can be sensitive and badly behaved, in particular at further out points. As a result, rather than extending the individual parameter estimates beyond the elicited age range, I use the CPS dataset from Appendix B.4 to construct age-earnings growth rates for each highest

degree. I apply these for extrapolation, which respects the level and shape of the individual earnings distributions but forces the growth to match the population values.

C.3 Four-year tuition

I similarly fit Beta distributions for the level of four-year tuition expectations. Since expected tuition is not conditioned on age or other variables, it is a single distribution and much more straightforward to estimate than the above procedure for earnings. Let $\mathcal{T}_i$ be the elicited tuition expectation. I set the left bound ℓ_i^{tu} to equal the left-bound of the left-most bin with positive probability. I set the right bound to $\min\{2 \times \mathcal{T}_i, \$200{,}000\}$, and find parameters $\alpha_i^{tu}, \beta_i^{tu}$ to most closely match the point expectation and the elicited PDF, where the point expectation is classified as a mean, median, or mode based on the result of the classification procedure from the earnings distribution.

D Model details

D.1 Earnings function

Log-earnings for an individual with characteristics Z_{it}, at age s_{it}, and with highest degree D_{it} follow a 4-parameter Beta distribution which is characterized by a lower-bound $\ell(Z_{it}, s_{it}, D_{it})$, a right-bound $r(Z_{it}, s_{it}, D_{it})$, and shape parameters $\alpha^{earn}(Z_{it}, s_{it}, D_{it})$ and $\beta^{earn}(Z_{it}, s_{it}, D_{it})$. In the rest of the presentation, I will abbreviate these parameters as (for example) μ_{itd} for conciseness.

Annual full-time earnings are denoted Y_{itd}, and let the log be $y_{itd} = \log(Y_{itd})$. The PDF of the distribution is:

$$f(y_{itd}; \alpha^{earn}_{itd}, \beta^{earn}_{itd}, \ell_{itd}, r_{itd}) = \begin{cases} 0 & \text{if } y_{itd} < \ell_{itd} \\ \dfrac{(y_{itd} - \ell)^{\alpha^{earn}_{itd}-1}(r - y_{itd})^{\beta^{earn}_{itd}-1}}{B(\alpha^{earn}_{itd}, \beta^{earn}_{itd})(r - \ell_{itd})^{\alpha^{earn}_{itd}+\beta^{earn}_{itd}-1}} & \text{if } \ell \leq y_{itd} \leq r_{itd} \\ 0 & \text{if } y_{itd} > r_{itd} \end{cases} \tag{37}$$

$B(\alpha, \beta) = \Gamma(\alpha)\Gamma(\beta)/\Gamma(\alpha + \beta)$, where $\Gamma(\cdot)$ is the gamma function.

Instead of working with these shape parameters, it is equivalent (and will be convenient) to instead use a mean parameter μ and a precision parameter ϕ,[48] which relate to the shape parameters according to

$$\mu = \frac{\alpha}{\alpha + \beta} \tag{38}$$

and

$$\phi = \alpha + \beta \tag{39}$$

The lower-bound ℓ is given by log-earnings for an individual working full-time at the federal minimum wage of \$7.25 per hour and is thus common across individuals.[49] The other parameters follow degree-specific Mincer-style functions in age. For the mean:

$$\mu_{itd} = \Gamma'_D Z_{it} + \gamma_{0D} + \gamma_{1D} s_{it} + \gamma_{2D} s^2_{it} \tag{40}$$

[48] I refer to ϕ as the precision because

$$\text{var}(x) = \frac{\mu(1 - \mu)}{\phi + 1}$$

so that the variance decreases with ϕ.

[49] Note that this is lower than the Maryland minimum wage; however, some individuals assign positive probability to earnings below this point, which may reflect biased beliefs or the possibility of under-the-table work. I take the lower federal minimum wage as a reasonable proxy for the lower-bound.

Similarly, the precision of the log-earnings distribution is:

$$\phi_{itd} = \Delta_D' Z_{it} + \delta_{0D} + \delta_{1D} s_{it} + \delta_{2D} s_{it}^2 \tag{41}$$

Finally, the upper bound evolves according to:

$$r_{itd} = \Lambda_D' Z_{it} + \lambda_{0D} + \lambda_{1D} s_{it} + \lambda_{2D} s_{it}^2 \tag{42}$$

The parameter space is thus $\theta^{earn} \equiv \{\Gamma_D, \gamma_D, \Delta_D, \delta_D, \Lambda_D, \lambda_D\}$, where θ^{earn} is restricted so that μ is interior to the bounds and $\phi > 0$.

Sheepskin effects

Readers will notice that this formulation, with degree-specific coefficients, imposes discrete jumps between degrees rather than allowing for earnings to be a smooth function of credits or semesters. The latter would reflect the incremental human capital accumulation from an additional year of schooling, while the imposed form appears more like the *sheepskin effects* of Jaeger and Page (1996). Part of this is due to necessary restrictions based on the data, which is in turn due to the necessary limitations of survey work where asking, for example, about earnings at various levels of credit would be quite costly. While the literature has tended to confirm the importance of these sheepskin effects, workers likely also boost their earnings through the human capital they build while studying (see Belfield (2013) for discussion in the community college context). Examining how students perceive these effects, and how they influence their transfer decisions (the focus of the aforementioned paper), is a promising area for further research and a potential module to include in the next round of my survey.

D.2 Tuition distribution

I similarly assume that net tuition, e.g. the actual cost students are responsible for paying after aid, follows a Beta distribution.[50] I assume that the parameters of this distribution depend on time-invariant characteristics only, denoted Z_i.[51] Tuition thus follows:

$$Tu_i^* \sim Beta(\mu^{tu}(Z_i), \phi^{tu}(Z_i), \ell, r^{tu}(Z_i)) \tag{43}$$

[50] In other words, the out-of-pocket cost, but this terminology is slightly inappropriate since it may be covered by loans.

[51] In part, this is motivated by the survey elicitation, which does not condition on potentially changing circumstances.

Where I specify linear functions:

$$\mu_i^{tu}(Z_i) = \Gamma'_{tu} Z_i \phi_i^{tu}(Z_i) \qquad = \Delta'_{tu} Z_i r_i^{tu}(Z_i) = \Lambda'_{tu} Z_i \tag{44a}$$

I assume $\ell = \$0$ for everyone.

D.3 Tuition timing

In the model, students learn the value of four-year tuition Tu_i^* after making the enrollment choice. In reality, the enrollment process would look something like:

1. Choose to apply to a set of schools.
2. Receive initial tuition offers from each school.
3. Make an enrollment choice and discover the final tuition offer (which may be affected by additional grants and aid not resolved at the time that the admission offer is made).

My specification simplifies this to two steps: enrollment is decided, and then all uncertainty is resolved. Alternatively, I could model CC students as receiving a four-year tuition offer in each period of CC enrollment and then deciding their enrollment.

Both specifications are simplifications of the true process, and parameter estimates seem robust to either. I choose the form presented here primarily for the following reason related to the counterfactual exercises in Section 6. Respondents are generally pessimistic about tuition, so that their subjective belief is that tuition will be higher than it really will be. When students make choices based on their subjective beliefs but realize uncertainty based on the "true" (or benchmark) distributions, when they draw a low tuition offer they view this as a positive surprise and choose to transfer early. When we then correct beliefs by informing agents that four-year tuition costs are lower than they think, this has the effect of delaying transfer: this is because they no longer need to take advantage of a "good draw" (since they realize it's not really a good draw – it is just representative of a more affordable distribution than they initially thought). Since either specification seems like a reasonable approximation, and the parameter estimates do not appear overly sensitive to the choice, I opt for the form which does not produce this counter-intuitive result.

D.4 Credits and degree progression

Credits update according to:

$$K_{it+1} = \begin{cases} K_{it} + 0.5 & \text{if } d_{it} = CC \text{ and } a_{it}^{CC} = PT \text{ or } d_{it} = 4Y \text{ and } a_{it}^{4Y} = PT \\ K_{it} + 1 & \text{if } d_{it} = CC \text{ and } a_{it}^{CC} = FT \text{ or } d_{it} = 4Y \text{ and } a_{it}^{4Y} = FT \\ K_{it} & \text{if } d_{it} = 0 \end{cases} \tag{45}$$

Highest degree then evolves following:

$$D_{it+1} = \begin{cases} AA & \text{if } d_{it} = CC, a_{it}^{CC} = PT, \text{ and } K_{it} = 1.5 \\ AA & \text{if } d_{it} = CC, a_{it}^{CC} = FT, \text{ and } K_{it} \in \{1, 1.5\} \\ BA & \text{if } d_{it} = 4Y, \ a_{it}^{4Y} = PT, \ K_{it} = 3.5, \text{ and } \omega_{it} = 0 \\ BA & \text{if } d_{it} = 4Y, \ a_{it}^{4Y} = FT, \ K_{it} \in \{3, 3.5\}, \text{ and } \omega_{it} = 0 \\ D_{it} & \text{otherwise} \end{cases} \tag{46}$$

Note that conditioning degree updating on d_{it} rather than just on K_{it} enforces the requirement that the AA is only earned from enrollment in CC.

D.5 Terminal value functions

Once agents retire, the only remaining uncertainty is over the exogenous risk of death, $P^d(s_{it})$. Flow utility in each period is simply $\alpha \log(Y_i^r)$, so we can write the value of state X_{iT_2} as:

$$V_{T_2}(X_{iT_2}) = \sum_{\tau=T_2}^{T_3-1} \beta^{\tau-T_2} \alpha \log(Y_i^r) + \sum_{\tau=T_3}^{T^*-1} \beta^{\tau-T_2} \prod_{s=T_3}^{\tau} \left(1 - P^d(s_{is})\right) \alpha \log(Y_i^r) \tag{47}$$

Furthermore, since labor supply is exogenous, we may also summarize the value function at T_1 in a similar way:[52]

$$V_{T_1}(X_{iT_1}) = \sum_{\tau=T_1}^{T_2-1} \beta^{\tau-T_1} \mathbb{E}_{iT_1} \left[\alpha \log(c_{i\tau})\right] + \beta^{T_2-T_1} \mathbb{E}_{iT_1} \left[V_{T_2}(X_{iT_2})\right] \tag{48}$$

[52] This can be used to solve the agent's problem, beginning with the choice in $t = T_1 - 1$ and using $V_{T_1}(X_{iT_1})$ for backwards recursion.

D.5.1 Choice probabilities

It will be useful to define a choice-specific value function which gives the expected lifetime value of a specific discrete choice d'_{it}. Define:

$$\mathbf{u}(d_{it}) \equiv \mathbb{E}_{it}\left[u(d_{it})\right] - \nu_{it}(d_{it})$$

Where we must take the expectation of $u(\cdot)$ because tuition, and thus consumption, is not known at the time the decision is made. The choice-specific value function is:

$$v_t(d_{it}|X_{it}) = \mathbb{E}_{it}\left[\mathbf{u}(d_{it}) + \beta V_{t+1}(X_{it+1})\right] \tag{49}$$

The standard representation for the probability of making choice d'_{it} given a value of Y_{it} but without knowing the value of $\nu_{it}(d_{it})$ (which the econometrician never observes) and Tu_{it} (which is not yet revealed) is:

$$\begin{aligned} P(d_{it} = d'_{it}|X_{it}) &= P(v_t(d'_{it}|X_{it}) + \nu_{it}(d'_{it}) > v_t(d_{it}|X_{it}) + \nu_{it}(d_{it}),\ \forall d_{it} \neq d'_{it}) \\ &= \int_{\nu} \mathbb{I}\left[\nu_{it}(d'_{it}) - \nu_{it}(d_{it}) > v_t(d_{it}|X_{it}) - v_t(d'_{it}|X_{it}),\ \forall d_{it} \neq d'_{it}\right]\ dF_{\nu} \end{aligned} \tag{50}$$

Because we have assumed that F_{ν} is the T1EV distribution, eq. (50) follows the logit form:

$$P(d_{it} = d'_{it}|X_{it}) = \frac{\exp(v_t(d'_{it}|X_{it}))}{\sum_{d_{it}\in\mathcal{D}_{it}} \exp(v_t(d_{it}|X_{it}))} \tag{51}$$

Where $\mathcal{D}_{it}$ is the set of feasible choices. It will be helpful to consider the probability of choosing d'_{it} from the perspective of the end of $t-1$, before Y_{it} is known. This means we must integrate (51) over possible states:

$$P(d_{it} = d'_{it}|X_{it-1}) = \int_{\mathbf{X}_{it}} \frac{\exp(v_t(d'_{it}|x))}{\sum_{d_{it}\in\mathcal{D}_{it}} \exp(v_t(d_{it}|x))} dF_i(x|X_{it-1}) \tag{52}$$

The survey provides subjective path-probabilities which can be written using combinations of per-period model probabilities from eq. (52).

D.6 Learning

I have deliberately excluded learning from the model, but it would be natural to allow the distributions to vary across time so that individuals hold beliefs $F_{it}(X_{it+s}|X')$ where it may be that $F_{it} \neq F_{it+1}$. This could happen, for example, in response to draws of income or grades. However,

estimating a learning process generally requires longitudinal data on both beliefs and outcomes. There are some papers which do this, notably Stinebrickner and Stinebrickner (2012) and Conlon et al. (2018), but such data are in general challenging to collect. Such an approach is infeasible in my context due to the limited nature of the longitudinal sample, but is a direction for future work as data collection continues.

Where this becomes challenging is when considering whether this learning process should be taken into account when projecting forward. The law of iterated expectations tells us that individuals cannot *expect* that their beliefs will change; otherwise they will take that into account today, and go ahead and update their beliefs. However, if they know that they will change in some way (even if they do not know how), they may well take into account this added uncertainty. This implies taking an expectation over future belief distributions.

This is a challenging problem both for the econometrician (who now needs to add new state variables in order to integrate over future distributions) as well as for the individual (who must consider all the ways they might learn). As far as I am aware, this is not generally done.

In *estimating* the current model, I do not need to assume that no learning will occur; I simply need to assume that individuals do not take into account the possibility of learning when they make their choices. While in estimation this is without much loss of generality, it will present more challenges in the counterfactuals, since simulating forward requires an explicit behavioral assumption.

E Estimation details

E.1 Calibration

The initial age, s_{i0}, is read directly from the survey data. Because individuals are captured in the survey (and thus enter the model) at different ages, the number of annual decision periods between entry at t_1 and the end of the educational stage at T_1 is individual-specific. Mortality risk is taken as the hazard rate from the Social Security Administration's 2022 actuarial table. Retirement benefits are calculated based on earnings from the last $T_r = 25$ years of work, which cover all working years from T_1 to T_2. The treatment of retirement benefits is a simplistic representation of the US social security system, however it is without much loss of generality in estimation. This is because I am primarily focused on the choices of young people, for whom discounting over a long horizon means that retirement consumption is of limited importance for early enrollment choices. For computational reasons, I further simplify when taking the expectation in eq. (48) by assuming that agents evaluate utility of the expected average earnings.

While community college is not formally free in MD, it is *de facto* free (as in many other states) through the Maryland Promise Scholarship, which provides up to $5,000 in last-dollar aid for costs not covered by federal grants. Given that the sticker price at most community colleges in Maryland is below this threshold, the system functions as essentially free.

The student consumption floor is set to $\underline{c}_s = \$11{,}170$ based on the Income Protection Allowance (IPA) used by the Department of Education to compute eligibility of federal student aid in 2026-27, adjusted to 2024 dollars. That this is a minimum reflects the fact that students are allowed to borrow to cover some consumption costs while enrolled. The 50% contribution towards tuition costs of income above this consumption minimum is based on the guidelines for federal student loans, which assess the expected family contribution as 50% of all income above the IPA threshold.

The interest rate on student loans is set to $r_B = 8\%$. This is higher than the July 2026 rate for federally subsidized student loans, which implies a real rate around 4%, but is much lower than the rates faced on the private market. The length of repayment, $\tau_B = 20$, is also longer than the typical term for a federal student loan (which is officially set at 10 years), but is close to the time the typical borrower requires to repay their loans (which are frequently extended). It is also the horizon at which borrowers who make qualified payments under Income Based Repayment (IBR) schemes may have their loans forgiven (recently replaced by Repayment Assistance Plan (RAP)). The cap on student loan payments at 20% of disposable income is based on the threshold used under the old income-contingent repayment program. Newer programs have lowered it somewhat, but also changed the calculation method. The 20% threshold can be viewed as incorporating federal income-based repayment under the old rules, or a combination of IBR with some required private payments not subject to the cap.

In the calibration, the non-student minimum income is set to $\underline{c}_{ns} = \$7,530$. This is 50% of the 2024 poverty line for a single person and reflects federal anti-poverty programs. However, this value is without much effect in the model since non-students are assumed to work full-time and earnings are bounded below at the full-time federal minimum wage, which is above this minimum.

Some of the simplifying restrictions in the model could be further relaxed by incorporating external data in the same way that I use the NLSY97 to identify the shape of the four-year dropout hazard. For example, rather than assuming that labor supply while in four-year school is independent of intensity, I could estimate the differential rate between PT and FT school in observed data and apply this to my individuals. Since it is generally infeasible to ask survey respondents for their expectations about every possible uncertain feature of an environment, this kind of data combination exercise is a promising direction for future work in the subjective expectations literature.

E.2 Model-implied probabilities

The model-implied counterparts for the elicited probabilities are based on the choice probabilities detailed in Appendix D.5.1. For each individual, I perform S simulations based on their same set of initial conditions.

Let $A_i^{(s)}$ indicate ever entering four-year school in simulation s, and let $D_{i,\tau^{4Y}}^{(s)}$ be the degree at the moment of four-year entry. Let $D_{i,T_1}^{(s)}$ be terminal degree status. Then define four path indicators:

$$I_{i1}^{(s)} = \mathbb{I}\{A_i^{(s)} = 0,\ D_{i,T_1}^{(s)} \neq AA\}$$

$$I_{i2}^{(s)} = \mathbb{I}\{A_i^{(s)} = 0,\ D_{i,T_1}^{(s)} = AA\}$$

$$I_{i3}^{(s)} = \mathbb{I}\{A_i^{(s)} = 1,\ D_{i,\tau^{4Y}}^{(s)} \neq AA\}$$

$$I_{i4}^{(s)} = \mathbb{I}\{A_i^{(s)} = 1,\ D_{i,\tau^{4Y}}^{(s)} = AA\}$$

The model-implied path probabilities are then:

$$\widehat{\pi}_{ij}(\theta_k) = \frac{1}{S}\sum_{s=1}^{S} I_{ij}^{(s)}$$

E.3 Granularity classification

The granularity for each individual, G_i, is the coarsest grid compatible with all of their reported probabilities. To calculate this, I pool the answers to 15 probability-based questions, including those not directly used in this paper:

1. Probabilities of being unemployed, being out of the labor force, and of working PT and FT hours, at three points in the lifecycle and for each highest degree (9 questions)
2. Path probabilities (1 question)
3. Probabilities for success in four-year school, own and population (4 questions)
4. Probability of intensive margin in four-year school (1 question)

The assumption is that individuals use the same reporting model for all probability-based questions on the survey. Note that for individuals who are seen pre- and post-treatment, I have each question two times.

For each question q, which is a vector of probabilities, I find the minimum grid tokens $G_i^{(q)}$. For example, the vector $\{0, 15, 65, 20\}$ would be assigned $G_i^{(q)} = 20$, since on this question the individual answered in increments of five. On the other hand, the vector $\{0, 80, 20\}$ would be assigned $G_i^{(q)} = 5$, since the individual answered in increments of 20. I consider $G_i^{(q)}$ across all questions, and choose the smallest compatible number of tokens consistent with all of their responses.

Formally, letting $R_{iqr1}, \ldots, R_{iqrJ_q}$ index the reported probabilities for question q, we find:

$$G_{iqr} = \frac{100}{\gcd(100, R_{iqr1}, \ldots, R_{iqrJ_q})}$$

Then we consider all of the G_{iqr} and select:

$$G_i = \text{lcm}\{G_{iqr} : q, r\}$$

Table 25 shows the results of this procedure: the vast majority of respondents show themselves capable of answering in fine increments of 1-percentage point, with substantial minorities answering in increments of 5- and 10-percentage points, but negligible amounts answering in other increments.

There are several assumptions in this procedure. First, as the number of questions grows larger, we would expect to see *some* response which takes advantage of the individual's granularity G_i, but with a finite number of questions this may not be the case. That is to say: if we see an individual only respond in increments of five across this set of questions, we assume that they only ever respond in increments of five, but we cannot actually rule out that they truly can respond in increments of 1, but it just so happened that their beliefs and measurement error draws resulted in a G_i of 20. On the other hand, the reverse is not true; someone who answers in increments of five in at least one question cannot truly be of a type who only ever answers in increments of 10. Second, I assume a stable G_i across types of probabilistic beliefs and across rounds. Finally, this is a discrete classification; a refinement would be a model which instead allows for individuals to

have propensities for each coarseness.

E.4 Likelihood

E.4.1 Reporting distribution

The reporting model in Section 5.4 can be derived in two steps as follows. π_i^* continues to represent the latent belief of individual i about their path probabilities. I assume that q_i is a noisy measurement of the latent variable, and follows a Dirichlet distribution. The Dirichlet distribution generalizes the Beta distribution, which is used for the earnings and tuition distributions, to multiple variables; for this reason, it is commonly used to model probability vectors with multiple elements. I assume q_i is centered at π_i^*, so it follows:

$$q_i \mid \pi_i^* \sim \text{Dirichlet}(\phi \pi_i^*)$$

q_i is not observed; it should be thought of as an auxiliary intermediate probability vector used to construct the measurement. As long as $\phi > 0$, it is positive, continuous, and interior to the probability simplex. This means it will never produce values at 0 or 1, and it will also not exhibit the kind of clustering at intervals of 0.05, 0.1, etc., that is known to occur in reported probabilities.

For that reason, I do not assume that the survey captures q_i. Instead, I model a count vector $\boldsymbol{C}_i$, which is an allocation of G_i trials across the discrete outcomes, and follows a multinomial distribution:

$$\boldsymbol{C}_i | q_i, G_i \sim \text{ Multinomial } (G_i, q_i) \tag{53}$$

The percentage chance measured in the survey is constructed from $\boldsymbol{C}_i$:

$$\boldsymbol{R}_i = 100\tilde{\boldsymbol{\pi}}_i = \frac{100}{G_i}\boldsymbol{C}_i \tag{54}$$

Where $\boldsymbol{R}_i$ will have positive mass at 0 and 100 and can reflect the tendency to report at specific intervals of 5, 10, etc. The Dirichlet-multinomial distribution, which is used in the maximum likelihood procedure, arises from integrating out the unobserved vector q_i in eqs. (53)–(54).

The Dirichlet-multinomial is well-suited to modeling the kind of discrete probability measurements contained in my survey. It has the advantage of allowing for heaping at integers and handling the natural coarseness with which some people report probabilities. Its PMF is:

$$\Pr(\mathbf{C} = \mathbf{c} \mid G, \phi, \boldsymbol{\pi}) = \frac{\Gamma(G+1)}{\prod_{j=1}^{J}\Gamma(c_j+1)}\frac{\Gamma(\phi)}{\Gamma(G+\phi)}\prod_{j=1}^{J}\frac{\Gamma(c_j+\phi\pi_j)}{\Gamma(\phi\pi_j)}, \qquad \sum_j c_j = G$$

Note that relative to the standard parameterization, $\boldsymbol{\alpha} = \phi\boldsymbol{\pi}$ so that $\sum_j \alpha_j = \phi$.

There is also a direct measurement-error interpretation:

$$\widetilde{\boldsymbol{\pi}}_i = \boldsymbol{\pi}_i^* + \boldsymbol{\varepsilon}_i$$

Where $\mathbb{E}[\boldsymbol{\varepsilon}_i \mid G_i, \boldsymbol{\pi}_i^*] = \mathbf{0}$. The assumption that $\boldsymbol{C}_i$ is Dirichlet-multinomial then yields the variance:

$$\text{Var}(\boldsymbol{\varepsilon}_i \mid G_i, \bar{\boldsymbol{\pi}}_i, \phi) = \frac{G_i + \phi}{G_i(1+\phi)} \left[\text{diag}(\bar{\boldsymbol{\pi}}_i) - \bar{\boldsymbol{\pi}}_i(\bar{\boldsymbol{\pi}}_i)'\right]$$

Which more clearly shows the role of ϕ as "precision", or controlling the reporting dispersion. As $\phi \to \infty$, the variance goes to its minimum, so that the Dirichlet-multinomial converges to a regular multinomial distribution (put another way, the q_i vector converges to the true $\boldsymbol{\pi}_i$ belief). Finite ϕ allow for additional dispersion around the true probabilities. As $\phi \to 0$, the variance reaches its maximum, and reports will heap all the probability on one outcome.

Under the correctly specified model and the true set of preference parameters, $\bar{\boldsymbol{\pi}}_{ir} = \boldsymbol{\pi}_{ir}(\theta_k)$, leading to the likelihood function used in Section 5.4.

E.5 Expectation-maximization loop

Let $\mathcal{R}_i$ denote the set of observations from respondent i that enter estimation. This is simply $r \in \mathcal{R}_i = \{0, 1\}$ for an individual in the experimental sample (i.e. excluding the control group), where $r = 0$ indexes pre-treatment and $r = 1$ indexes post-treatment. For all other individuals, $r = 0$.

For an observation in round r, the likelihood conditional on latent type k is:

$$\mathscr{L}_{irk}(\Theta) = \text{DM}\left(\boldsymbol{C}_{ir} \mid G_{ir}, \phi\boldsymbol{\pi}_{ir}(\theta_k)\right) \tag{55}$$

Thus, the type-specific likelihood contribution for respondent i is:

$$\mathscr{L}_{ik}(\Theta) = \prod_{r \in \mathcal{R}_i} \mathscr{L}_{irk}(\Theta) \tag{56}$$

Expectation step

In the $q+1$ E-step, I use the current parameter values $\Theta^{(q)} = \left(\boldsymbol{\phi}^{(q)}, \boldsymbol{\theta}^{(q)}, \boldsymbol{w}^{(q)}\right)$ to calculate the individual-specific posterior type probabilities: $\tau_{ik}^{(q+1)}$:

$$\tau_{ik}^{(q+1)} = \mathbb{E}\left[\mathbb{I}\left[\varphi_i = k\right] \mid \{\boldsymbol{C}_{ir}, G_{ir}\}_{r \in \mathcal{R}_i}; \Theta^{(q)}\right]$$

By Bayes' rule,

$$\tau_{ik}^{(q+1)} = \frac{w_k^{(q)} \mathscr{L}_{ik}\left(\Theta^{(q)}\right)}{\sum_{k'=1}^{K} w_{k'}^{(q)} \mathscr{L}_{ik'}\left(\Theta^{(q)}\right)} \tag{57}$$

Maximization step

In the M step, I take $\tau_{ik}^{(q+1)}$ as fixed and maximize the expected complete-data log-likelihood (the "Q-function") to update $\boldsymbol{w}$, $\boldsymbol{\theta}$, and $\boldsymbol{\phi}$. That is, I construct:

$$Q^{q+1} = \sum_{i=1}^{N} \sum_{k=1}^{K} \tau_{ik}^{(q+1)} \left[\log(w_k) + \sum_{r \in \mathcal{R}_i} \log\left(\mathrm{DM}\left(\boldsymbol{C}_{ir} \mid G_{ir}, \phi \boldsymbol{\pi}_{ir}(\theta_k)\right)\right) \right] \tag{58}$$

I optimize (58) to find this round's parameter estimates:

$$\left\{\boldsymbol{w}^{(q+1)}, \boldsymbol{\theta}^{(q+1)}, \boldsymbol{\phi}^{(q+1)}\right\} = \arg\max_{\boldsymbol{w},\boldsymbol{\theta},\boldsymbol{\phi}} Q^{q+1}$$

In practice, the population-weight vector is directly found as:

$$w_k^{(q+1)} = \frac{1}{N} \sum_{i=1}^{N} \tau_{ik}^{(q+1)}.$$

And I then optimize Q^{q+1} over $\boldsymbol{\theta}$ and $\boldsymbol{\phi}$. The E-step is repeated using the updated parameters, and the loop continues until convergence.

E.6 Standard errors

I calculate standard errors from the likelihood's observed information matrix. Let ϑ collect the estimated structural parameters and the $K-1$ unrestricted type shares and let $\ell_{\text{obs}}(\vartheta)$ denote the observed-data log likelihood. Then the observed information matrix is:

$$\mathcal{J}(\hat{\vartheta}) = -\left.\frac{\partial^2 \ell_{\text{obs}}(\vartheta)}{\partial \vartheta \partial \vartheta'}\right|_{\vartheta=\hat{\vartheta}}$$

As is standard in maximum likelihood, the estimated covariance matrix is the inverse:

$$\widehat{\mathrm{Var}}(\hat{\vartheta}) = \mathcal{J}(\hat{\vartheta})^{-1},$$

and the standard error for each parameter is the square root of the corresponding diagonal element.

Because the latent types are unobserved, I perform a "missing data" correction to account for the additional uncertainty introduced by estimating the type shares. This correction was derived by Louis (1982) and is helpfully laid out in Section 4.4 of Peng (2022).

The standard errors reported in Table 18 are the information-matrix standard errors and do not reflect additional uncertainty from the fitted Beta distributions. They should thus be taken as a lower bound.

F Data benchmarks

F.1 Four-year tuition

I use the High School Longitudinal Study of 2009, which followed a sample of students who were in the 9th grade in 2009, to study tuition. While the survey dates mean that the information on tuition reflects a slightly older period, it has the advantage of containing detailed information on each component of tuition. Most crucially for the purposes here, it contains direct tuition costs, net of grants and aid, which is the variable of interest.

I clean the extract in the following way. I filter for respondents with non-missing values of the covariates described below, and, for those who attend 4-year school, non-missing tuition and fees. I construct net tuition as the sticker price for tuition and mandatory fees net of federal, state, and institutional grants. I set negative or missing grant amounts to zero and express all monetary amounts in 2024 dollars using the PCE deflator. I classify institutions as in-state public, out-of-state public, and private. Family income is provided in categories; I assign each individual the midpoint of the bracket they fall into, and then similarly convert to 2024 dollars.

The assumption in the model is that individuals draw net tuition from a distribution for school of type k, where k indexes in-state public, out-of-state public, and private school. Importantly, I assume that individuals are only choosing between one of these school types, k_i, and no school, 0, based on the school type which they assigned the highest probability to. A concern in estimating this distribution on realized net tuition from the HSLS is that we only observe tuition for people who have selected into school of type k, where this selection may depend on factors also influencing net tuition. As such, I will perform a Heckman-style selection correction.

Denote the selection indicator as:

$$S_{ik} = \mathbb{I}\left[\gamma_k X_i + \delta_k Z_i + e_{ik} > 0\right] \tag{59}$$

Which is 1 if an individual attends school of type k and 0 if the individual attends school of another type or does not attend school at all. I specify e_{ik} to follow a standard normal distribution. X_i represents a parsimonious vector of observable characteristics, which are observed in both the HSLS and in my survey data, which influence net tuition and the attendance decision. I use:

1. Whether at least one parent has a BA
2. Family income
3. High school GPA

Z_i is a vector of variables observed in the HSLS but not necessarily in my survey data, which shift the decision to attend school type k, but not the net tuition cost. I use the following set of

variables which describe ways in which the students' high schools may prepare them for the labor force:

1. Whether the high school has a "counselor designated for workforce preparation/placement."
2. The percentage of counselor and staff time spent on "occupational choice/career planning."
3. Whether the high school "offers job fairs."

The necessary assumption is that these factors influence the probability that students attend college of type k, but that conditional on family resources, parental education, and school type k, do not directly affect their potential net price at a school of that type; that is, Z_i affects S_{ik} but conditional on X_i does not affect Tu_{ik}.[53]

Let $Y_{ik} = \dfrac{Tu_{ik} - \ell}{r - \ell}$ be normalized net tuition. As in Appendix D, I define its distribution as:

$$Y_{ik} \sim \text{Beta}(\alpha_k(X_i), \beta_k(X_i)) \tag{60}$$

This variable is observed only when $S_{ik} = 1$. I set the bounds of the distribution based on the minimum and maximum values of net tuition in the sample, plus a small buffer.

With the model specified, I now follow the method detailed in Gomes et al. (2019) to implement a Gaussian copula. Define:

$$U_{ik} = \Phi^{-1}\left(F_{\text{Beta}}(Y_{ik}|\alpha_k(X_i), \beta_k(X_i))\right) \tag{61}$$

Where U_{ik} follows a standard normal distribution due to the probability integral transform. I assume that U_{ik} and e_{ik} are jointly normal with a correlation parameter ρ_k:

$$\begin{pmatrix} U_{ik} \\ e_{ik} \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_k \\ \rho_k & 1 \end{pmatrix}\right)$$

For convenience, let $\eta_{ik} = \gamma_k' X_i + \delta_k' Z_i$ be the index in the selection equation. I estimate the parameters $[\alpha_k, \beta_k, \gamma_k, \delta_k, \rho_k]$ by maximum likelihood. The contribution for someone who attends school of type k is:

$$f(Y_{ik}, S_{ik} = 1|X_i, Z_i) = f_{\text{Beta}}(Y_{ik}; \alpha_k(X_i), \beta_k(X_i))\Phi\left(\frac{\eta_{ik} + \rho_k U_{ik}}{\sqrt{1 - \rho_k^2}}\right) \tag{62}$$

[53] This would be violated if these job-training programs correlated with other school characteristics which do influence net tuition, for example counseling services to help students fill out financial aid documents. While the HSLS does contain information on this, the survey data do not; since we must restrict X_i to variables common between the two datasets, we cannot use this as a control variable. I will test robustness to alternative values of ρ_k to test the sensitivity of model results to alternative levels of correlation between the two distributions.

For someone who does not attend school k, the contribution is:

$$f(S_{ik} = 0|X_i, Z_i) = \Phi(-\eta_{ik}) \tag{63}$$

The log-likelihood function is thus:

$$\begin{aligned}\ell_k = \sum_{i=1}^{N} \Bigg(& S_{ik} \left[\log(f_{Beta}(Y_{ik}; \alpha_k(X_i), \beta_k(X_i))) + \log\left(\Phi\left(\frac{\eta_{ik} + \rho_k U_{ik}}{\sqrt{1-\rho_k^2}} \right) \right) \right] \\ & + (1 - S_{ik}) \log(\Phi(-\eta_{ik})) \Bigg)\end{aligned} \tag{64}$$

I then impute this distribution onto my sample using the survey responses for each covariate. Since tuition is elicited conditional on the most likely type of school (in-state public, out-of-state public, or private), I plug in the relevant value for each individual.

F.2 Earnings

The benchmark earnings distribution uses the same cross-sectional CPS sample as Appendix B.4. I use this dataset to fit the general log-Beta earnings model laid out in Appendix D.1. Besides educational attainment D_{it} and age s_{it}, the vector of observables which influences earnings, X_{it}, consists of:

1. Gender
2. Race and ethnicity
3. State
4. Year

I will handle selection in a similar, but more reduced-form, way to the above Gaussian copula method used for net tuition. First, let H_{it} be an indicator variable for whether an individual i is observed to work full-time in year t. Second, define D_{it} as the highest degree held by individual i in year t. Finally, define potential full time earnings of i at t with degree d by Y_{it}^d. Y_{it}^d is only observed when:

$$R_{itd} = \mathbb{I}[H_{it} = 1, D_{it} = d] \tag{65}$$

This equation describes nonrandom observations; it is not a structural model of selection into work with degree d, in part because these are sequential decisions. For each d, any individual who is not observed to work with $D_{it} = d$ has $R_{itd} = 0$. I then parameterize the observation rule as:

$$R_{itd} = \mathbb{I}\left[\gamma_d' X_{it} + \delta_d' Z_{it} + e_{itd} > 0\right] \tag{66}$$

Z_{it} is a vector of variables which influence whether Y_{itd} is observed. I use the number of children and age of the youngest child, which influence whether an individual selects into employment. As before, the maintained assumption is that Z_{it} affects the propensity to work but does not affect potential earnings conditional on X_{it}.[54]

Let $y_{itd} = \dfrac{\log(Y_{itd}) - \log(\ell)}{\log(r) - \log(\ell)}$ be normalized log earnings. They are distributed:

$$y_{itd} \mid X_{it} \sim \text{Beta}(\alpha_d(X_{it}), \beta_d(X_{it})) \tag{67}$$

As with the subjective earnings distributions, I assume that ℓ is bound by the full-time minimum wage. I set the upper bound r slightly above the largest observed full-time wage in the CPS sample. For each degree d, I transform the conditional Beta CDF of y_{itd} to a standard-normal rank and assume that this rank and e_{itd} are jointly normal with correlation ρ_d, exactly as in the tuition model. I estimate parameters of eq. (67), eq. (66), and the copula dependence parameter by maximum likelihood.

I then impute the parameters for my sample. I plug in 2024 and 2025 for the two survey waves respectively, and set the state to Maryland. I input gender and race, and then each distribution is forecast at each age and each highest degree.

F.3 Dropout

NLSY97 dataset

To study four-year dropout events as well as outcomes from CC, I use the National Longitudinal Survey of Youth (1997), abbreviated as the NLSY97. The NLSY97 is a longitudinal study which tracks a cohort of young people beginning in 1997. It contains a rich set of covariates and events, reported on the monthly level for earlier years, which makes it well suited for this purpose.

I filter the sample to individuals who have graduated from high school and have some experience in community college. I consider periods after HS graduation and classify each month's enrollment status as no school, community college, four-year college, or graduate school. I then divide the sample into enrollment spells, which is a consecutive sequence of months in the same enrollment state, where spells are classified as part-time or full-time. I keep only CC and four-year spells.

A community college spell is classified as ending in dropout if the individual neither holds a 2-year degree nor is enrolled in four-year school within four months of the end of the last month of CC attendance. The spell is classified as ending in a terminal AA if the individual has earned an AA but is not enrolled in four-year school within four months of the end of the last month of

[54] Because children may influence earnings through career-disruptions and other factors, as before, I will report sensitivity of the results to alternative levels of correlation.

CC attendance. A spell can also end in transfer, if the student **is** enrolled in four-year within four months of the last month of CC enrollment; this may happen with or without first earning AA.

I construct four-year spells based on enrollment episodes separated by no more than nine months (which allows for a single semester to be taken off before classifying this as a dropout). I classify the spell as ending in dropout if there is an enrollment gap of (at least) nine months and the individual does not hold a BA.

I use this dataset for three purposes. First, as I do for earnings and tuition, I use it to estimate a benchmark distribution for four-year dropout risk. Second, I use it to distribute the total dropout risk (both from the subjective expectations and from the benchmark distributions) into a per-period hazard. Finally, I use observed CC outcomes from the NLSY to reweight the benchmark outcomes in my survey sample.

F.3.1 Benchmark dropout distribution

I use the NLSY97 sample to estimate a probit model for four-year dropout:

$$\pi_i = \Phi\left(\beta_{0,\pi} + X_i'\beta_\pi\right)$$

where a spell ends in *dropout* as defined above. The model conditions on:

- Gender
- Age at beginning of enrollment spell (and its square)
- (Log) high school GPA
- PT vs. FT attendance

Because Maryland has a slightly lower rate of four-year dropout among transfers than the national average, I use the *slopes* from the benchmark model but adjust the intercept to match the Maryland data. After estimating $\hat{\beta}_\pi$, I select $\tilde{\beta}_{0,\pi}$ such that the mean predicted dropout probability in the NLSY97 sample equals the Maryland dropout rate, which I set to the midpoint of the two bounds provided in Section 3, $\pi^{MD} = 45\%$:

$$\tilde{\beta}_{0,\pi} \in \arg\min_b \left[\pi^{MD} - \frac{\sum_{i\in\mathcal{N}} w_i \Phi\left(b + X_i'\hat{\beta}_\pi\right)}{\sum_{i\in\mathcal{N}} w_i}\right]^2$$

Where $\mathcal{N}$ gives the NLSY97 sample and w_i their weights. I then use $\tilde{\beta}_{0,\pi}$ rather than $\hat{\beta}_\pi$ in the benchmark distribution.

As with the other benchmark exercises, this approach assumes that the relationships between observables and four-year dropout in the NLSY97 are transportable to my survey sample. I then

impute person-specific benchmark four-year dropout risks for my survey respondents using their observable characteristics.

F.3.2 Distributing the hazard rate

Respondents report a single total (or cumulative) probability of four-year dropout conditional on transfer; this is also the statistic generated from the benchmark distribution. To estimate the structural model, I must convert this into a per-period hazard rate. I do so using four-year spells from the NLSY97 to understand how dropout risk evolves over the course of a spell, conditional on intensity. This allows me to take the *shape* of the hazard rate from the NLSY97 and apply it to the subjective beliefs and benchmark probabilities without altering the total probability of dropout.[55]

Let $D_{jt} = 1$ indicate that individual j drops out during period t, conditional on remaining enrolled through the beginning of that period. I estimate the per-period hazard model:

$$\Pr(D_{jt} = 1 \mid D_{j1} = \cdots = D_{j,t-1} = 0) = \Lambda\left(\eta_o + \rho_o K_{t,o}\right),$$

where $o \in \{FT, PT\}$ denotes enrollment intensity (so that both the intercept and slope are intensity-specific) and $K_{t,o}$ are accumulated credits in full-time-equivalent semesters, at the beginning of period t, assuming attendance with intensity o since transfer. I use the shape of this model to understand how dropout risk changes with progress under each intensity. For each respondent, intensity, and the source of the probability ($s \in \{S, B\}$, where S denotes the subjective belief and B the benchmark probability) I add an intercept shift a_{io}^s such that the per-period conditional dropout risk (under each intensity) is:

$$h_{it}^{o,s} = \Lambda\left(\hat{\eta}_o + \hat{\rho}_o K_{t,o} + a_{io}^s\right)$$

Where $\Lambda(\cdot)$ is a logit function. I select a_{io}^s so that the cumulative risk equals the relevant reported or benchmark cumulative dropout probability. For convenience, let π_{io}^s denote the cumulative dropout probability used under intensity o and source s. Because the survey elicits a single subjective probability, $\pi_{i,FT}^S = \pi_{i,PT}^S = \pi_i^S$. I find a_{io}^s to match:

$$\pi_{io}^s = 1 - \prod_{t=1}^{L_o} \left(1 - h_{it}^{o,s}\right).$$

I apply this procedure once for both $s = S$ and $s = B$. Because the vast majority of respondents expect transfer to take place with an AA, I assume that full-time four-year enrollment lasts $L_{FT} = 2$ annual periods and part-time enrollment $L_{PT} = 4$ periods. Thus, the NLSY97 model determines the relative timing of dropout risk over a four-year spell, while the subjective report or benchmark

[55] A simple alternative would be to assume a constant hazard rate.

probability determines each individuals' *level* of risk.

F.3.3 Reweighting community college outcomes

Finally, I use the CC spells from the NLSY97 sample to estimate a data benchmark for the expected outcomes from the survey sample. Define by Z_{ij}, $j \in \{1, 2, 3, 4\}$ a binary indicator for person i equal to one if their first CC enrollment spell ends in dropout, terminal 2-year degree, transfer without an AA, and transfer with an AA, and zero otherwise. I estimate the multinomial logit model:

$$\pi_{ij}^{\text{nlsy}} = \frac{\exp\left(\delta_j + X_{it}'\Delta_j\right)}{\sum_{\ell=1}^{4}\exp\left(\delta_\ell + X_{it}'\Delta_\ell\right)},$$

where π_{ij}^{nlsy} is the NLSY-implied probability of outcome j. X_{it} contains the same observable characteristics as used in the four-year dropout distribution, as well as accumulated CC progress and attendance intensity. I normalize the coefficients for CC dropout to zero.

I then adjust the model to respect the overall MD statistics, denoted by π_j^{MD}. Let $\hat{\pi}_{ij}^{\text{nlsy}}$ give the fitted probabilities. I find new intercepts $\tilde{\delta}_j$ (maintaining $\tilde{\delta}_1 = 0$) to minimize:

$$\sum_{j=1}^{4}\left[\pi_j^{MD} - \frac{\sum_{i\in\mathcal{N}} w_i\hat{\pi}_{ij}^{\text{cal}}(\tilde{\delta})}{\sum_{i\in\mathcal{N}} w_i}\right]^2,$$

where

$$\hat{\pi}_{ij}^{\text{cal}}(\tilde{\delta}) = \frac{\hat{\pi}_{ij}^{\text{nlsy}}\exp(\tilde{\delta}_j)}{\sum_{\ell=1}^{4}\hat{\pi}_{i\ell}^{\text{nlsy}}\exp(\tilde{\delta}_\ell)}$$

I then use the re-centered model to predict the probability of each outcome in my sample and take the average, which produces the NLSY-reweighted totals used in Section 6.5.

G Supplementary tables

Table 21: Race assignment

Category	Population	Elicited	Normalized
White	49.5	62.7	53.5
Black	20.3	22.6	16.4
Hispanic	17.0	17.9	17.9
Asian	5.1	11.2	7.6
American Indian or Alaska Native	0.4	2.4	–
Native Hawaiian or Pacific Islander	0.2	0.9	–
Middle Eastern or North African	–	2.3	–
Multi-race	7.6	17.0	2.3
Other	–	–	2.3

Table 22: Expected payoffs and subjective path odds

Dependent variable	Log path odds relative to HS/dropout					
Sample	Cross-section				Individual fixed effects	
Model	(1)		(2)		(3)	
Estimator	Huber	OLS	Huber	OLS	Huber	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Log expected payoff ratio	0.980**	0.946**	0.898*	0.850*	0.473	0.293
	(0.347)	(0.355)	(0.366)	(0.360)	(0.405)	(0.611)
Observable controls	No	No	Path-specific	Path-specific	No	No
Path fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Schooling tastes	No	No	No	No	Yes	Yes
SE method	Sandwich	Sandwich	Sandwich	Sandwich	Bootstrap	Sandwich
Fit statistics						
Observations	894	894	894	894	1,392	1,392
R^2	0.278	0.241	0.320	0.275	0.751	0.679

* indicates $p < 0.05$,** indicates $p < 0.01$.

Table 23: Survey response and cleaning summary

Survey	Completed	Final standard sample	Attention-check failures
Initial survey (2024)	477	356	14.4%
Follow-up survey (2025)	150	110	20.0%
Cross-sectional survey (2025)	393	298	14.2%

Table 24: Sample demographics

Variable	Overall	Cross-section	Longitudinal	Experimental	Population
N	630	242	114	298	6,888
Age	21.83 (0.16)	22.02 (0.26)	21.74 (0.38)	21.70 (0.23)	21.49
Female	0.69 (0.02)	0.69 (0.03)	0.73 (0.04)	0.68 (0.03)	0.60
White	0.54 (0.02)	0.52 (0.03)	0.54 (0.05)	0.55 (0.03)	0.49
Black	0.17 (0.01)	0.20 (0.03)	0.18 (0.04)	0.12 (0.02)	0.20
Hispanic	0.17 (0.02)	0.19 (0.03)	0.13 (0.03)	0.19 (0.02)	0.17
Asian	0.08 (0.01)	0.05 (0.01)	0.10 (0.03)	0.09 (0.02)	0.05
Other	0.02 (0.01)	0.02 (0.01)	0.00 (0.00)	0.03 (0.01)	0.01
Multi-race	0.02 (0.01)	0.02 (0.01)	0.04 (0.02)	0.02 (0.01)	0.08
FARM	0.46 (0.02)	0.45 (0.03)	0.40 (0.05)	0.48 (0.03)	
Parent BA	0.45 (0.02)	0.44 (0.03)	0.51 (0.05)	0.44 (0.03)	
Employed	0.70 (0.02)	0.73 (0.03)	0.73 (0.04)	0.65 (0.03)	
Has children	0.11 (0.01)	0.12 (0.02)	0.11 (0.03)	0.11 (0.02)	
Part-time employment	0.48 (0.02)	0.48 (0.03)	0.50 (0.05)	0.47 (0.03)	
Full-time employment	0.22 (0.02)	0.26 (0.03)	0.23 (0.04)	0.18 (0.02)	
HS GPA	3.24 (0.02)	3.20 (0.04)	3.25 (0.05)	3.28 (0.03)	
Mean GPA	3.33 (0.03)	3.28 (0.05)	3.43 (0.06)	3.35 (0.04)	
Mean GPA (male)	3.37 (0.05)	3.34 (0.09)	3.47 (0.11)	3.36 (0.08)	
Mean GPA (female)	3.31 (0.04)	3.26 (0.06)	3.40 (0.07)	3.34 (0.06)	
Median GPA	3.50	3.33	3.58	3.50	
Median GPA (male)	3.50	3.46	3.65	3.50	
Median GPA (female)	3.50	3.30	3.50	3.50	
Enrolled PT	0.45 (0.02)	0.43 (0.03)	0.42 (0.05)	0.49 (0.03)	0.62
Wage	18.79 (0.35)	19.37 (0.57)	19.71 (1.08)	17.84 (0.38)	
Arts and Humanities	0.11 (0.01)	0.12 (0.02)	0.12 (0.03)	0.10 (0.02)	0.14
Business and Economics	0.13 (0.01)	0.14 (0.02)	0.10 (0.03)	0.13 (0.02)	0.12
Medicine and health	0.30 (0.02)	0.29 (0.03)	0.24 (0.04)	0.32 (0.03)	0.23
STEM	0.25 (0.02)	0.24 (0.03)	0.32 (0.04)	0.23 (0.02)	0.22
Social sciences	0.07 (0.01)	0.06 (0.02)	0.06 (0.02)	0.08 (0.02)	0.08
Transfer studies	0.15 (0.01)	0.14 (0.02)	0.17 (0.04)	0.14 (0.02)	0.20
STEM+	0.75 (0.02)	0.75 (0.03)	0.72 (0.04)	0.75 (0.03)	
Humanities and social sciences	0.25 (0.02)	0.25 (0.03)	0.28 (0.04)	0.25 (0.03)	

Table 25: Reporting granularity classification

G	increments	% of sample
1	100%	0.3%
2	50%	0.3%
4	25%	0.2%
5	20%	0.2%
10	10%	5.2%
20	5%	16.8%
25	4%	0.3%
50	2%	1.2%
100	1%	75.5%

Classification is based on the coarsest grid compatible with all valid responses.