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ABSTRACT

We examine how disadvantaged students make postsecondary education decisions, focusing on why they often opt for relatively short programs with lower expected returns. Prior literature emphasizes information deficits and financial constraints. We draw upon qualitative data collected via open-ended interviews conducted with a sample of economically disadvantaged Black youth in Baltimore to develop and explore a complementary narrative: students who have faced disadvantage, including disruptive events, or "adverse shocks" (e.g., violence, eviction or incarceration of a family member), anticipate future shocks that could derail their educational plans. They thus opt for shorter educational programs that they expect they can complete despite anticipated shocks. We corroborate this narrative using publicly available, large-N data sets such as the National Longitudinal Survey of Youth 1997 (NLSY97). Finally, we formalize this narrative as a dynamic structural model of educational decisions that incorporates how students often enroll in, but do not complete, degree programs. Estimated utility costs of schooling—and thus policy conclusions—hinge on what we assume individuals believe about the likelihood of completing school. While the NLSY97 provide indirect measures, future data collection could measure these beliefs directly. More broadly, our approach is a novel application of mixed methods research: using qualitative data—learning about decisions from those who make them—to aid in the specification of a structural model. This approach could be applied in other contexts where behavior is poorly understood to inform data collection priorities, hypothesis testing, and model specification.

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1 Introduction

Most high school students now enroll in some type of higher education after graduation (Rosenbaum et al., 2017; Rosenbaum and Rosenbaum, 2015; Bailey and Dynarski, 2011). Their modal outcome, however, is not a bachelor's degree, nor an associate's degree, but "some college" with no degree at all. While obtaining some postsecondary education can still be a better outcome than never enrolling at all (Darolia et al., 2023; Liu et al., 2015; Jepsen et al., 2014), returns are relatively low compared to a four-year degree (Webber, 2016; Hillman, 2014; Oreopoulos and Petronijevic, 2013). Earlier literature has generally found such lower attainment to be more common among lower-income and non-white students (Baker et al., 2018; Dahill-Brown et al., 2016; Ma et al., 2016; Bailey and Dynarski, 2011). Many of them never enroll in a four-year college at all, opting instead for shorter-duration programs, some at for-profit institutions like occupational colleges and trade schools (Gelbgiser, 2018; Ma et al., 2016; Deming et al., 2012). Enrollment in these types of institutions is associated with lower completion rates and, like the "some college" outcome, lower returns in the labor market, especially for those pursuing for-profit credentials (Cellini and Turner, 2019; Goodman et al., 2017). Yet relatively little is known about how these enrollment decisions are made.

In this study, we develop and explore an explanation that builds on literature from both sociology and economics: anticipation of personal and household adverse events is an important and overlooked mechanism connecting disadvantage to diminished educational outcomes. Our approach is unique: we use qualitative interview data to develop hypotheses, motivate secondary data analysis, and ultimately inform a structural model of decision-making about education to be used in policy simulations. While a common explanation for individuals' apparently suboptimal educational choices is a lack of information about the returns to or funding options for four-year programs (a "deficit model" explanation), our unique mixed-methods approach suggests individuals may be making insightful and rational decisions based on information they *do* have. In particular, sub-baccalaureate pathways may be optimal for some students, especially those with unstable home lives or living in neighborhoods that are violent or under-resourced, as these students have not only experienced adverse shocks or events, but may also anticipate future adverse shocks that could derail their education. They thus opt for shorter and less lucrative educational programs that they expect they can finish.

The path to a four-year degree can be fraught. The research team interviewed Tiffany, a 20-year old from Baltimore, who described her worries about college: "What if I don't have money next month for a cell phone? . . . what if I ran out of soap or toothpaste? . . . it's like who should I call for this? It's so stressful to think about. I'm thinking I shouldn't be thinking about stuff like this. I should just be in my books and trying to get good grades and that makes me sad." Terry, 21, who was homeless when last interviewed, put it another way: "I know when I get in there [college] I wanna be serious . . . I want to be able to really focus and not have these other things pullin', interfering with my focus."

The idea of linking anticipated shocks and educational investments emerged from rich qualitative data: systematically sampled interviews from youth in high poverty areas in Baltimore, like those conducted with Tiffany and Terry. Most respondents reported having experienced adverse events (which we henceforth refer to as "shocks" or "adverse shocks"), such as housing instability, incarceration of a family member, or violence. Many of those who experienced shocks in childhood also anticipated future shocks that could interrupt their educational path. Based on some of their accounts, it is likely that this anticipation influenced their postsecondary choices.

We draw on large-N quantitative data from publicly available, nationally representative longitudinal surveys to corroborate, albeit indirectly, this link between household shocks and educational decision-making. We focus on the National Longitudinal Survey of Youth 1997 (NLSY97) in this paper.[1] Respondents who have experienced shocks have lower expectations regarding the probability that they will earn a bachelor's degree. These lower expectations are associated with those same individuals' increased fears about future adverse events and dropping out and are also correlated with a tendency to enroll in two-year educational programs after high school rather than four-year bachelor's degree programs.[2] We note, though, that the variables available in large data sets do not allow us to analyze the anticipation of shocks as fully or as deeply as is possible in the smaller qualitative data set.

To formalize how anticipated shocks affect educational pathways, we develop a dynamic structural model of postsecondary decision-making. The model envisions students maximizing their lifetime utility, which is affected by the opportunity cost and consumption value of schooling as well as future income. A longer degree program entails higher upfront financial sacrifices but is more lucrative. Anticipated shocks are incorporated as a positive probability that students who enroll in an educational program do not progress in it, delaying or precluding degree completion and thereby lowering returns to educational investments. This model captures the idea that students may anticipate shocks that derail long-run education plans. As Tyler, 19, another young adult from Baltimore, vividly explains, "I'm looking to,

[1] The Educational Longitudinal Study (ELS) and the High School Longitudinal Study (HSLS) can also be used to investigate some of the issues we examine related to education decisions. We analyze these data sets to corroborate our main findings using the NLSY97 where possible.

[2] We focus on two-year- versus four-year degree programs in our main analyses even though there are other options, including certificate or training programs that are often shorter.

you know, build. I'm young, I'm still laying my foundation for the house someday. This is lifetime, it's like you building a house brick by brick, hand by hand ... I don't have time for nobody to come and run over my foundation with a steamroller ... 'cause that's how a lot of people do, they try to ruin your life." Anticipating such shocks, students may opt for shorter degree programs they believe they can finish or none at all, even if doing so implies lower eventual returns on the labor market.

Specifying this model of educational decision-making serves several purposes. First, it formalizes how an *anticipation* of future shocks—not just realized shocks—affects students' choices. The model can thus shed light on how students who have faced instability and poverty throughout their lives make decisions about their future, anticipating that similar instability will continue to plague them. Second, the model shows how a failure to incorporate anticipated shocks (e.g., relying only on a deficit model of decision-making) can generate incorrect conclusions about the utility cost of schooling and thus lead to misleading conclusions about policy. Our estimates of the disutility of schooling vary widely depending on students' probability of shock-related derailment. Even among high socioeconomic-status white students, the estimated disutility of a year in a bachelor's degree program is $610 when we assume they rationally account for the noncompletion rates, which we calculate indirectly using the NLSY97 data, but rises to $5,538 when we omit noncompletion from the model. These values have meaningfully different implications for counterfactual policies designed to insulate students from shocks or that otherwise incentivize disadvantaged youth to choose more lucrative educational pathways (e.g., more flexible rules governing scholarships, educational grants, or permission for leaves-of-absence).

More broadly, our cohesive process of data collection, hypothesis formulation, and model building is widely applicable and merits further clarification. Recent innovative research has incorporated qualitative data to help identify mechanisms underlying experimental results (Bergman et al., Forthcoming). Our approach demonstrates another novel application of mixed methods research: using qualitative data to aid in the specification of a structural econometric model. The model we develop is rooted in economic theories of dynamic decision-making, but crucial insights come from qualitative interviews with actual decision-makers (a relatively rare approach in economics but one used frequently by sociologists). Moreover, the process of data analysis and model development is potentially iterative. Open-ended interviews can provide narratives used to specify a model of decision-making, while large-N data can be used to corroborate the basic narrative and test whether it holds in a nationally representative sample. Meanwhile, appeals to economic theories of dynamic decision-making generate novel hypotheses about how people make choices, leading to fresh analyses of qualitative data. Finally, the narrative-driven model highlights what is missing from larger data sets—in our case, direct measures of what students believe about the likelihood of noncompletion when they enroll—thus informing priorities for future data collection efforts. Such an approach could be applied in other contexts where behavior is poorly understood to inform how we collect data, how we develop and test hypotheses, and how we specify models of behavior to evaluate policy.

Our methodological approach, like any other, requires us to make and defend a host of choices and assumptions. We effectively employ three approaches in this paper—qualitative interview analysis, descriptive statistical analysis, and structural modeling. Thus, this hurdle must be cleared three times, while maintaining conceptual cohesion across all three methods. In the end, we intend for our use of these various methods to show that the results we generate and the stories we tell are not due to arbitrary assumptions or a single empirical approach. Decisions about how to code and interpret interviews, what large-N data to examine and how, and on what questions to focus our structural estimation were not made in isolation but in concert; the data sets and the models that we employ complement one another, each filling in gaps the others leave open.

This study contributes to several strands of existing research on factors affecting educational decisions and educational attainment gaps. Increasingly, studies in economics examine returns to sub-baccalaureate pathways (often subsumed into the category "some college"). This is difficult in part because the appropriate comparison group is unclear, but findings typically suggest that benefits to even some postsecondary coursework outweigh costs (Liu et al., 2015; Jepsen et al., 2014). Still, individuals with "some college" but no degree better resemble people with no college than bachelor's degree holders along multiple dimensions (Hillman, 2014), meaning it is important to continue improving our understanding of who chooses or ends up on these pathways and why. Traditional and recent explanations of educational choices have emphasized information, family background, and resource constraints (Dynarski et al., 2021; Hoxby and Turner, 2015; Bettinger et al., 2012; Attewell et al., 2011; Perna and Li, 2006; Keane and Wolpin, 2001) and are generally focused on four-year enrollment or degrees.

While resource and information constraints likely play a role, research from sociology (and more recently from economics) has identified other factors. Together, these factors constitute what sociologists call the *social context* within which students make decisions. Some are subsumed into the broader concept of family background and resource constraints, such as neighborhood quality and characteristics (Wodtke et al., 2011; Sharkey, 2010; Sampson et al., 2008) or school-based inputs like guidance counselors (Ilic et al., 2020; Bettinger and Evans, 2019; Castleman and Goodman, 2018). Additional research, mostly from sociology, shows that inadequate housing, exposure to violence, food insecurity, or lack of access to supportive teachers can derail a student's educational plans (Jack, 2019; Goldrick-Rab, 2016; Desmond, 2016; Roderick et al., 2011; Harding, 2010; Jones, 2010; Iloh, 2018; Iloh and Tierney, 2014; Chyn, 2018), but their costs can be an insurmountable barrier to disadvantaged students. Indeed, a field experiment carried out at a large community college campus in Texas found that access to individual case managers who helped students navigate "life barriers" significantly increased persistence and degree completion among female students, while financial assistance alone had no effect (Evans et al., 2020). Also relevant are the less easily measured factors that comprise *social capital*, including social ties and networks as well as social norms surrounding education (Chetty et al., 2022).

Educational barriers can be lowered if institutions are designed for disadvantaged students, but many are not (Jack, 2019; Roderick et al., 2011; Persell and Peter W. Cookson, 1985). A consequence is that shorter, more occupationally focused degree programs frequently offered by for-profit institutions become more attractive to students from low-income backgrounds (Holland and DeLuca, 2016). Students facing instability may (correctly or not) perceive a higher likelihood of success at such institutions—relative to traditional colleges—due to their shorter time to degree and more ostensible connections to employers (Rosenbaum et al., 2006).

This principle also links our work to research that considers the role of beliefs and expectations in educational decisions (Belzil and Leonardi, 2013; Wiswall and Zafar, 2015; Bozick et al., 2010). Raley et al. (2012) show an association in the NLSY97 between higher subjective probabilities of young pregnancy and reduced enrollment in and persistence at postsecondary programs. As Jacob and Wilder (2010) note, a great deal of literature dating back to the 1970's shows that parents' and students' own educational expectations are a strong predictor of final attainment even conditional on many background characteristics, while Papageorge et al. (2020) show that high school teachers' expectations affect youths' attainment as well. However, the exact mechanisms through which these effects operate remain unknown. We examine the effect of a specific set of expectations—anticipation of shocks—shaped by the social context in which students make decisions.

Finally, a wealth of prior work explores mixed-methods research in the social sciences (Hesse-Biber and Johnson, 2015; Small, 2011; Tashakkori and Teddlie, 2003). Over the years, researchers have called for increased use of qualitative methods in economic research to complement analyses of large data sets (Grigoropoulou and Small, 2022; Akerlof, 2020; Moffitt, 2000). While there is some growth in acceptance of this approach (DeLuca et al., Forthcoming; Bergman et al., Forthcoming; Kling et al., 2005), economics still lags behind other fields (Thelwall and Nevill, 2021). Moreover, how best to use qualitative methods in economics remains an open question. The approach that most closely resembles ours is the use of qualitative data to generate a theory or formulate a question that is then combined with population-representative quantitative data (e.g., Myers and Oetzel (2003)). Our approach integrates methods more thoroughly—we treat the structural econometric model as a tractable, estimable representation of a conceptual model that emerges directly from the gathering and synthesis of qualitative data. This is a manifestation of the insight of Moffitt (2000) that theoretical economic rationales are necessarily qualitative. If a structural econometric model is an attempt to quantify a qualitative story, then that story itself can and should have support in qualitative data. But even further, the descriptions decision-makers provide of their own processes can provide a richer informational foundation on which to build an economic *model*—not just a research question—than a researcher's guess.

The rest of the paper proceeds as follows. Sections 2 and 3 present our data analysis and findings using small-N qualitative data and large-N quantitative data, respectively. Section 4 details a dynamic structural model of educational decision-making based on this data analysis, as well as estimates from that model and counterfactual policy simulations. Section 5 concludes.

2 Qualitative Interview Data Analysis

2.1 Introduction to Qualitative Interview Data

How the anticipation of negative shocks relates to postsecondary decision-making is an inductive finding that emerges from the stories of youth who participated in in-depth, semi-structured interviews as part of an evaluation of the impacts of the Moving to Opportunity (MTO) housing mobility experiment in Baltimore, Maryland. We use data from a mixed-methods study of families and children in the Baltimore site of MTO. A total of 636 families in Baltimore participated in this program, all of which were Black.[3] In 2010, a qualitative interview component was added to the study with the goal of understanding the transition to adulthood for the MTO participants and for disadvantaged youth more broadly. A stratified random sample of 200 youth (ages 15 to 24) were chosen from the Baltimore MTO sample, and 75 percent of these youth agreed to participate in the qualitative portion of the study (N=150).[4]

We draw on qualitative interview data from these 150 low-income youth and young adults,

[3] A potential limitation of these data is that the sample consists only of Black youth. The addition of a sample of disadvantaged non-Black students would help us understand whether some of the patterns in these data generalize to other racial or ethnic groups. Indeed, DeLuca and Burland (2023) have asked this question directly to a sample of mostly white students and have found similar patterns. Our quantitative analyses reported in Section 3, using nationally representative data (which include respondents of different races) show that main patterns generalize to other populations.

[4] Kathryn Edin and Susan Clampet-Lundquist were Co-PIs with DeLuca for the MTO Q10 Transition to Adulthood Study.

all of whom initially lived in Baltimore's highest-poverty neighborhoods, concentrated mostly in high- and mid-rise public housing developments. Although the interviews focused on youths' experiences changing neighborhoods as a result of MTO, they covered a wide range of topics concerning respondents' transition into adulthood (see DeLuca et al. (2016) and Boyd and DeLuca (2017) for more information on sample and interview design). These semi-structured, in-depth interviews covered open-ended questions about employment, education, neighborhoods, friends and family, risky behavior, and mental health. Youth were asked about their college and career preparation, postsecondary decision-making process, and, for youth who were interviewed after high school, their experiences in postsecondary institutions. Most interviews were conducted in respondents' homes, and 96% of respondents still lived in the Baltimore area at the time of the interview. All names used in this paper have been changed to pseudonyms chosen by the respondents themselves.

The interview approach used to collect these data builds on long-standing methods in urban sociology used to observe social life and the ways in which individuals make meaning of their everyday routines (Edin and Lein, 1997; Anderson, 1990; Burawoy, 1979; Liebow, 1967; Becker et al., 1961). Specifically, the data were collected using *narrative interviewing*, a semi-structured approach that employs open-ended questions. This approach allows for a wide range of responses to emerge along with targeted follow-up probes, which help to ensure all interviews cover the same material. Interviews conducted with this approach tend to create natural, in-depth conversations, rather than a clinical series of short questions and answers. Interviewers focus on empathetic, non-judgmental listening in order to signal to study participants that they, not the research team, are the experts on the topics of the study and invite them to tell their own stories within semi-structured question modules. When successful, this interviewing method invites descriptive narratives about social processes, such as educational decision-making, to emerge naturally.

Rather than asking detailed probes or highly structured questions up-front—which runs the risk of leading respondents or closing off unanticipated themes (Becker, 1990)—interviewers posed open-ended prompts such as "tell me how you ended up at the community college," using verbal cues, eye contact, and body language to signal interest. Respondents therefore answered at length with detailed and often unsolicited information, in an order that made sense to them. This approach thus generated stories and insights that informed both pre-existing research aims and topics unanticipated by the researchers, many of which would likely have been missed by standard survey questions with pre-ordained, also called "forced choice" answer sets.

Once respondents had a chance to reply to open-ended prompts, interviewers followed with more detailed "probes" to support less talkative respondents and ensure systematic topic coverage. Probes were typically questions about "how" rather than "why" events happened and included specific topics we wanted to ask about—such as financial aid—that might not come up unsolicited from the respondent. Alternating between open-ended questions and detailed probes, interviews took on the form of extended conversations, usually lasting two or more hours. This allowed interviewers to collect data on processes while avoiding the impression that respondents' answers would be judged.

This interview style is based upon the idea that decision-makers themselves may have necessary, untapped insight about how decisions are made. The question is not whether young people make decisions *for some specific reason or not*, with the reason determined *a priori*. Instead, we want to know how the decision-making process works, broadly speaking. To find this answer, we need to acknowledge that many of the reasons students choose certain educational paths might not readily occur to any one researcher (or indeed any eight researchers). Our goal is to take lessons from narrative interview data that inform further examination on a generalizable scale in both data collection and modeling, each of which we address in later sections of the paper.

For the present analysis, interview transcripts were systematically coded for the following: negative shocks; anticipation of negative shocks; postsecondary plans (including four-year, two-year, and for-profit school enrollment; employment; military enlistment; and illicit activity); rationales for adopting specific postsecondary plans; any discussion of the costs, benefits, and tradeoffs of postsecondary plans; and beliefs about the future.

The research team read full interview transcripts and field notes for all respondents in the sample and reviewed coded segments concerning postsecondary decision-making, adverse life events, and any specific language around respondents' anticipation of future negative shocks. In the next few sections we leverage the interviews to describe: the prevalence of adverse shocks and how they derail educational pathways; the anticipation of future shocks and its connection to youths' expectations regarding their future outcomes; and how a few youths explicitly connected their anticipation of shocks to their postsecondary decisions, especially about sub-baccalaureate programs. We have more data on how youth discuss postsecondary education and adverse events in general and less on the specific connections between the anticipation of shocks and postsecondary choices and outcomes. However, that evidence is at least suggestive of our story and warrants the further exploration we embark on in the subsequent sections.

2.2 Findings in the Qualitative Data

2.2.1 Adverse Shocks: Experiences and Derailments

To begin, we describe respondents' experiences of adverse shocks, as well as instances in which those shocks led to *actual* disruption of their long-term educational paths.[5] Accounts of unexpected adverse life events were pervasive among the 150 youths who were interviewed. Table 1 reports experiences of significant shocks in childhood and adolescence. Each row of Table 1 is a specific type of shock or adverse event. To understand the table, consider "Arrested/incarcerated (self)" referring to the respondent being arrested or incarcerated. Column 1 shows how many individuals reported experiencing this shock at least once (40 people); column 2 divides this number by 150 to show the proportion of the sample who experienced this shock at least once (26.7%); and column 3 shows the total number of instances reported throughout the interviews (57), allowing for multiple instances per individual.

Looking at Table 1, only one individual out of the sample of 150 reported no adverse shock or event. More than half (54.7%) described having a parent or friend who had been incarcerated or was involved in illegal activity, often drug sales or other illicit employment. About 30 percent of respondents had experienced a period of parental absence during their childhood, and a little over a quarter (26.7%) of respondents had been arrested or were put in jail or on probation. More than one half of youth interviewed had experienced the death of someone close to them (52.7%), including parents, siblings, cousins, friends, and other family members.[6] Housing shocks—unplanned moves resulting from events such as evictions, foreclosures, fire, housing voucher inspection failure, and financial insecurity—were also experienced by almost 30 percent of respondents. While only about 10 percent of youth reported being victims of violent crime themselves, over a quarter reported seeing violence at school (26.7%), about 20 percent reported domestic violence in their household (20.7%), and over eight percent (8.7%) witnessed violence elsewhere. Importantly, these percentages likely all undercount the prevalence of these adverse events, as we did not ask about more of them directly.

Further analysis in DeLuca et al. (Forthcoming) of the same data set shows that, while just one individual reported no adversity or shocks, several report 15 or more distinct adverse events. Over half of the sample, 52 percent, reported between two and eight adverse shocks. In other words, these types of shocks, often considered important sources of child-

[5] The link between observed past and expected future shocks is not limited to the sample of 150 respondents discussed here. As we will detail in Section 3, many students in the NLSY97 who anticipated adverse events in their lives but pursued a bachelor's degree anyway ended up unable to achieve their goal, suggesting that anticipation of derailing shocks is a rational expectation for many students.

[6] This figure does not include the deaths of grandparents due to natural causes, which many respondents had experienced as well.

hood trauma and instability (Kalmakis and Chandler, 2013), were commonplace in the lives of our respondents. As twenty-one-year-old Karen told interviewers, "it's like, when you wanna move one step forward, it's like you getting knocked back five more steps, and it's driving me insane." Given the prevalence of adverse shocks among our respondents, it is no surprise that educational derailments were common as well: roughly one third of those who enrolled in postsecondary education left before finishing, many of whom were enrolled in trade schools. This is likely a significant underestimate of the final dropout rate in this sample due to right-censoring.

The need to care for family prompted Chanel, 21, to change her postsecondary pathway. After high school, Chanel enrolled in a nearby university and started working towards a bachelor's degree in psychology. After Chanel had spent two and a half years at the university, her mother suffered an injury requiring knee replacement surgery, prompting her mother to leave work to recover. Chanel explained: "She hadn't been workin' for a while so that's why, you know, she needed like some extra income." As the only child still living at home, Chanel took on the responsibility of caring for her mother. She left her four-year university and instead enrolled in a for-profit institution to focus her training in the medical field. She explains the appeal of the occupational credential, given her family's situation: "I wanted to start immediately so I could have some money to help out." Having a credential in the medical field after a few months meant that Chanel was able to both help care for her mom and enter the workforce sooner than she would have, had she finished her bachelor's degree.

Thus, despite the time and effort that Chanel had already invested in her bachelor's degree, the sudden onset of caretaking responsibilities and financial need led to a choice to pursue a quicker credential and, in turn, earlier access to jobs. This choice is not difficult to rationalize given the circumstances and constraints Chanel faced but does not reflect an information deficit or initial resource constraint.

Sierra, 20, echoed the sentiment that unpredictability and family instability might affect her postsecondary educational trajectory when she described her initial plans to attend college after graduating from high school: "I mean times get hard. One day times get, you know, they be good, everything paid on time then next time we might have a downfall." She also talked about how her family was currently experiencing a "hard time" that was disrupting her postsecondary plans. As Sierra was graduating from high school, her mother lost her job and her sister became pregnant, so, for the sake of supporting her family, Sierra chose to work in the service industry rather than attend school.

> We had like this little downfall in our family whereas I had to wait a while [to go to school], I had to wait . . . I remember my mother had got laid off and my sister was pregnant so, you know, my mother was like, you know, she gotta pay

> the bills. She was all looking forward, we were all looking forward so much.

Sierra and her family had been "looking forward" to a future in which she followed through on her original plans to go to college. Sierra still wanted to pursue some sort of college but, as of her interview, remained hesitant about the path forward: "So I mean I waited and I waited but now I feel as though I'm ready. So now I'm looking into it—like should I take a all year-round school or should I just take some classes? You know, I'm looking into it. I wanna make sure."

The onset of familial responsibilities for Sierra, then, was accompanied by a significant change in her college-going plans. Rather than pursuing the bachelor's degree that she and her family had been anticipating, she became hesitant about her path forward in a context in which a family "downfall" was always possible.

Issac's (23) story shows how different kinds of negative shocks can happen in quick succession and compound the difficulties students face in their postsecondary educational trajectories. As Isaac finished high school, he received scholarship opportunities from multiple four-year schools to play basketball, but he wanted to remain close to his family and ultimately chose to attend a community college in South Bend, Indiana (his family left Baltimore after our study began). He managed to stay on this track despite getting arrested after high school and spending six months in jail. However, just as Isaac was preparing to finish his two-year program, his sister was diagnosed with a rare disease and fell into a coma. Isaac explained how this unforeseen development in his family caused him to leave school, just on the verge of getting his degree:

> She was in a coma for about two months, and she passed away, which, I would have almost—I would have almost finished my Associate's Degree, but I came back here. So she had my nephew, she passed away, and right now it's just me. I had a scholarship, and that's when my sister was still alive, you know, everything went downhill from there.

In this recollection, Isaac revisited his choice to stay close to family instead of taking advantage of one of the basketball scholarships he was offered with some regret. As of his last interview, he had not returned to school after leaving his two-year program and had instead cycled through jobs, working in warehouses, with temp agencies, and as a hotel security agent in order to provide for his nephew. Despite the planning and significant effort that Isaac put into his postsecondary pathway, the sudden shift in his caretaking responsibilities made it increasingly unlikely that he would return to earn any postsecondary credential.

In addition to instability within one's immediate family, relationships with romantic partners also came with the possibility of unexpected caretaking responsibilities and shocks.

For example, in the case of Vicky, 20, her boyfriend had been living with her and her family for a handful of years when he was involved in a violent altercation that put him in a coma and left him with lasting cognitive impairments. As a result, Vicky became his full-time caregiver, helping him bathe and feed himself. Vicky's mother remained unemployed and struggled with alcoholism, which Vicky said caused her to feel that she was "the responsible one" in the house. The sudden shift to this role of caregiver left Vicky feeling uncertain about the future. As she described, "Some nights I go to sleep wondering like what's goin on, what's gonna happen the next day." She had been attending a nearby community college but, similarly to Chanel, left to enroll in a medical certificate program at a for-profit school. She preferred this to the community college because it was more directly focused on the medical field, in which she hoped to get a job quickly so that she could bring more money into the household. In fact, Vicky considered getting multiple certificates in different occupational areas to hedge her bets.

In at least one case, experiences with death caused adolescents to abandon postsecondary education not because they lost interest but because the impact of loss derailed their daily lives. After graduating from high school, for instance, Tiara, 19, enrolled at a community college but dropped out due to several unanticipated deaths in her family. When we last spoke with her, she had personally arranged a funeral for one of her cousins. She explained, "Just, people kept dying. Every month I done had somebody in my family that died or somebody that was real close to my family. I actually dropped my classes because I kept having a death in family like, even like, if you miss too many days you automatically fail, so instead of failing, I just withdrew from the classes."

Given the pervasiveness of parental incarceration, absence, and death in their lives (see Table 1), a number of youth in our sample experienced a sudden onset of new responsibilities as they prepared to leave high school or shortly thereafter. As scholars have previously noted, it is not uncommon for children and youth living in highly disadvantaged contexts to undergo a process of "adultification," where they prematurely take on more adult roles and responsibilities (Burton, 2007; Roy et al., 2014). Many adolescents in this study similarly found themselves unexpectedly thrust into such roles. Such experiences also left respondents with the sense that they would continue to be called upon to provide caregiving or financial resources for their family members in the future, limiting their postsecondary options and affecting their decision-making process. We examine this anticipation next.

2.2.2 Expectations: Reasoned Unease

Some of the youth interviewed associated their experiences of adverse shocks with the expectation that similar events would happen again in the future. Taniya, 18, experienced a tumultuous childhood because of her father's alcohol abuse, and she described how these experiences had made her worry about his early death: "If he started drinking again, I see him drinking I'm just gonna have to prepare [...] like one day he's just not gonna be here. I guess I just got mentally prepared for that." Taniya was not alone in expressing these feelings: all but one of the youth in our sample spoke of their own accord about anticipating future adverse shocks.

Some respondents reported that experiencing and anticipating these events made them feel out of control and uncertain about their futures. Erica, 21, described experiencing the deaths of several aunts and uncles, her father, and a classmate in a brief span of time. She explained that these losses left her feeling anxious about death, including her own: "I really don't take death well. I have anxiety [...] my grieving process is not so much 'Oh, I miss the person,' it's 'Oh, will I die from that,' or death, facing death, yeah." Matthew, 21, felt he could not anticipate when his life might end. He had been arrested multiple times starting at age 14 and lived in a neighborhood where, as he describes it, violence is a part of everyday life. When asked where he thought he would be in five years, Matthew responded, "I ain't going to call it. I can't call it. Not when anything could happen." In response to questions about his goals for the future, he replied, "I'm trying to live right now [...] I ain't thinking about the future. I might not even make it to the future, so."[7]

Death and violence, in particular, appeared frequently in respondents' discussions about their neighborhoods and families. They described violence and death as being regular occurrences and yet still unpredictable. Some of their friends or acquaintances died over minor disagreements, or even for seemingly no reason at all. As Sierra noted, "Nowadays you fight, you either getting stabbed, shot up, you losin' your life over a little argument, over a little argument." Bridget, a junior in high school, commented: "You just wake up and hear someone just got killed. Like, DANG can't people go one day without killing?" Christopher, 21, described the violence in his former public housing neighborhood and the potential for responding to such violence if it affected his family, "Every day you would hear a gunshot, or every day you would see somebody fighting, and you never know, like, when is that going to happen to you, or when, you know, it was gonna be your family member, or when you was gonna have to bear it all just go out there and just fight a war or whatever." Many respondents made comments such as "life is short" and "you can die today or tomorrow." Certainly, such concerns would loom large in youths' decision-making about the future.

These experiences and the choices that rationally follow them make the educational trajectories of so many of our respondents fraught and utterly uncertain. At 21 years old,

[7]As we show in the next section using NLSY97 data, this concern about dying in the near future is much more common among young people, especially disadvantaged youths, than might be expected.

Tony had experienced a somewhat stable childhood in comparison to other respondents. Of course, this is true only relatively—he had witnessed several incidents of violence throughout his childhood and suffered periods of anxiety and depression. He had two brothers who sold drugs and lived with him sporadically between stints in jail. However, Tony also benefitted from a solid support system and an older sister whom he considered a role model. Still, he worried about making the same mistakes as his brothers. Although Tony hoped to pursue a bachelor's degree and become a pharmacist, he was concerned about his ability to finish his current program at community college. As he put it, "I'm just tryin' to, I want everything to stay like it is now. I really don't want no changes until I get my degree."

When asked where he expected to be in five years, he responded, "I still don't think that's enough time, but I'll probably still be here, still be in school, chasing my education, yep." Thus, even Tony—enrolled in a degree program, planning to pursue a bachelor's degree, and feeling that "everything is good"—still struggled to predict how long his educational trajectory would last, or whether unanticipated circumstances might derail it.

2.2.3 Choices: Anticipation of Shocks and Decision-Making

Shock-induced derailment of the kind experienced by Tiara and other respondents illustrates how youths' educational plans were thrown off course by unexpected family needs and the loss of friends and relatives. However, some youths' experiences affected their education not just directly via interruption but also indirectly through shifts in how they thought about their future, including the plausibility of longer-term plans.

For example, Elijah's experiences with instability led him to continuously re-optimize his educational decision-making. Elijah took a year off after graduating from high school and worked with his cousin, an experience that inspired a professional interest in the auto industry. Yet, despite his aspiration to work with cars, his postsecondary strategy was to pursue multiple, distinct educational options so that if one career possibility did not work out, he would have an alternate plan: "Like I thought about givin' like, like getting in the automotive industry and get a couple big, get a couple years in here and then go back to school for the heating and ventilation, so I could have two certificates." Like Vicky, Elijah described his educational decisions as if they were backup plans. He explained: "Just do what you can and if [something bad] happen, it happen, just make sure you know what to do for it not to happen next time." Rather than pursuing a longer degree, Elijah sought multiple short-term programs to obtain credentials focused on specific skills, and thus serve as an insurance policy against any instability that he might encounter in the future. This perceived need to try to accumulate multiple credentials quickly or to develop educational or professional back-up plans may have diverted some youth like Elijah off the pathway to a four-year degree.

Few stories, though, could be as stark an example of uncertainty-induced postsecondary choice as that of Rhiannon, 22. When Rhiannon was in 11th grade, her older brother was murdered, the victim of a random shooting while out with friends. As a result, her mother became very protective of Rhiannon and her younger brother. Rhiannon told us, "I wasn't able to be in high school and do much of anything, my mom was always worried that something would happen to me." Nevertheless, as a high school senior, at one of the best high schools in Baltimore, she applied to ten colleges and was accepted to all of them, some with substantial scholarship offers. Ultimately, though, she decided she would choose the school closest to home because, as she explained, "I had never really been outside of Baltimore and I was just *afraid that something would happen while I was away*, and [this school] was close enough to home but far enough away to get away from Baltimore" (emphasis added). In this instance, the negative shock of losing her brother did not create a concrete obstacle to college-going for Rhiannon; rather, it shaped her thinking about what kind of school was reasonable, given her competing desires to leave home and to be nearby in case some kind of tragedy befell her family again.

These experiences are emblematic of a larger narrative that emerges from the 150 interviews, a narrative that we examine further and model more explicitly in the rest of this paper: disadvantaged youth anticipate that the instability to which their lives are subject may make it impossible or unreasonable to complete a bachelor's degree, leading them to rationally opt for shorter and less lucrative degree programs. The impact of adverse shocks on choices and outcomes is clear in these instances. However, a narrative interview is not necessarily emblematic of a population-level pattern. We thus turn to an analysis of a large-N data set. It is important to note, though, that it is on the foundation of the qualitative interviews that we are able to propose a novel narrative of postsecondary decision-making among disadvantaged youth.

3 Nationally Representative Data Analysis

3.1 Introduction to the NLSY97

If we believe that adverse shocks (and histories thereof) influence young people's educational decision-making in the ways suggested in Section 2, we would next want to demonstrate that this relationship is policy-relevant and economically significant. In Section 4, we accomplish this by formulating a structural model of that decision-making process. However, rather than assume that shocks and derailment are important factors in educational decisions beyond the small and relatively homogenous sample examined in the previous section, in this section we explore the idea using a nationally representative non-MTO population. The goal is to provide more generalizable evidence for the concern that motivates the structural model—namely, that anticipation of adverse-shock-related derailment influences individuals' decisions about their educational trajectories.

We examine how adverse shocks relate to expectations and educational decisions using data from the National Longitudinal Survey of Youth 1997 (NLSY97). The NLSY97 sampled 8,984 individuals born between 1980 and 1984 who lived in the U.S. at the initial survey date in 1997, surveying them at first annually and then (starting in 2011) biennially. In addition to the traditional background variables we use as controls, including race, ethnicity, family income, and mother's education, the NLSY97 survey contains a wealth of questions regarding respondents' childhood experiences of what we have termed adverse shocks, as well as their expectations about their own futures, including educational and adverse-shock-related outcomes. All data regarding childhood shock histories and expectations for the future were gathered at the initial survey in 1997, when respondents were all approximately high-school-aged. We utilize this nationally-representative data through the 2015 survey, and thus can observe individuals' responses regarding their educational and employment outcomes through at least age 30.

The results reported here qualitatively replicate in the Education Longitudinal Study[8] (ELS) and High School Longitudinal Study[9] (HSLS) given variable availability. However, the NLSY97 has the advantages of tracking longer records of adult outcomes and, importantly for our purposes, includes questions about students' expectations regarding future adverse shocks as well as a more detailed question about expectations regarding future bachelor's degree attainment. Moreover, as it is based on a household (versus individual) sampling frame, the data continue to track individuals who have left school. Thus, the NLSY97 provides more precision in corroborating the qualitative story that emerged in Section 2, as well as more flexibility in specifying a model that conforms to that story in Section 4. Accordingly, we focus our analysis on NLSY97 data . To be clear, the results of this analysis

[8] We present some analogous ELS results in Appendix A. The ELS is a nationally representative longitudinal survey of individuals who were in 10th grade and thus likely aged 15 or 16 in 2002, with the first survey wave occurring in that year and subsequent surveys administered in 2004, 2006, and 2012 (the most recent). Respondents were asked in each wave, among other things, about adverse events in their lives. They were asked about their expectations regarding their own educational attainment in the first two waves. However, the educational expectation question was cruder than that in the NLSY97 (where respondents picked a degree type they felt they were most likely to earn), expectations about other kinds of events are missing, and individuals are only observed through about age 25.

[9] We present additional results using the HSLS results in Appendix B. The HSLS is a nationally representative longitudinal survey of individuals who were in 9th grade in 2009, with the first survey wave occurring in that year and subsequent surveys administered in 2012 and 2016. Student expectations regarding financial aid and academic ability in a postsecondary context are the relevant additional variables we explore. However, like with the ELS, HLS respondents are quite young, which does not allow us to analyze noncompletion as the NLSY97 does.

are descriptive; while causal stories can be told, our goal in this section is merely to show that the model we posit in Section 4 makes sense in the world described by a nationally representative data set *and* the qualitative data.

Table 2 summarizes key variables for the full NLSY97 analytic sample, as well as by race and family income. Column 1 of Panel A shows that about 67% of the sample is white and 15% is Black. About 34% are considered low-income, with a household income below $35,000. About 44% and 9% are middle- and high-income, respectively, where incomes greater than $100,000 are considered high. Columns 2 through 6 of Panel A show that Black students and students from low-income households have significantly lower GPAs and standardized test scores and are significantly less likely to have a college-educated mother than white students and students from more advantaged households, respectively.

Panel B of Table 2 summarizes the ultimate educational attainment of individuals in our analytic sample. Overall, column 1 shows that 10% fail to complete high school, 31% earn only a high school diploma or equivalent, 30% complete some college, and 30% earn a college degree. In accordance with the group differences observed in Panel A, there are notable racial and socioeconomic status (SES) disparities in educational attainment.

Panel C of Table 2 summarizes the incidence of adverse shocks in the NLSY97 analytic sample. These shocks can broadly be classified as either "family shocks" (e.g., changes in household structure or adverse shocks to a parent) or "victimization shocks" (e.g., seeing a shooting or being the victim of a crime). The first nine shocks in panel C are "family shocks" and the final four are "victimization shocks." The rarest shocks, which include experiencing homelessness, a parent in jail, or a parent death, each occur in about 2 to 3% of the sample. The most common shocks include experiencing a non-parental family death (50%) and no father in the household (24%). Other shocks occurred for about 10% of respondents and include things such as changing schools, being bullied, crime victimization, or experiencing a parental divorce or job loss. Lastly, in accordance with the group differences observed in Panels A and B, there are notable racial and SES disparities in exposure to adverse shocks, though not all gaps occur in the same direction. For example, some shocks, like exposure to divorce and bullying, are more common among white than Black students. And some shocks, like witnessing a shooting and having no father in the household, are more than twice as likely among Black relative to white respondents. All the adverse shocks were more (or just as) common among low-income households, suggesting that an examination of the role of shocks in individuals' lives is indeed relevant beyond the sample of highly disadvantaged youth that was the focus of Section 2. This is noteworthy especially since the NLSY97 data does not follow many youth who are as economically disadvantaged as respondents observed in the qualitative data.

Lastly, Panel D of Table 2 summarizes NLSY97 respondents' beliefs about the future—their subjective probabilities of earning a bachelor's degree by the age of 30 and their subjective probabilities of experiencing a few shock events in the year following the first interview (when all respondents would be teenagers of high school age). Many of the patterns here echo those observed elsewhere in Table 2. For example, with the exception of getting drunk, Black students place significantly higher probabilities on a variety of adverse events including being the victim of a crime, being arrested, dying, and having an early pregnancy. There are also strong income gradients in the likelihood of anticipating these adverse shocks, again with the exception of the "getting drunk" question. In sum, the descriptives presented in Table 2 are consistent with the narrative that evolved in the qualitative data: Black and economically disadvantaged youth have lower educational attainment, experience more adverse shocks in childhood, and *anticipate* more frequent adverse shocks in the future.

3.2 Verifying Narratives in the Large-N NLSY97 Dataset

In this section, we estimate descriptive multivariate regressions using the NLSY97 data that correspond to the themes described in Section 2. There, our analysis focused on an economically disadvantaged sample of Black youth in Baltimore. To demonstrate the generalizability of these narratives, we use the entire NLSY97 sample, which is intended to be nationally representative. However, we corroborate that the same patterns exist, and in some cases are more pronounced, in subsamples of Black and low-income individuals in Appendix C.

We begin by showing that a history of adverse shocks is indeed related to lower educational attainment, as the stories of Sierra and Vicky in Section 2.2.1 suggested. Next, we demonstrate that students' beliefs about the future (expectations) are correlated with personal histories of adverse shocks just as they were for Taniya, Erica, and Matthew in Section 2.2.2. Finally, we show that lower expectations are associated with lower attainment, and we explore an explanation for the connections between shocks, expectations, and outcomes: students' decisions about where and how to attend postsecondary school, like the choice Rhiannon made to stay near her family in Section 2.2.3. We show that individuals who are more pessimistic about their probability of completing a bachelor's degree, or about the likelihood of experiencing adverse events in their own futures, are less likely to enroll in four-year bachelor's degree programs.[10]

3.2.1 Adverse Shocks Predict Educational Attainment

Do students actually have to worry about adverse shock events derailing their educational paths as suggested by our interview respondents' stories? This is difficult to directly verify

[10]Unless otherwise indicated, regression tables report robust Huber-White standard errors.

in the NLSY97 data, but the first two columns of Table 3 suggest it is the case. In column 1, we regress an indicator for dropping out of college, conditional on enrollment, on demographic and background variables as well as generic indicators for having experienced a "family shock" (such as parental incarceration, unemployment, or death) or a "victimization shock" (like seeing a shooting or being the victim of a crime). Experiencing either type of shock has a positive, statistically significant effect on the likelihood of dropping out once enrolled. In column 2, we disaggregate the shock indicators and control for a vector of indicators for experiencing each specific shock recorded in the NLSY97. These coefficients are jointly statistically significant, and three are individually significant and of the expected sign: changing schools, seeing a shooting, and feeling unsafe all significantly predict dropping out of college.

These regressions do not identify causal effects, of course, as shocks are endogenous; however, precisely identifying causal effects is not the objective of this analysis. Rather, we document that the patterns observed in the qualitative data also occur in a nationally representative quantitative dataset. More generally, the regression in column 1 and those like it make the empirical connection between shocks and subsequent educational outcomes. Still, the correlations documented in columns 1 and 2 of Table 3 are consistent with credibly causal estimates of the effects of similar experiences on various mid- and long-term outcomes (Ang, 2021; Dobbie et al., 2018; Sharkey, 2010; Schwartz et al., 2017).[11,12]

A caveat of the NLSY97 analysis is that it only contains information about respondents' recollections of adverse shocks experienced in childhood (i.e., as of the first interview), which poses concerns about recall and social desirability bias, as well as the practical issue of whether and how concurrent shocks affect schooling. In Appendix A, we augment the NLSY97 results with analyses of ELS data showing that adverse shocks experienced *during* postsecondary school are associated with derailed educational trajectories just like those of Chanel, Vicky, Isaac, and Tiara. If true, this would validate concerns individuals had about the probability of similar outcomes in their own futures, which we explore next.

[11] This statistically significant positive relationship between childhood shocks and dropout remains in the NLSY97 even after controlling for the high school performance variables (GPA and test scores).

[12] In an attempt to account for potential correlation between our shock variables and omitted variables (Altonji et al., 2005), we collapsed the variables of interest into a single indicator for having experienced at least two childhood shocks and, for the estimated relationship with dropouts and calculated Oster (2017) bounds. With race, household income, and mother's education as controls, an Oster-method delta value of approximately 0.18 would drive the estimated effect to zero. However, we suspect that the true unobserved correlation with shocks would not be even this large, as the controls we include are rich and likely capture most of the relationship between shocks and the uncontrolled error term. Moreover, we view adverse shocks themselves as a significant part of the "unobserved" variation that has generated concern in estimating models of these relationships in the past. We performed similar analyses with the other two outcomes in Table 3 (expectations regarding attainment and future shocks) and found similar results.

3.2.2 Adverse Shocks Shape Beliefs and Expectations

Columns 3 through 6 of Table 3 report regression estimates for models with the same right hand side specification as columns 1 and 2, which were discussed in section 3.2.1. Here, the outcomes are students' self-reported subjective probabilities of future events: earning a college degree (columns 3 and 4) and experiencing an adverse shock (columns 5 and 6).[13] Conditional on the same basic student and household characteristics, columns 3 and 5 show that experiencing any type of childhood shock significantly reduces respondents' educational expectations and increases their expectation of experiencing a future adverse shock. In columns 4 and 6, where the childhood shock indicators are broken out into a set of shock type indicators, we see that the same incidents that derail schooling are also the most predictive of expecting poor postsecondary educational outcomes and additional adverse shocks in the future, namely changing schools, parental incarceration, witnessing a shooting, and feeling unsafe.

We thus have evidence from nationally-representative data that beliefs about the future are informed by adverse shocks experienced in childhood, corroborating the thought processes described by several interviewees. In Section 3.2.3, we explore the importance of these beliefs.

3.2.3 Expectations and Beliefs Predict Educational Attainment

Jacob and Wilder (2010) show that ELS respondents who expect to complete college are more likely to enroll in postsecondary education. Our interest lies in how expectations about educational outcomes and future adverse shocks affect *where*, and in what type of program, students enroll, as well as whether they ultimately complete a degree. In Table 4 we regress indicators for bachelor's degree attainment conditional on enrolling in some kind of postsecondary school on sets of background, experienced shock, college expectation, and anticipated shock variables.

Column 1 only includes the background controls and verifies the race, gender, and SES disparities in college completion rates that are well documented elsewhere (Baker et al., 2018; Dahill-Brown et al., 2016; Ma et al., 2016; Bailey and Dynarski, 2011). Column 2 adds to this the set of experienced adverse shock indicators studied in sections 3.2.1 and 3.2.2, again showing that these shocks are associated with failing to earn a degree even conditional on enrolling. Columns 3 and 4 instead add to the baseline control specification of column 1 indicators for expectations regarding college completion and future adverse shocks, respectively. In column 3, there is a clear and statistically significant positive gradient between college

[13] Specifically, the shock outcome is the simple average across the five future adverse shocks summarized in Table 2. Importantly, similar results are obtained from estimating five separate regressions for each of the five shock-specific subjective probabilities.

expectations and college completion. Similarly, column 4 shows that anticipating each of the five adverse shocks has negative associations with college completion, four of which are statistically significant.

Finally, in column 5 of Table 4 we include the shock history, college expectation, and anticipated shock variables in the same model. The estimated coefficients on the prior shock and college expectation variables are qualitatively unchanged. Together with the qualitative evidence described in section 2.2.1 and the credibly identified studies described in section 3.2.1, this result suggests that there is a causal relationship between college expectations and college completion. However, some of the anticipated shock variables lose their statistical significance when we also control for college expectations. The striking exception to this is the subjective probability of death, which continues to reduce the likelihood of completing a degree by about 11 percentage points. This suggests two things. First, expectations about future shocks are associated with expectations about educational success. Second, anticipating extremely adverse shocks (e.g., death) affects educational success.

We have thus provided some evidence that adverse shocks are correlated with expectations regarding future instability and educational attainment, and that, in turn, these expectations are correlated with educational outcomes, potentially mediating the relationship between past shocks and future attainment. This evidence represents a new way of thinking about youths' educational decision-making—an addition to the information set that we consider relevant for individuals like Sierra, Chanel, and Rhiannon.

A specific mechanism through which expectations may translate into educational outcomes is the choice of what kind of postsecondary institution to attend. One way in which expectations regarding attainment seemed to manifest themselves in our interview participants' stories is through their choice of educational institution after high school, as with Elijah and Rhiannon. We probe this hypothesis in the NLSY97 data by estimating models similar to those in Table 4, but replacing the graduation outcome with an indicator for initially enrolling in a two-year program. The thought processes identified in section 2.2.3 suggest that students who were exposed to past adverse shocks, expect subsequent adverse shocks, and do not expect to compete a four year degree are more likely to enroll in two-year and shorter post-secondary programs for strategic reasons. The results are presented in Table 5. These estimates are consistent with the results described thus far. Specifically, prior shocks such as feeling unsafe, changing schools, and being bullied predict choosing a two-year postsecondary program. So too does expecting future adverse shocks (e.g., death). Finally, there is a clear negative gradient in the relation between expecting to complete a four-year degree and enrolling in a two-year institution. Institution type selection is therefore a candidate mechanism through which attainment and adverse shock expectations affect educational outcomes. This response to anticipated shocks may explain why so many of our interview respondents ended up at short-term credentialing institutions—their choice of postsecondary institution was in part an expression of their beliefs about, or fears for, the future.

Before moving on to the structural analysis, we should make a few remarks about the results in this section. We have been careful to acknowledge that these regressions likely do not precisely identify causal effects. At a basic level, this is because a causal interpretation would require a strong selection-on-observables assumption that we are uncomfortable making and there is no readily apparent source of exogenous variation in student beliefs.

A secondary issue is that the questions in the NLSY97, ELS, and HSLS surveys regarding educational expectations are rather vague compared to the conceptual objects in which we are interested. For instance, NLSY97 respondents are asked to assign a probability to their earning a bachelor's degree in the future. However, the probability they assign is really an amalgam of other probabilities—how likely they are to apply, to get financial aid, to enroll, to experience a shock, to be derailed because of that shock, to be up to the academic challenge, to transfer, and so on. We are interested in individuals' subjective probabilities of experiencing shocks and related derailment, but those get lost in the *concatenation* of events that culminate in a degree, which is the only event that is actually assigned a probability in the data. The NLSY97 expectations data are thus suitable for the provision of *prima facie* evidence that our story is consistent with the data, but less so for showing causality or for precise estimation of our relationships of interest in a reduced-form framework.

4 Structurally Modeling Post-Secondary Educational Decision-Making with Non-completion Risk

To this point, we have used qualitative interviews and a nationally representative data set to provide evidence that adverse shock events are common in the lives of disadvantaged youth. Moreover, we have demonstrated that these shocks are associated with more frequent derailment of educational trajectories, students dropping out or transferring into shorter and less lucrative programs, and more generally, the ways in which students think about the future, financial crisis, family tragedy, and death. If we take our evidence of such a story seriously, we might also take seriously the possibility that reverberations of these shocks influence outcomes such as educational trajectories, which in turn may have implications for policies designed to increase educational retention or attainment.

In this section, we assess this possibility with a structural model of dynamic discrete choices. Each year, agents in the model can choose to invest in their post-secondary education attending two-year- or four-year-degree granting programs or to not attend school. A crucial feature of the model is that the agent may choose to enroll in a year of education but not complete it. Resulting noncompletion is operationalized in the model as a probability faced by each agent that, even if they pay the upfront cost of enrolling in school, their accrued educational attainment does not increase. The increment of educational attainment is thus stochastic, and enrolling is a risky investment. The probability of noncompletion is computed using the NLSY97 and varies by demographic characteristics that capture different sources of disadvantage. We show that model estimates—and thus policy conclusions—hinge on the noncompletion rates we incorporate into the model. While the probabilities we estimate using the NLSY97 are likely an improvement upon simply assuming away noncompletion risk, direct measures of noncompletion probabilities that agents hold when making education decisions would be better still.

4.1 Model Specification

In each period t, $t = 1, ..., T-1$ (corresponding to ages 18 to 29), agents indexed by i maximize their expected lifetime utility by choosing to work and earn income or to enroll in a four-year (bachelor's) degree program or a two-year (associate's) degree program. Period T (corresponding to age 30) is a terminal period in which agents receive as a lump sum the present-discounted value of the utility that would be generated by an infinitely-lived agent consuming out of income corresponding to their highest degree attained.

4.1.1 State Variables

The state variables that play a role in the decision-making process include demographic and background variables as well as educational histories. The three key background variables we use capture three potential sources of disadvantage that could affect noncompletion and thus educational trajectories: indicators for underrepresented minority ("URM") status, a low-income family of origin ("Low-income"), and a history of adverse shocks ("Shocks"; at least two of the shocks listed in Table 2). These three binary variables are summarized below as X_i and we use possible combinations of their values to generate eight distinct groups of agents. Age (denoted age_{it}) is also a relevant state variable, since it dictates the time remaining in the model for each agent to complete their education.

The variable y_{it}^s represents the total years *completed* by individual i at time t and in each enrollment type $s \in \{1, 2\}$, where superscript $s = 1$ represents two-year programs and $s = 2$ four-year programs. $r_{i,t-1}^s$ indicates enrollment and completion of a year from school type $s \in \{1, 2\}$ in the prior period. D_{it}^s indicates possessing a degree from a school of type $s \in \{1, 2\}$. Finally, we assume that $D_{it} \in \{0, 1, 2\}$ (absent the superscript) indicates the highest degree attained prior to period t. We collect all these state variables, including X_i, in the vector Z_{it}.

4.1.2 Choices and Flow Utility

Agents derive utility from earned income and, if enrolled in school, the utility cost of one year in education, with the choice for agent i at time t denoted d_{it}. Options are work ($d_{it} = 0$), which generates income, or educational enrollment ($d_{it} = 1$ for a two-year program and $d_{it} = 2$ for a four-year program).[14] The income generated by work depends on degree attainment status not only after the model ends at age 30 but in any year before that when individuals decide to work—if an agent has already earned a degree, they earn a larger income. The flow utility function of choice $d \in \{0, 1, 2\}$[15] is specified as:

$$\mu_d(Z_{it}) + \varepsilon_{itd} = \frac{(e_{D_{it}})^{1-\gamma}}{1-\gamma} + u_d(X_i) + \varepsilon_{itd}, \tag{1}$$

where $e_{D_{it}}$ is income (measured in ten-thousands of 2013 dollars) generated by highest degree D_{it}, and $u_d(X_i)$ is the utility of the schooling choice (which could be positive or negative), where we normalize the flow utility of the non-school option to zero ($u_0(X_i) = 0$). The ε_{itd} is a mean-zero idiosyncratic preference shock distributed Type 1 Extreme Value. Individuals derive utility from income e through a constant relative risk aversion (CRRA) utility function with parameter γ. The estimated parameters of interest are the $u_d(X_i)$, which capture enrollment utility relative to the non-school option.

4.1.3 Noncompletion Probabilities

A key feature of our model is that while educational *enrollment* is a choice, educational *completion* is the result of a random draw; an individual's probability of noncompletion in each period of enrollment is denoted $\alpha^s(X_i)$, again for each enrollment type $s \in \{1, 2\}$, where superscript $s = 1$ represents two-year programs and $s = 2$ four-year programs. We describe how we calculate $\alpha^s(X_i)$ directly from the data in Section 4.2.1. Agents rationally forecast their probability of noncompletion based on the rate of its occurrence in their demographic group, i.e., they know the probability $\alpha^s(X_i)$ of noncompletion but must make enrollment decisions before a completion outcome is realized. If an individual enrolls but does not complete the educational year, they incur the flow utility cost of a year in school $u_d(X_i)$, but their total years of education does not increase in the following period. When deciding whether and in what type of program to enroll, agents in the model consider flow utilities and

[14] Our focus on two-year- versus four-year degrees is due to data limitations. In the NLSY97, students are asked about enrollment in these two types of institutions.

[15] For clarification, $s \in \{1, 2\}$ can take two values, one for each of the two educational enrollment options, while $d \in \{0, 1, 2\}$ can take three values, corresponding to the two educational options along with the third option $d_{it} = 0$ of not choosing school.

the enhancement to future income that education can yield but also the risk of derailment and the opportunity cost of lost earned income in an educational pursuit that does not result in such a future income enhancement.[16]

4.1.4 State Transition Probabilities

At $t = 1$, all values in Z_{it} are equal to zero except X_i and age_{it}. All variables contained in X_i are constants, and age evolves deterministically ($age_{it} = age_{i,t-1} + 1$). Let $r^s_{i,t-1} \in \{0, 1\}$ indicate enrollment and completion for educational choices $s \in \{1, 2\}$, i.e., $r^1_{i,t-1} = 1$ if the student enrolled in and completed a year at a two-year institution and is equal to zero if the student did not enroll in a two-year institution or did enroll but did not complete the year. Completed years evolve according to the following formula for all $s \in \{1, 2\}$:

$$y^s_{it} = y^s_{i,t-1} + r^s_{i,t-1}. \tag{2}$$

For example, if an agent had completed two years in a bachelor's program as of time $t - 1$, chose $d_{it} = 2$ at that time, and received a favorable completion draw, their number of completed bachelor's program years would increment up to three at the start of period t. With an unfavorable draw, $r^2_{i,t-1} = 0$, the recorded number of completed educational years for that agent would remain two.

Students who enrolled in a school of type $s \in \{1, 2\}$ at time $t - 1$ will have a degree of that type as of time t if they have completed the requisite number of years at that type of school; individuals who were not enrolled at time $t-1$ retain their degree attainment status from that period to time t. This progression is captured by state variables D^s_{it}, so that:

$$D^1_{it} = D^1_{i,t-1} + \left(1 - D^1_{i,t-1}\right)\left(\mathbb{1}\left[y^1_{i,t-1} = 1\right]\right)\left(\mathbb{1}\left[r^1_{i,t-1} = 1\right]\right) \tag{3}$$
$$D^2_{it} = D^2_{i,t-1} + \left(1 - D^2_{i,t-1}\right)\left(\mathbb{1}\left[y^2_{i,t-1} = 3\right]\right)\left(\mathbb{1}\left[r^2_{i,t-1} = 1\right]\right). \tag{4}$$

That is, if an agent lacks a degree of the relevant type, has one completed year in an associate's program or three in a bachelor's program, and successfully completes another in the relevant program type, then they are recorded as having earned the degree for that program type. Each degree attainment status is an absorbing state, i.e., once a student possesses a degree, they cannot lose it. Annual income is affected by an agent's highest attained degree status, so earning a bachelor's degree while already possessing an associate's

[16]We do not model a direct cost to re-enrolling after noncompletion, but as time T approaches, the fact that individuals are "running out of time" to complete a degree will mechanically reduce the option value of enrollment.

affects earnings, but not the reverse.[17]

4.1.5 The Dynamic Programming Problem

Agents make enrollment decisions to maximize their expected lifetime utility, which means they take expectations over future realizations of ε_{itd} as well as the evolution of their experience and degree-earning state variables, in part dictated by draws against $\alpha^s(X_i)$ if they ever decide to enroll in school. A solution to an agent's problem is a set of policy functions that map each period's potential sets of state variables to choices. Under standard assumptions, including stationarity and the distribution of the flow utility error term ε_{itd}, we can rewrite this problem using a Bellman equation. Using derivations discussed in Rust (1987), we can express the net-of-error value of expected lifetime utility of choice d given state variables Z_{it}, denoted $\bar{v}_d$ as follows:

$$\begin{aligned}\bar{v}_d\left(Z_{it}\right) = \mu_d(Z_{it}) &+ \mathbb{1}\left[d=0\right]\beta E\left[V(Z_{i,t+1}|Z_{it})\right] \\ &+ \mathbb{1}\left[d=s\right]\left\{\alpha^s(X_i)\beta E\left[V(Z_{i,t+1}|Z_{it}, r^s_{it}=0)\right]\right. \\ &\qquad \left. +(1-\alpha^s(X_i))\beta E\left[V(Z_{i,t+1}|Z_{it}, r^s_{it}=1)\right]\right\}\end{aligned} \tag{5}$$

for $s \in \{1,2\}$, β is the annual discount rate, $\mathbb{1}[\cdot]$ is an indicator function, and V is the value function that captures continuation payoffs, including future realizations of $\alpha^s(X_i)$ and ε_{itd}. We solve the dynamic programming problem via backward induction, starting with optimal enrollment choices in the last period in which decisions are made ($T-1=12$, or age 29 based on the potential to earn a new degree and enhance the future earnings stream, and working backwards to time $t=1$.[18]

4.2 Empirical Implementation, Estimation, and Identification

4.2.1 Empirical Implementation

We continue to use the NLSY97 data for this structural estimation because they provide us with lengthy individual histories of educational completion and post-educational earnings. The sample we use is limited to individuals with information on the state variables described above and observed education choices between ages 18 to 29, leaving 6,904 individuals.[19] A

[17] While earning an associate's degree and then transferring to a bachelor's program with a year or two worth of existing credit is possible in principle, actually earning a bachelor's degree on this path is rather rare (see discussion in Odle and Russell (2023)), so we do not incorporate this in the model.

[18] At T, agents receive $\frac{1}{1-\beta}$ times the utility of the average annual income earned by individuals with their particular degree attainment status.

[19] This is smaller than the full sample used in Section 3, but larger than estimation samples that require other covariates and outcome variables (Tables 3-5), particularly because the state variables used to construct

summary of this sample is provided in Table 6 for the full sample and for each of the possible combinations defined by the three binary indicators: URM, Low-income and Shocks. Panel A defines each group (e.g., Group 1 is not URM, not Low-income, and did not experience shocks). In Panel B, we show graduation rates conditional on enrollment for each group (which are used to construct noncompletion rates). For example, Group 8 individuals (URM, Low-income and experienced shocks) complete an associate's degree within two years of starting it with 10% probability and within four years with a 22% probability. If they enroll in a bachelor's degree program, they complete the degree within six years with a 32% probability. Group 1 individuals, who are not URM or Low-income and did not experience shocks, finish a bachelor's degree within 6 years with 61% probability conditional on enrollment.

We assume that all individuals who work in a given decision period, as well as all individuals throughout their infinite lives after time T, earn an approximation of the average income earned in the NLSY97 data by workers in their degree-attainment category in 2013,[20] rounded to the nearest thousand.[21] In 2013 dollars, this happens to be \$48,000 per year for bachelor's degree holders, \$31,000 per year for associate's degree holders, and \$24,000 per year for those without a postsecondary degree of either type (including high school graduates who never enroll in postsecondary school and those who enroll but drop out before earning any degree).[22] For each agent i and in each period t, consumption equals income $e_{d,D_{it}}$, determined by d_{it} and D_{it}^d. This simplification eases estimation and elides concerns about income growth or interruptions in work after age 30 without obscuring the main point of our results.

We assign rates of noncompletion ($\alpha^1(X_i)$ and $\alpha^2(X_i)$) in each type of postsecondary enrollment (associate's or bachelor's programs, respectively) for each of the eight demographic groups on which we estimate the model, i.e., there are 16 different non-completion rates used in the model. Obtaining these values is indirect because there are no explicit variables recording noncompletion. Instead, we assume fixed annual rates of noncompletion $\alpha^s(X_i)$,

the structural estimation sample are also present in the models estimated in Section 3.

[20] We measure in 2013 because NLSY97 respondents are in their late 20's and early 30's at this time and have mostly stopped attending school, and thus reported incomes have begun to stabilize for even the most educated.

[21] Allowing income to vary for each combination of years of schooling is a plausible extension to the model. We omit this variation since it is unclear if students with a single year of school and no two- or four-year degree, for example, have a certificate or some kind of coursework. We have experimented with various potential specifications that incorporate returns to a single year of post-secondary education that does not result in a degree and generally find that doing so has a relatively impact on our main results.

[22] The median earned income amount reported by individuals enrolled in postsecondary school is about \$4,000. Certainly students are consuming in some form while in school, so we use this dollar amount as their base consumption with all additional utility coming from the flow utility of enrollment itself and the idiosyncratic error term.

which we must infer from data on the number of times students enrolled and whether or not they completed a degree. For example, students who enroll in an associate's degree program may report an associate's degree after exactly three years rather than two. This would suggest that at least one year did not count fully (i.e., was disrupted by a shock), which we interpret as a single instance of noncompletion. The $\alpha^s(X_i)$ must account for these instances in addition to dropouts, so we need to develop a method for calculating their annual probability.

$\alpha^s(X_i)$ are not measured in the NLSY97 and must be calculated. Our preferred approach uses on-time graduation rate for each group in each program type. On-time graduation reflects an educational history devoid of *either* a continuously enrolled noncompletion or a dropout. Thus, if p is the probability that an individual experiences either of these two types of educational derailment in a given year, m is the number of years an on-time student would need to graduate, and π is the on-time graduation rate in the relevant group and program type,

$$\pi = (1 - p)^m. \tag{6}$$

For instance, the on-time bachelor's degree graduation rate in Group 1 is 35 percent. Solving equation 6 with $\pi = .35$ and $m = 4$, we find that $p = 0.23$, which is the noncompletion rate we use for Group 1 students in four-year programs in the structural model. We have experimented with alternative methods to calculate the $\alpha^s(X_i)$ that use additional information on post-educational trajectories, e.g., that take explicit account of all possible permutations of years completed versus enrolled that support the data.[23] We discuss these approaches in Appendix D, but find that they yield $\alpha^s(X_i)$ that are virtually identical to the values we calculate with our preferred method.

We report the $\alpha^s(X_i)$ we construct in Table 6. For instance, our calculations suggest that Group 1 individuals experience one of these kinds of educational setbacks in around 54 percent of years enrolled in associate's programs and in 23 percent of years enrolled in bachelor's programs. Rates are higher for all other groups, reflecting the disadvantaged status of agents who are URM, come from a low-income household, or a history of prior adverse shocks.[24]

[23] For example, if we observe that an individual enrolled six different years in a four-year granting institution and the obtained a four-year degree, there are many possible sequences of noncompletion, which a more elaborate procedure could explicitly account for.

[24] It is difficult to calculate similar values in the ELS or HSLS for comparison since those surveys were not performed every year like the NLSY97. However, it is worth noting that 36 percent of ELS respondents who enroll in some postsecondary school never earn a degree of any kind and a further 11 percent earn only a certificate of some sort, to say nothing of those who may take extra years to finish. The National Center for Education Statistics (2022) find that, in keeping with data from the recent past, around two-thirds of four-year-program enrollees in the U.S. earn a degree within six years. DeLuca et al. (2016) compiled data

4.2.2 Identification and Estimation of Structural Utility Parameters

Identification arguments for the type of dynamic discrete choice model we have specified here are standard and discussed in Magnac and Thesmar (2002). If we specify how agents form expectations over transitions to future states and fix the discount factor β, we can identify the utility parameters $u_d(X_i)$, subject to a normalization. We first impose the assumption that agents in the model hold rational expectations calculated from the data as discussed in the previous section; in fact, this is one of our main points: young people making educational decisions act on rational beliefs about their probability of completing an educational program, which is a function of their demographic characteristics and earlier life circumstances. As we show, moreover, different $\alpha^s(X_i)$ would lead to different estimates of the utility parameters.

We thus set β to 0.95 and normalize the utility cost of choosing to work to zero. This means that the utility costs of education are properly interpreted as relative to the cost of not going to school, i.e., working. As noted, we also assume that the idiosyncratic preference shocks ε_{itd} are drawn from a Type 1 Extreme Value distribution. Finally, we fix the CRRA parameter $\gamma = 0.8$, which lies in a range established by prior estimates in the literature (see, for instance, Hurd (1989) or Blau and Gilleskie (2008)).[25] Given these assumptions, agents' choices in the data identify the $u_d(X_i)$.[26]

With the model and noncompletion rates specified, we estimate the $u_d(X_i)$ separately for each of the eight demographic groups via maximum likelihood in a nested fixed-point algorithm (Rust, 1987), using the NLSY97 data. Given candidate parameters, values of the net-of-error choice specific value functions $\bar{v}_d(Z_{it})$ are calculated by backward induction

for colleges in the Baltimore area that show overall graduation rates as low as 14 percent, with many around one-third, in bachelor's degree-granting institutions. All these numbers are generally in keeping with the numerical values we employ here.

[25]While other values of γ affect the absolute magnitudes of our estimates of the $u_d(X_i)$, they do not affect the qualitative patterns we show. In principle, our setup would allow us to estimate γ, but doing so would likely require more variation in income and thus consumption arising from agents' choices, which would in turn require a more elaborate model.

[26]It is important to note that the identification arguments we rely on focus on the existence of a unique set of parameters that best fit the data—in this case, that maximize the log likelihood function. There remains a possibility of bias in estimates. In our case, a concern might be, for example, that individuals who faced adverse shocks systematically over-estimate the probability of completion relative to what we observe in the NLSY97 data (and use to model their expectations). If so, students go to school not because it is a low-utility-cost option, but because they believe they are likely to finish and thus over-estimate the payoff. This would lead us to over-estimate the utility of school (or under-estimate the utility cost of school). Our data work, however, has shown that stated expectations are predictive of choices and outcomes. Moreover, we argue that using estimates of completion rates from the NLSY97 data, despite the types of concern we raise here, leads to better estimates than assuming noncompletion risk is zero, which is not empirically supported. Below, we illustrate the impact on parameter estimates and policy conclusions if we ignore noncompletion risk. Broadly, this type of concern underscores why direct measurement of beliefs about noncompletion could improve estimates.

from time T (age 30) based on the relevant group's value of the noncompletion probabilities $\alpha^s(X_i)$. Given distributional assumptions on ε_{itd}, the $\bar{v}_d(Z_{it})$ are used to calculate the implied probability that each individual would make the work or enrollment choice they did in each year they appear in the NLSY97 data, and this probability becomes their contribution to the overall likelihood. The natural logs of these probabilities are summed, and the algorithm finds the parameters that maximize this sum.[27]

4.3 Utility Parameter Estimates and Interpretation

Utility parameter values for each group on whom the model is estimated $u_d(X_i)$ are reported in Table 7.[28] The key result to note comes from the comparison of the estimated valuation students apply to schooling in two divergent cases, one in which we model them as rationally worrying about the possibility of noncompletion and another in which we assume they do not account for it. Individuals are estimated to value school much less if we do not account for their rational expectations about noncompletion and derailment.

A translation of the utility value of school into dollars is reported for both models in Table D13, in Appendix D.[29] The results make immediately clear that when we do not account for individuals' concerns about noncompletion, we overestimate their distaste for school: with $\alpha^s(X_i)$ in the model, two-year programs generate negligible utility penalties, and the disutility of four-year enrollment is valued in the hundreds of dollars (e.g., \$507 per year for Group 1, non-minority high-income individuals with little or no shock history); when we assume $\alpha^s(X_i)$ away, we estimate that individuals' disutility from two-year programs is in the thousands of dollars per year (e.g., \$1,040 for Group 1) and that from four-year programs is several times larger (e.g., \$3,381 for Group 1).[30] By ignoring the anticipated probability of noncompletion, we estimate disutility from enrollment in a bachelor's program by at least an order of magnitude.

We can demonstrate the basic role of $\alpha^s(X_i)$ in the model by asking a straightforward question: given students' estimated *actual* valuation of school under rational expectations, what would be the effect of reducing their anticipated probability of derailment? Using the parameters estimated in our main specification, we calculate enrollment probabilities at

[27]See Appendix D for an expression of the likelihood function, as well as details regarding the computation of standard errors.

[28]The model fits group-specific choices virtually perfectly largely because there are separate utility parameters estimated for each group and educational option.

[29]This appendix also reports the numerical values that generate Figures 1 and 2.

[30]In the no-α model, estimates of schooling disutility are hundreds or thousands of dollars larger for all other groups. Keane and Wolpin (1997) estimate a "cost" of college attendance, including consumption value and tuition, of around \$3,000 for young white men in the 1979 cohort of the NLSY while not modeling rational noncompletion risk assessment, so our no-α estimates are similar to those from other models that ignore such risk.

age 18 under reduced noncompletion rates for all groups. Results are reported in Table 8. If noncompletion rates are reduced by one quarter of their existing level (and individuals are allowed to see and anticipate this change), enrollment in bachelor's degree programs increases by 3 percentage points (about 11 percent of the baseline rate) for Group 1, while enrollment in associate's programs actually declines by about 1 percentage point for the same group. Across the board, two-year enrollment remains mostly stagnant for this noncompletion rate decrease while four-year enrollment increases to varying degrees. Examining results for Group 8, minority individuals from low-income backgrounds with a history of adverse shocks in childhood, shows that for a one-quarter reduction in noncompletion rates, predicted bachelor's program enrollment rates nearly double (from 7.7 percent to 14 percent). All these effects are stronger when noncompletion is further reduced to half its true frequency, and the bachelor's enrollment gap between high-SES non-minority individuals with no adverse shock history (Group 1), and low-SES minority individuals with extensive adverse shock histories (Group 8) shrinks by around 11 percentage points, over half the original gap.

These numbers are dramatic, but they suggest the potentially immense importance of the risk of derailment in individuals' decisions about their educations. Programs aimed specifically at student support and retention (Rosenbaum et al., 2006; Evans et al., 2020) may affect student decision-making on this margin, increasing educational attainment and reducing inequality. However, it may be unrealistic to assert that noncompletion risk could be halved as supposed in this analysis. What does our model have to say about the potential effect of a more straightforward policy approach: subsidies paid to enrolled students? Does the presence of $\alpha^s(X_i)$ in the model affect our predictions?

4.4 Counterfactual Exercise: Predicting Subsidy Effects

Here, we calculate enrollment probabilities at age 18 for individuals from each group, first under parameters estimated using our main specification, then under parameters from our no-α specification. We compare the effects across the two cases of adding 0.1 to the consumption value e if an individual is enrolled in any educational program in a given period, effectively a subsidy to students of $1,000 per year enrolled. Table D14 in Appendix D presents the effect of such a subsidy. Enrollment in two-year programs does not change significantly in either case in response to the financial incentive, and in fact declines slightly for most groups. This drop is more than made up for by increases in four-year enrollment in both models, though. The subsidy is predicted to increase bachelor's degree program enrollment rates at age 18 by over 2 percentage points for Group 1 when we acknowledge that students rationally anticipate the probability of noncompletion and dropping out. However, this prediction changes to a 1.2 percentage point increase in enrollment if we use utility estimates generated by a model that excludes expectations about noncompletion.[31] The predicted subsidy effect is similarly meaningfully larger in the α-inclusive model for all groups.

Our estimated parameters do not produce precisely identical predictions across the two α-cases even for the zero-subsidy scenario—enrollment rates with no subsidies are marginally higher across the board for the rational-α case—but our focus is on the dramatic *growth* of this difference as the subsidy value increases. We can see this clearly in Figure 1, in which we depict the change in enrollment rates within demographic groups that results from increasingly large subsidies to students. When individuals consider noncompletion risk (and their utility parameters are estimated under this consideration), a subsidy alleviates the financial concern associated with that risk; associate's degree program enrollment is relatively flat, and bachelor's degree program enrollments skyrocket for each group. The effect is larger for disadvantaged individuals, as is the difference between the effect estimated by the rational model and the effect estimated by the naive model. We can see this in Figure 2, which shows that while the subsidy's effect is predicted to be larger in the rational model for all groups, its effect is in particular larger for individuals who are more disadvantaged and more likely to be derailed. The gap between the most well-off individuals (Group 1) and the least well-off (Group 8) in bachelor's enrollment rates closes as subsidies grow, in an absolute sense (from 20 percentage points to 17 percentage points) and especially in a proportional sense, if we assume rational risk assessment; however, if we ignore $\alpha^s(X_i)$ in the model, we predict that this gap *widens* dramatically (to 30 percentage points).

When we assume individuals ignore noncompletion risk and estimate their utility parameters under that assumption, subsidization does much less to mitigate the disutility that enrollment is estimated to generate, particularly for groups with large true probabilities of noncompletion (Group 8, specifically). There are smaller increases in bachelor's enrollment, and associate's enrollment falls somewhat dramatically in well-off groups, indicating that much of the change for them may be coming from those who change enrollments between program types. As noted, bachelor's enrollment gaps between demographic groups are also widened in this naive version of the model.

It should also be noted that the implications of this counterfactual exercise are all derived while holding derailment risk constant—increased subsidies are not permitted to affect $\alpha^s(X_i)$, only the utility value derived from enrollment. However, we might suspect that subsidy dollars could be used to avert the kinds of adverse shock events we have argued lead to such derailment, lowering that risk. For instance, a subsidy of sufficient size could

[31] Surveying prior work including that of Abraham and Clark (2006) and Kane (2007), Deming and Dynarski (2009) find that the best estimates predict that a \$1,000 decrease in tuition costs increase college enrollment by about 4 percentage points, so again our exercises yield reasonable effect sizes, and may in fact be a bit conservative in terms of overall effect magnitude.

substitute for lost family income or rent payments in the case of a "downfall" like those Sierra described in her interview. This might mean that a student whose family endures such an event can afford to keep taking classes, rather than transferring to a less lucrative or more local program or dropping out of school entirely. As we demonstrated above, if decision-makers are accurately assessing derailment risk, this could compound the positive enrollment effect that the model predicts subsidies would generate.

In summary, our results suggest that, by ignoring individuals' rational consideration of noncompletion and derailment risk in modeling their educational decision-making process, we lay the foundation for erroneous evaluation of the impacts of counterfactual policies, and therefore may discount the value of certain approaches to the related problems of enrollment and completion.

5 Discussion

This paper examines the idea that anticipated future adverse events affect students' choices of postsecondary pathways. This idea emerges from the analysis of qualitative data based on interviews with disadvantaged Black youth in Baltimore describing how they make choices about postsecondary education: adverse shocks have been common occurrences for them that have affected how they conceive of the future—often making them wonder if they would even *have* a future—and thus all sorts of decision-making processes, including educational ones. This emergent story suggests that disadvantaged young people might make choices about their education that appear from the outside to be suboptimal or due to resource deficits, but are in some cases actually a rational response to an unstable context. If this were the case, it would be a consideration that is missing from economic models of these decision-making processes. And, to the degree possible, we corroborate the generalizability of this narrative in this paper using nationally representative survey data from the NLSY97.

Given this evidence, we formalize the narrative as a dynamic choice model of educational decisions wherein students not only face a tradeoff between the short-run losses and long-run returns of educational investments, but must also acknowledge that any educational investment may be derailed by future shocks. Using the model, we show that different assumptions about probabilities of completion imply vastly different estimates of the upfront utility costs of education—relevant values for counterfactual policy analysis. Put another way, absent data on students' perceived likelihood of non-completion, which may be far from zero for many, it is difficult to identify utility costs associated with school. Our approach thus sheds light on what data might be missing and helps to set priorities for future data collection. An improved model would use direct measures of individuals' beliefs about noncompletion, which extant data do not contain and that future data collection efforts could priorities.

A more elaborate model for the purposes of policy analysis might include a richer set of degree program options, differences in unemployment rates for each type of educational outcome, and the possibility of returning to school at a later point in the lifecycle, among other features. The relationship between the anticipation of shocks and earlier-life instability could also be explicitly modeled. In this manner, anticipation of future adverse shocks becomes an indirect channel through which shocks witnessed or experienced during childhood and adolescence negatively affect future educational outcomes, and thus another mechanism through which disadvantage affects those outcomes. Even if no future shocks ever occur, childhood shocks can (rationally) shift how students perceive the future, including how they view the plausibility of different educational options. A fully applicable version of the model would also explicitly incorporate factors that could help break the link between anticipated shocks and educational attainment. For example, modeling scholarship or federal grant rules would allow us to directly consider policies that loosen those rules to assess whether doing so shifts expectations about the likely *impact* of shocks (not just their probability) and thus encourages disadvantaged students to choose longer and more lucrative programs.

More broadly, our mixed-methods approach builds directly on qualitative data to characterize a discrete choice model designed to approximate the emergent narrative. This is the essence of what structural modeling is often after: an internally consistent framework that quantifies a particular set of tradeoffs that can help to explain behavior and evaluate counterfactual policy. We propose that qualitative evidence from narrative interview data can help in the specification of such models, especially in contexts where behavior is not fully understood and extant data make it difficult to develop and to directly test plausible hypotheses. Examples include housing, migration, crime, and health decisions, some of which have traditionally seemed puzzling to researchers (see Bergman et al. (Forthcoming) for an example on housing).

This is particularly important when studying behavior among disadvantaged groups, i.e., individuals who often have little say in large-N data collection efforts. Such data sets are often designed to include information that prior research has deemed important, but which may not fully reflect the barriers, circumstances, and constraints that disadvantaged groups face or the rational thought processes in which they engage. This can lead to model misspecification—including inappropriately labeling disadvantaged individuals as irrational or deficient, since they appear to make poor decisions according to models specified using extant data, or as having seemingly nonstandard or self-defeating preferences that they in fact do not harbor. Seeking insight from decision-makers themselves could improve model specification and thus help to generate more useful policy proposals in these areas, and we hope this paper contributes to a push in that direction.

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6 Tables & Figures

Table 1: Categories of Adverse Shocks in Youth Interview Sample

Adverse Shock	(1) Indiv.	(2) Pct.	(3) Instances
Neighborhood violence/drug activity/gang presence	91	60.7	107
Arrested/Incarcerated (family/friend)	82	54.7	117
Death of family/friend	79	52.7	112
Substance abuse (family/friend)	55	36.7	66
Police interaction	52	34.7	57
Unplanned pregnancy	49	32.7	49
Absent parent	46	30.7	48
Arrested/incarcerated (self)	40	26.7	47
School violence (respondent not involved)	40	26.7	40
Housing instability (forced/reactive move, eviction)	39	26.0	44
Physical/mental health issue (family/friend)	35	23.3	35
Physical/mental health issue (self)	34	22.7	49
Domestic violence/abuse	31	20.7	37
Experience of violence (self)	16	10.7	16
Witnessing violence	13	8.7	14
Experience of non-violent crime	11	7.3	11
Parental separation/divorce	11	7.3	11
Experience of violence (family/friend)	10	6.7	12
Forced school transfer	10	6.7	10
Experience of bullying (self)	8	5.3	8
Substance abuse (self)	7	4.7	7
Family estrangement	5	3.3	6
School disorder	5	3.3	5
Other moves	5	3.3	5
Lost job (self)	4	2.7	4
Foster care	2	1.3	2
No adverse shocks	1	0.7	–
Observations	150	100.0	919

Table adapted from DeLuca et al. (Forthcoming). Each row reports the frequency of different categories of adversity in three different ways. Column 1 shows the number of people who report experiencing it at least once over the course of the interview. Column 2 divides the number in column 1 by 150 to obtain the proportion of the sample that reports experiencing the category of adversity at least once. Column 3 reports how many times specific instances of this category of adversity are mentioned over the entirety of the 150 interviews and differs from the number in column 1 because some people report multiple instances. Individuals reporting multiple adverse shocks, both across and within categories, is common with a per-individual rate of 6.13 adversities; over half the sample (52 percent) reported between two and eight such events.

Table 2: NLSY97 Summary Stats by Demographics

	(1) All	(2) Black	(3) White	(4) Low Inc	(5) Mid Inc	(6) High Inc
Panel A: Demographics & Background						
White non-Hisp	0.67	0.00	1.00	0.53*	0.76	0.84
Black	0.15	1.00	0.00	0.24*	0.09	0.05
Hispanic	0.13	0.00	0.00	0.18*	0.10	0.05
Low income	0.34	0.54*	0.27	1.00	0.00	0.00
Mid income	0.44	0.27*	0.50	0.00	1.00	0.00
High income	0.09	0.03*	0.12	0.00	0.00	1.00
Mom no diploma	0.17	0.23*	0.11	0.31*	0.10	0.03
Mom HS diploma	0.36	0.42*	0.37	0.39*	0.37	0.22
Mom some college	0.25	0.24*	0.27	0.21†	0.30	0.22
Mom bachelor's	0.21	0.11*	0.25	0.08*	0.23	0.53
GPA 3 and up	0.44	0.28*	0.49	0.33*	0.48	0.61
GPA 2-3	0.48	0.58*	0.44	0.54*	0.46	0.36
GPA 1-2	0.07	0.12*	0.06	0.11*	0.06	0.03
Verbal score	0.03	-0.60*	0.17	-0.23*	0.08	0.30
Math score	0.01	-0.59*	0.16	-0.30*	0.08	0.39
Panel B: Final Attainment						
No degree	0.10	0.12*	0.08	0.16*	0.05	0.03
HS or GED	0.31	0.36*	0.30	0.41*	0.28	0.15
Some coll/assoc.	0.30	0.34*	0.28	0.29†	0.31	0.26
Bachelor or more	0.30	0.19*	0.34	0.15*	0.36	0.57
Panel C: Adverse Shocks						
No father in HH	0.24	0.46*	0.19	0.44*	0.13	0.05
Changed schools	0.11	0.11	0.11	0.16*	0.08	0.08
Break-in	0.10	0.12*	0.09	0.11	0.09	0.09
Bullied	0.11	0.09*	0.12	0.12	0.10	0.09
Seen shooting	0.10	0.21*	0.08	0.15*	0.08	0.06
Parent died	0.03	0.05*	0.03	0.04*	0.02	0.01
Other family died	0.50	0.57*	0.50	0.51	0.50	0.52
Parent hospitalized	0.09	0.10	0.09	0.09	0.09	0.10
Parent jailed	0.02	0.02	0.02	0.03†	0.02	0.01
Parents divorced	0.09	0.07*	0.09	0.10*	0.09	0.04
Parent unemp	0.08	0.09*	0.08	0.09*	0.07	0.05
Victim of crime	0.07	0.07	0.07	0.08*	0.07	0.04
Ever homeless	0.02	0.02	0.02	0.02*	0.01	0.00
Panel D: Expectations						
Coll exp 0-25	0.13	0.13	0.13	0.20*	0.11	0.03
Coll exp 25-50	0.17	0.18	0.16	0.22*	0.15	0.07
Coll exp 50-75	0.13	0.11	0.13	0.14†	0.13	0.10
Coll exp 75-100	0.57	0.58	0.58	0.45*	0.61	0.79
Exp: crime victim	0.14	0.17*	0.13	0.16*	0.14	0.12
Exp: arrest	0.10	0.13*	0.09	0.12*	0.09	0.07
Exp: death	0.18	0.23*	0.17	0.20*	0.17	0.13
Exp: pregnancy	0.07	0.11*	0.06	0.09*	0.06	0.05
Exp: get drunk	0.22	0.12*	0.24	0.22†	0.22	0.24
Observations	8984	2334	4413	3588	3478	671

NLSY97 sample-weighted means. Verbal and math scores have been standardized. "Low Inc" indicates childhood household income of less than $35,000; "Mid Inc," in the range $35,000-$100,000; "High Inc," above $100,000. Values marked with $*$ and † are statistically different from paired groups' means according to t-tests with p-values of 0.01 and 0.1, respectively; for these tests, Black means are paired with white, and low-income means are paired with high-income.

Table 3: Attainment and Expectations' Relationship to Past Shocks

	(1) Dropout	(2) Dropout	(3) Exp Coll	(4) Exp Coll	(5) Exp Shocks	(6) Exp Shocks
Black	0.11***	0.10***	0.08***	0.09***	0.03***	0.03***
Hispanic	0.10***	0.09***	0.02	0.03*	0.03***	0.03***
Asian or PI	-0.02	-0.02	0.10***	0.10***	-0.01	-0.01
Native American	0.03	0.02	0.03	0.04	-0.05	-0.05
Multiple races	0.02	0.00	-0.04	-0.00	0.09*	0.08*
Male	0.09***	0.09***	-0.09***	-0.09***	0.02***	0.02***
Sibling count	0.01	0.01	-0.00	-0.00	-0.00	-0.00*
Low income	0.06***	0.05**	-0.12***	-0.10***	0.02***	0.02**
Mid income	-0.00	-0.00	-0.05***	-0.04***	0.01	0.01
Mom no diploma	0.23***	0.22***	-0.23***	-0.22***	0.00	-0.00
Mom HS diploma	0.18***	0.18***	-0.16***	-0.15***	0.00	-0.00
Mom some college	0.09***	0.09***	-0.08***	-0.08***	-0.00	-0.01
Family shocks	0.02***		-0.01*		0.01***	
Victimization	0.07***		-0.02***		0.03***	
No father in HH		0.02		-0.03*		0.01
Changed schools		0.13***		-0.05**		0.04***
Parent died		0.02		-0.06*		0.03*
Other family died		-0.00		0.01		0.00
Parent hospitalized		0.00		0.04**		-0.02*
Parent jailed		0.06		-0.08*		0.04**
Parents divorced		0.04		-0.01		-0.00
Parent unemp		0.00		0.01		0.01
Break-in		0.04		0.02		0.02***
Bullied		0.03		-0.00		0.01
Seen shooting		0.10***		-0.02		0.05***
Feels unsafe		0.06***		-0.06***		0.02***
Victim of crime		0.01		-0.02		0.01
Ever homeless		0.13		-0.01		0.01
Constant	0.09***	0.02	0.99***	1.07***	0.07***	0.05***
Adjusted R^2	0.09	0.09	0.14	0.17	0.07	0.08
Outcome mean	0.23	0.23	0.74	0.74	0.13	0.13
Observations	4206	4194	2596	2586	2608	2598

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Regressions of an indicator for leaving college without a bachelor's degree after enrolled (Dropout), the NLSY97 subjective probability of earning a bachelor's degree (Exp Coll), and the average subjective probability of future shocks including pregnancy, arrest, and death (Exp Shocks) on various covariates. In columns 1, 3, and 5 indicators of past shocks are summed to arrive at two summary measures, "family shocks" (such as parental incarceration or unemployment or a death in the family) and "victimization" (such as seeing a shooting or being the victim of a crime). In columns 2, 4, and 6 individual shock indicators are included as covariates. "Outcome means" for each column's outcome variable calculated within that regression's estimation sample. All estimation is weighted using NLSY97 sampling weights.

Table 4: LPM for Bachelor's Degree, Given Enrollment

	(1)	(2)	(3)	(4)	(5)
Black	-0.04*	-0.00	-0.07***	-0.03	-0.03
Hispanic	-0.09***	-0.09***	-0.09***	-0.08***	-0.09***
Asian or PI	0.11	0.09	0.07	0.10	0.05
Native American	-0.12	-0.04	-0.11	-0.15	-0.07
Multiple races	-0.11	-0.06	-0.09	-0.08	-0.05
Male	-0.10***	-0.09***	-0.06***	-0.09***	-0.07***
Sibling count	-0.01	-0.01	-0.00	-0.01	-0.01
Low income	-0.23***	-0.16***	-0.18***	-0.22***	-0.13***
Mid income	-0.08***	-0.06**	-0.06**	-0.08***	-0.04
Mom no diploma	-0.40***	-0.36***	-0.31***	-0.39***	-0.29***
Mom HS diploma	-0.34***	-0.33***	-0.27***	-0.34***	-0.28***
Mom some college	-0.23***	-0.22***	-0.19***	-0.23***	-0.18***
No father in HH		-0.03			-0.02
Changed schools		-0.11***			-0.09***
Parent died		-0.08			-0.07
Other family died		-0.04*			-0.04**
Parent hospitalized		-0.03			-0.05
Parent jailed		-0.13**			-0.10*
Parents divorced		-0.05			-0.04
Parent unemp		0.01			0.01
Break-in		-0.07**			-0.07***
Bullied		-0.04			-0.04
Seen shooting		-0.10***			-0.07***
Feels unsafe		-0.09***			-0.07***
Victim of crime		-0.04			-0.03
Ever homeless		-0.14***			-0.13***
Coll exp 25-50			0.03		0.02
Coll exp 50-75			0.17***		0.15***
Coll exp 75-100			0.30***		0.26***
Exp: crime victim				-0.09*	0.00
Exp: arrest				-0.13**	-0.03
Exp: death				-0.12***	-0.11***
Exp: pregnancy				-0.06	0.04
Exp: get drunk				-0.06*	-0.06*
Constant	0.78***	0.98***	0.48***	0.83***	0.71***
Adjusted R^2	0.19	0.23	0.25	0.20	0.28
Observations	2503	2503	2503	2503	2503

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Linear probability model (LPM) with earning a bachelor's degree as the outcome, conditional on postsecondary enrollment. "Coll exp X-Y" are indicators for the individual's subjective probability of earning a bachelor's degree being between X and Y percent. The other "Exp" controls represent the subjective probabilities placed on the specified adverse future events. Enrolled sample rate of bachelor's degree attainment is 30 percent, or 0.30. All estimation is weighted using NLSY97 sampling weights.

Table 5: LPM for Starting at a Two-Year Program, Given Enrollment

	(1)	(2)	(3)	(4)	(5)
Black	0.05	0.00	0.05	0.02	0.00
Hispanic	0.18***	0.18***	0.16***	0.16***	0.16***
Asian or PI	-0.06	-0.04	-0.03	-0.05	-0.02
Native American	0.26	0.13	0.23	0.27*	0.14
Multiple races	0.12	0.09	0.13	0.07	0.09
Male	0.05*	0.04*	0.02	0.04*	0.03
Sibling count	0.00	0.00	-0.00	0.01	0.00
Low income	0.21***	0.14***	0.17***	0.20***	0.11***
Mid income	0.09***	0.06*	0.07**	0.09***	0.05
Mom no diploma	0.24***	0.21***	0.19***	0.23***	0.16***
Mom HS diploma	0.22***	0.22***	0.18***	0.22***	0.18***
Mom some college	0.16***	0.15***	0.13***	0.16***	0.12***
No father in HH		0.06*			0.05
Changed schools		0.13***			0.10**
Parent died		0.13*			0.12
Other family died		-0.00			-0.00
Parent hospitalized		0.01			0.04
Parent jailed		0.14			0.07
Parents divorced		0.06			0.06
Parent unemp		0.04			0.03
Break-in		0.05			0.04
Bullied		0.12***			0.12***
Seen shooting		0.08**			0.06
Feels unsafe		0.11***			0.09***
Victim of crime		0.02			0.02
Ever homeless		0.06			0.05
Coll exp 25-50			-0.02		0.00
Coll exp 50-75			-0.19***		-0.15***
Coll exp 75-100			-0.33***		-0.25***
Exp: crime victim				0.06	-0.06
Exp: arrest				0.10	0.00
Exp: death				0.18***	0.20***
Exp: pregnancy				0.24***	0.12
Exp: get drunk				0.03	0.04
Constant	0.17***	-0.03	0.50***	0.12***	0.22***
Adjusted R^2	0.10	0.15	0.15	0.12	0.19
Observations	1784	1784	1784	1784	1784

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Linear probability model (LPM) with choice of a two-year postsecondary program as the outcome. "Coll exp X-Y" are indicators for the individual's subjective probability of earning a bachelor's degree being between X and Y percent. The other "Exp" controls represent the subjective probabilities placed on the specified adverse future events. Enrolled sample rate of two-year program enrollment is 51 percent, or 0.51. All estimation is weighted using NLSY97 sampling weights.

Table 6: Summary Statistics, Outcomes, and Noncompletion Rates by Group in Structural Model Sample

	All	1	2	3	4	5	6	7	8
Panel A: Group Definition									
URM	.	No	Yes	No	Yes	No	Yes	No	Yes
Low-income	.	No	No	Yes	Yes	No	No	Yes	Yes
Shocks	.	No	No	No	No	Yes	Yes	Yes	Yes
Panel B: On-Time Grad Rates									
Assoc. 2 Yr	.	0.21	0.14	0.17	0.12	0.16	0.10	0.17	0.10
Bach. 4 Yr	.	0.35	0.26	0.23	0.19	0.34	0.19	0.21	0.17
Panel C: Derived Noncompletion Probabilities									
$\alpha^1(X_i)$	0.54	0.54	0.63	0.59	0.65	0.60	0.68	0.59	0.69
$\alpha^2(X_i)$	0.23	0.23	0.29	0.31	0.34	0.24	0.34	0.32	0.36
Observations	6904	1779	837	414	665	926	687	531	1065

Relevant statistics for subsamples used in structural estimation. Columns represent subsamples of respondents who had certain characteristics or not as indicated by Panel A: individuals from URM (underrepresented minority) groups; those from low-income households (total less than \$35,000); and those who experienced at least two of our recorded adverse shocks in childhood. Panel B displays on-time graduation rates for those in each group who enroll in the relevant program type. The α in Panel E are annual probabilities of academic noncompletion—either a failure to earn a year of credit or a dropout in the following year—for various demographic groups, determined using values in Panel B and with Group 1 values used in the point-of-reference full sample specification (marked "All" in the figures below). Noncompletion probabilities differ between two-year programs ($\alpha^1(X_i)$) and four-year programs ($\alpha^2(X_i)$).

Table 7: Parameter Values by Demographic Group

Group	1	2	3	4	5	6	7	8
URM	No	Yes	No	Yes	No	Yes	No	Yes
Low-income	No	No	Yes	Yes	No	No	Yes	Yes
Shocks	No	No	No	No	Yes	Yes	Yes	Yes
Panel A: Rational consideration of failure probability								
$u_1(X_i)$	-0.54	-0.15	-0.86	-0.34	-0.37	-0.07	-0.82	-0.45
	(.033)	(.029)	(.035)	(.031)	(.031)	(.028)	(.035)	(.032)
$u_2(X_i)$	-1.99	-1.83	-1.88	-1.78	-1.26	-1.50	-1.97	-1.66
	(.021)	(.021)	(.019)	(.021)	(.021)	(.020)	(.020)	(.020)
Panel B: No consideration of failure probability								
$u_1(X_i)$	-2.34	-2.62	-3.31	-3.09	-2.65	-3.73	-3.31	-3.24
	(.037)	(.036)	(.031)	(.033)	(.035)	(.035)	(.031)	(.032)
$u_2(X_i)$	-3.45	-3.85	-4.17	-4.32	-3.80	-3.91	-4.36	-4.31
	(.020)	(.022)	(.021)	(.022)	(.021)	(.021)	(.022)	(.022)

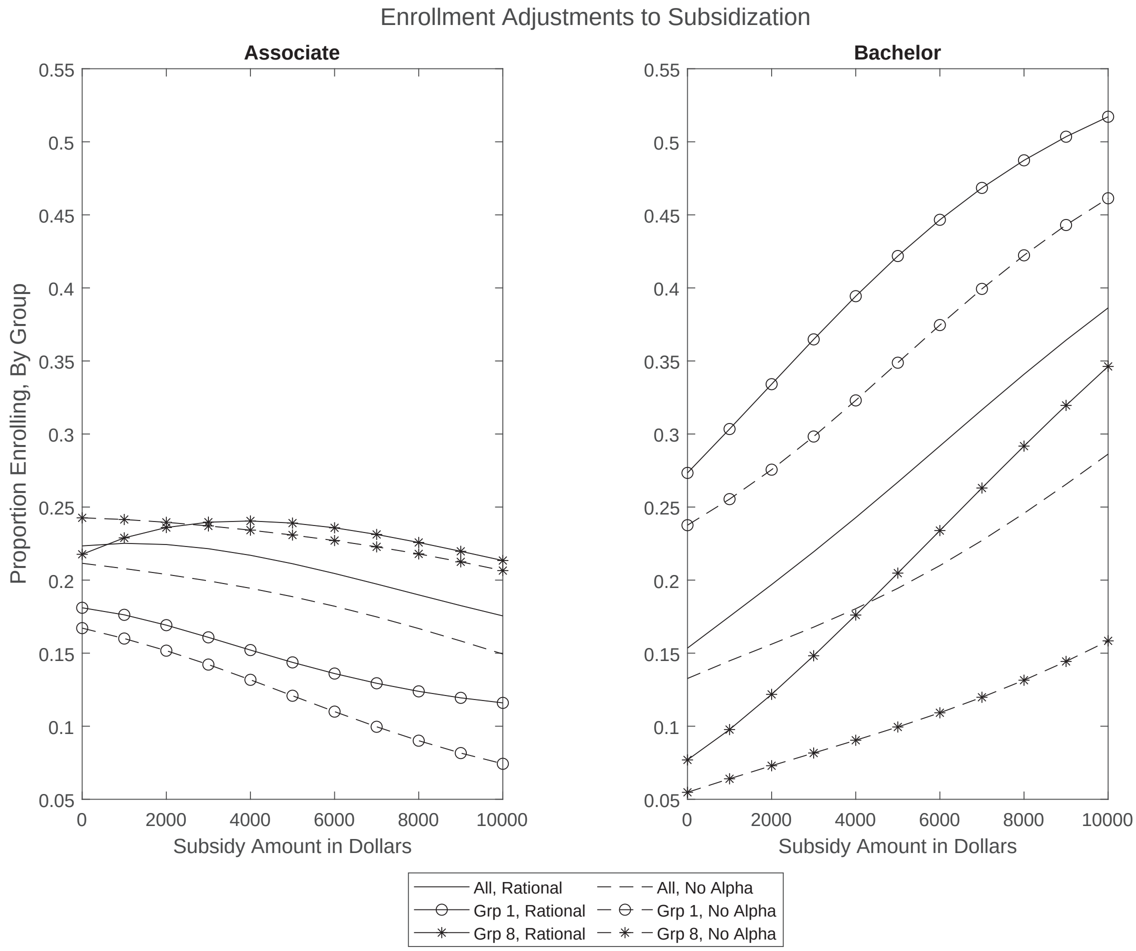
Estimated utility parameter values for various demographic groups. In Panel A, individuals rationally consider probabilities of noncompletion; in Panel B, we assume they ignore these probabilities. Parameters u_1 and u_2 are the flow utility values of attending an associate's and a bachelor's program, respectively. Columns represent subsamples of respondents who had certain characteristics or not as indicated by the top three rows: individuals from URM (underrepresented minority) groups; those from low-income households (total less than $35,000); and those who experienced at least two of our recorded adverse shocks in childhood. Standard errors, calculated as described in Appendix D, appear in parentheses below each estimate.

Table 8: Enrollment Probability at Age 18, Reduced Noncompletion Risk

Group	1	2	3	4	5	6	7	8
URM	No	Yes	No	Yes	No	Yes	No	Yes
Low-income	No	No	Yes	Yes	No	No	Yes	Yes
Shocks	No	No	No	No	Yes	Yes	Yes	Yes
Panel A: Two-year (Associate's) enrollment probability								
Baseline	0.19	0.24	0.22	0.25	0.21	0.23	0.24	0.22
3/4 Rate	0.17	0.23	0.22	0.27	0.22	0.23	0.25	0.25
1/2 Rate	0.15	0.20	0.17	0.23	0.20	0.17	0.21	0.20
Panel B: Four-year (Bachelor's) enrollment probability								
Baseline	0.28	0.17	0.14	0.08	0.21	0.16	0.08	0.08
3/4 Rate	0.31	0.21	0.20	0.12	0.22	0.22	0.13	0.15
1/2 Rate	0.36	0.28	0.30	0.21	0.26	0.34	0.22	0.27

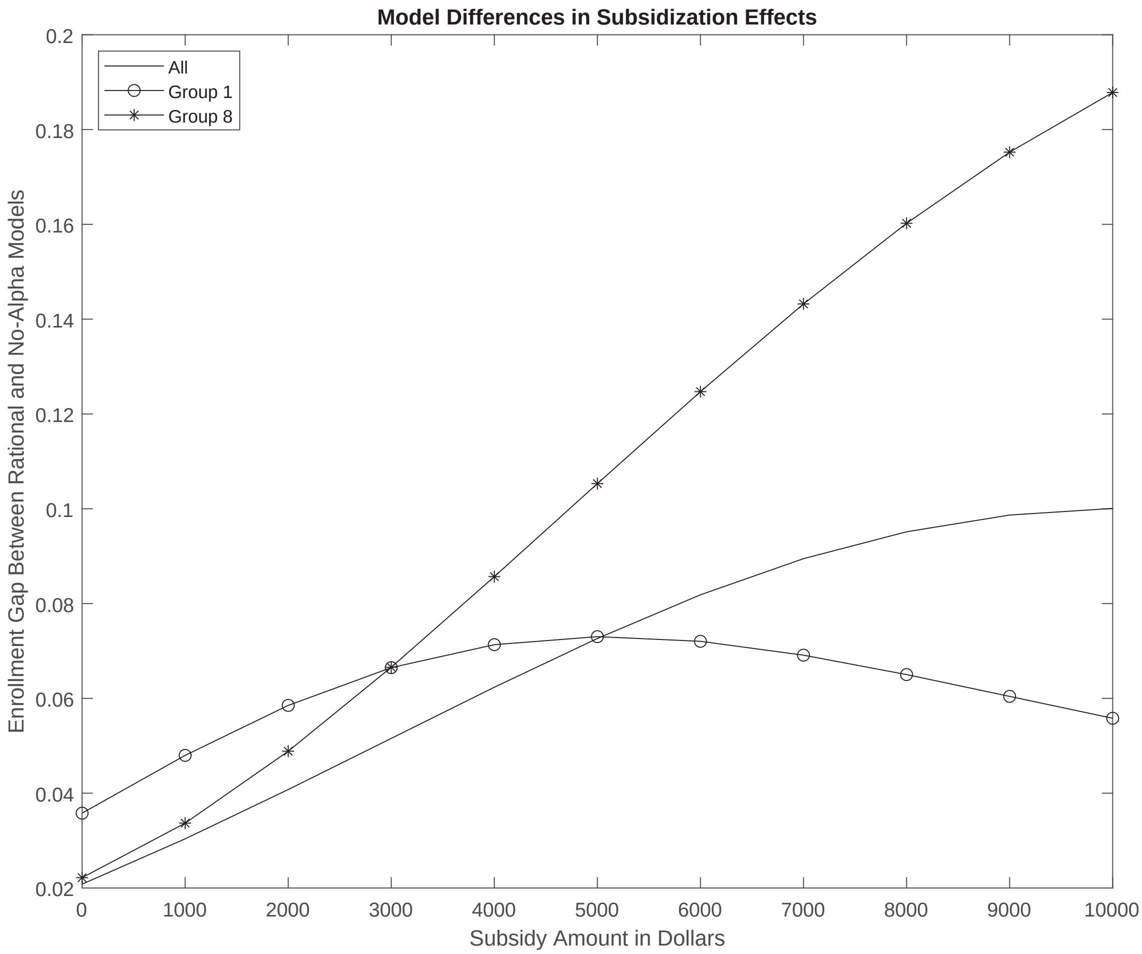
Predicted choice probabilities for enrollment at age 18 by demographic group. Probabilities of enrolling in a two-year program are reported in Panel A, with four-year program enrollment probabilities in Panel B. "3/4 Rate" rows contain enrollment probabilities when noncompletion probabilities are reduced to three-fourths the rate reported in Table 6; "1/2 Rate" rows reduce noncompletion probabilities to half that base rate. Columns represent subsamples of respondents who had certain characteristics or not as indicated by the top three rows: individuals from URM (underrepresented minority) groups; those from low-income households (total less than $35,000); and those who experienced at least two of our recorded adverse shocks in childhood.

Figure 1: Counterfactual Subsidy Evaluation Assuming Noncompletion Risk



Curves depict changes in the proportion of each demographic group enrolling in each type of school at age 18 given increasing levels of subsidization for students. The left panel regards associate's degree programs; the right, bachelor's programs. The solid lines depict decision-makers that rationally account for educational non-completion risk; the dashed lines, decision-makers ignore this possibility (and have correspondingly estimated utility parameters). "Grp 1" are non-minority individuals from high-SES families with little to no history of adverse shock events; "Grp 8" are racial or ethnic minority individuals from low-SES families with at least two adverse shock events in their pasts.

Figure 2: Counterfactual Subsidy Evaluation with vs. without Noncompletion Risk



Curves depict differences in the proportion of each demographic group enrolling in bachelor's degree programs at age 18 between the baseline ("rational") and no-α models, given increasing levels of subsidization for students. "Group 1" are non-minority individuals from high-SES families with little to no history of adverse shock events; "Group 8" are racial or ethnic minority individuals from low-SES families with at least two adverse shock events in their pasts.

Appendix A Evidence of Shocks and Their Effects in the ELS

Do students actually have to worry about adverse shock events derailing their educational paths? This is difficult to verify in the NLSY97 data, though as we have seen above there is certainly an association between adverse shocks in general and lower attainment. However, in this instance the ELS, for which summary statistics are supplied in Table A1, can provide more conclusive results. Respondents to that survey supplied information regarding events that occurred in their lives in the period just *after* their expected date of graduation from high school, when those who attended postsecondary schools would have been enrolled. This information is not available in the NLSY97. Relevant shock events include whether their parents divorced, became unemployed, or died, whether another loved one died, whether the student or an immediate family member fell seriously ill, or whether the student was the victim of violence. We sum these indicators (labeled "shocks in college") and treat this sum as representative of the level of instability in a college student's life. This sum is visibly correlated with final attainment in Table A1. Now we can more formally analyze the effect of such instability among only those students who actually enroll in some kind of postsecondary program and look for evidence of adverse-shock-related derailment.

In Table A2, we report results from estimation in the ELS of an ordered probit model of final educational attainment, with the possible outcomes being (in the following order) no credential, a certificate, an associate's degree, and a bachelor's degree or more. Adverse shock events have a significant negative relationship with final attainment given enrollment, even in the presence of controls for demographic and socioeconomic background as well as high school academic performance and standardized test scores. Similarly significant relationships can be found in a linear probability model of bachelor's degree attainment. It would appear, then, that adverse shocks—typically subsumed into an error term and thus treated as unobserved heterogeneity—likely help to derail educational paths. Any young person who is concerned about life-altering negative events happening in their futures might further reason that such events would make it difficult to complete a bachelor's or other degree.

Appendix A.1 Tables

Table A1: ELS Summary Stats by Attainment

	All	No Deg	HS	Some Coll	Bachelor
White	0.54	0.31	0.52	0.51	0.64
Black	0.12	0.19	0.12	0.15	0.07
Hispanic	0.14	0.28	0.17	0.16	0.08
Low income	0.28	0.49	0.42	0.31	0.15
Mid income	0.53	0.38	0.46	0.54	0.56
High income	0.15	0.02	0.04	0.10	0.27
Mother: No degree	0.13	0.38	0.23	0.13	0.05
Mother: HS diploma	0.27	0.33	0.40	0.29	0.18
Mother: Some college	0.33	0.20	0.28	0.37	0.31
Mother: Bachelor	0.27	0.09	0.09	0.21	0.45
GPA: 0-1	0.02	0.17	0.04	0.02	0.00
GPA: 1-2	0.17	0.59	0.36	0.20	0.02
GPA: 2-3	0.41	0.22	0.47	0.51	0.25
GPA: 3-4	0.40	0.02	0.13	0.28	0.73
Math score	50.71	40.73	44.36	49.04	56.87
Reading score	50.53	40.85	44.66	49.17	56.39
Composite score	50.66	40.16	44.13	49.04	57.08
No degree	0.03	1.00	0.00	0.00	0.00
HS diploma	0.10	0.00	1.00	0.00	0.00
Some college	0.48	0.00	0.00	1.00	0.00
Bachelor	0.38	0.00	0.00	0.00	1.00
Shocks in college	0.93	1.05	1.04	1.00	0.80
Observations	16197	356	1388	6406	5100

ELS means for group indicator variables, standardized test scores, and a count of adverse shock events during college. Test scores have themselves been statistically standardized. The "Some Coll" column includes all individuals who attended some kind of postsecondary institution but never earned an associate's or bachelor's degree.

Table A2: ELS: Ordered Probit for Attainment Given PS Enrollment

	(1)	(2)	(3)	(4)
Black	-0.53***	-0.51***	-0.41***	0.04
Hispanic	-0.49***	-0.48***	-0.32***	-0.07*
Asian or PI	0.08**	0.07*	0.15***	0.08*
Native American	-0.66***	-0.63***	-0.49***	-0.15
Multiple races	-0.26***	-0.24***	-0.22***	-0.12**
Male	-0.12***	-0.13***	-0.17***	-0.09***
Shocks in college		**-0.10*** **	**-0.09*** **	**-0.06*** **
Low income			-0.42***	-0.29***
Mid income			-0.22***	-0.17***
Mother: no degree			-0.62***	-0.34***
Mother: HS diploma			-0.49***	-0.29***
Mother: some college			-0.38***	-0.24***
GPA: 3-4				1.25***
GPA: 2-3				0.56***
GPA: 1-2				0.13
Reading score				0.01***
Math score				0.02***
HS Cutoff	-0.61***	-0.71***	-1.21***	1.19***
Associate Cutoff	-0.33***	-0.42***	-0.92***	1.52***
Bachelor Cutoff	-0.09***	-0.18***	-0.67***	1.81***
Observations	9239	9239	9239	9239

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Ordered probit for final attainment in ELS data. “Shocks in college” refers to the count of adverse events that happen to respondents while they are in postsecondary school, including parental divorce, unemployment, and death, the death of other loved ones, serious illness befalling the student or a family member, and violent victimization. A significant negative effect suggests that college-period shocks do reduce eventual attainment, even in the presence of increasing sets of covariates.

Appendix B Expectations and Institution Type Choice in the HSLS

Summary statistics for the High School Longitudinal Study (HSLS) sample on essential demographic characteristics are shown in Table B3, while the unique variables are summarized in Table B4. The latter include students' own beliefs regarding their ability to earn a bachelor's degree as well as whether they expect to do so, whether they anticipate qualifying for financial aid after high school, and even whether and why they would eventually take a break from postsecondary school. When we estimate the relationship between these variables and what kind of institution students eventually graduate from, these other new kinds of expectations do not eliminate a statistically significant estimated link between attainment expectations and outcomes. Results are provided in Table B5. Students who expect to earn a bachelor's are more likely to end up at four-year programs of the public and non-profit varieties, and less likely to get a credential from a two-year school. These results demonstrate that students' predictions regarding their own academic ability and financial aid eligibility do not drive the relationship between attainment expectations and institution choice we found in the NLSY97, enhancing the case for a direct causal link.

Appendix B.1 Tables

Table B3: HSLS Means

	All	No Deg	HS	Some Coll	College
White	0.51	0.44	0.50	0.51	0.53
Black	0.10	0.12	0.13	0.12	0.03
Hispanic	0.16	0.23	0.19	0.17	0.14
Asian, HI, PI	0.09	0.04	0.05	0.06	0.14
Male	0.51	0.56	0.57	0.49	0.27
Low income	0.20	0.34	0.30	0.22	0.08
Mid income	0.30	0.18	0.29	0.36	0.32
High income	0.21	0.05	0.08	0.16	0.31
Mother no degree	0.09	0.25	0.16	0.09	0.00
Mother HS only	0.46	0.54	0.59	0.50	0.39
Mother Assoc.	0.18	0.13	0.15	0.22	0.27
Mother Bachelor	0.27	0.08	0.10	0.20	0.33
Math score	0.03	-0.76	-0.42	-0.04	0.48
Observations	23503	747	3670	3935	59

HSLS means for group indicator variables and standardized test scores. Test scores have been statistically standardized. The "Some Coll" column includes all individuals who attended some kind of postsecondary institution but never earned an associate's or bachelor's degree.

Table B4: HSLS Means for Expectations and Shocks Variables

Exp Bachelor's	0.62
Thinks capable of BA	0.49
Fin aid: will qual	0.43
Fin aid: won't qual	0.26
Fin aid: unsure	0.31
Plans 4yr enroll, 2009	0.53
Break: Academic	0.00
Break: Family	0.03
Break: Financial	0.02
Break: Work	0.02
Break: Unknown	0.01
Observations	23495

HSLS means for postsecondary school type indicator variables, adverse shocks, and expectations. "Shocks" variables are sums of various types of adverse shocks over the relevant time period (2009-2011 or 2012-2016). Expected earnings are in thousands of dollars per year.

Table B5: MNL for First Postsecondary Program Type Given Plan to Enroll in Four-Year: HSLS

	Pub2	FP2	Pub4	NP4	FP4
Exp Bachelor's	-0.09***	-0.01**	0.06*	0.05*	0.01
Break: Academic	0.68	-0.19	2.07	-1.86	0.04
Break: Family	0.08**	0.02***	0.00	-0.12	-0.00
Break: Financial	0.10**	0.01	-0.13	-0.03	0.02***
Break: Work	0.03	0.01	0.04	-0.13	0.01
Break: Unknown	0.07	0.00	-0.12	0.07	-0.10
Thinks capable of BA	-0.02	-0.00	0.02	0.01	-0.00
Fin aid: will qual	0.00	0.00	0.00	0.00	0.00
Fin aid: won't qual	-0.01	-0.00	0.05**	-0.04**	0.00
Fin aid: unsure	-0.02	-0.00	0.01	-0.01	0.00
Black	-0.09***	-0.00	0.04	0.07***	0.01*
Hispanic	0.00	0.00	-0.03	0.02	0.00
Asian, HI, PI	-0.10***	0.01	0.11***	-0.03	0.00
Native American	-0.00	-0.14	0.15	0.07	-0.09
Multiple races	0.01	0.01	-0.02	-0.02	0.01**
Male	0.01	-0.02***	0.05***	-0.02*	-0.00
Low income	0.09***	0.01	-0.05*	-0.05**	0.00
Mid income	0.07***	0.02**	-0.07***	-0.03*	0.00
Mother no degree	0.12***	0.01	-0.00	-0.11**	-0.00
Mother HS only	0.05***	0.01*	-0.03	-0.03**	-0.00
Mother Associate's	0.07***	-0.00	-0.04*	-0.03*	-0.01
GPA: Academic	-0.09***	-0.01***	0.08***	0.06***	-0.01*
GPA: CTE	-0.02*	-0.00	0.04**	-0.01	-0.00
Math score	-0.05***	-0.01**	0.04***	0.03***	0.00
Observations	3768	3768	3768	3768	3768

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. "Break" variables indicate that the respondent took a break from school for the stated reason. "Fin aid" variables regard respondents' expectations for educational financial aid qualification. "CTE" indicates Career and Technical Education; "HI" and "PI" indicate Hawaiian and Pacific Islander, respectively. Column titles are "Public Two-Year Institution," "For-Profit Two-Year Institution," "Public Four-Year Institution," "Non-Profit Four-Year Institution" and "For-Profit Four-Year Institution," respectively.

Appendix C Supplemental Analyses with Demographic Subsamples

In this appendix, we perform a few of the same analyses as in Tables 3 and 4, as well as a tweaked version of the analysis in Table 5, using two relevant demographic subsamples: Black individuals and those from low-income backgrounds. These subsamples more closely resemble the narrative interview sample explored in Section 2. The change in the program-type choice analysis is that the outcome is choosing to enroll in a four-year public or non-profit school, and the other available option is *any* other enrollment choice, including not enrolling in postsecondary school at all. Patterns are broadly similar to those in the main text: a history of adverse shocks predicts lower attainment and more dire expectations about the future, and those worse expectations are correlated with lower final attainment, potentially through the mechanism of program choice.

Appendix C.1 Tables

Table C6: Black Subsample: Attainment and Expectations' Relationship to Past Shocks

	(1) Dropout	(2) Exp Coll	(3) Exp Shocks
Male	0.14***	-0.01	0.06***
Sibling count	0.04***	-0.02*	-0.00
Low income	0.05	-0.11***	0.00
Mid income	-0.06	-0.07*	-0.01
Mom no diploma	0.14**	-0.21***	-0.03
Mom HS diploma	0.21***	-0.10***	-0.03
Mom some college	0.10*	-0.09**	-0.04*
Family shocks	0.02	0.01	0.01
Victimization	0.06***	-0.01	0.03***
Constant	0.17***	0.99***	0.13***
Adjusted R^2	0.08	0.07	0.06
Observations	945	658	660

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Regressions of an indicator for leaving college without a bachelor's degree after enrolled (Dropout), the NLSY97 subjective probability of earning a bachelor's degree (Exp Coll), and the average subjective probability of future shocks including pregnancy, arrest, and death (Exp Shocks) on various covariates. Indicators of past shocks are summed to arrive at two summary measures, "family shocks" (such as parental incarceration or unemployment or a death in the family) and "victimization" (such as seeing a shooting or being the victim of a crime). All estimation is weighted using NLSY97 sampling weights.

Table C7: Low-Income Subsample: Attainment and Expectations' Relationship to Past Shocks

	(1) Dropout	(2) Exp Coll	(3) Exp Shocks
Black	0.12***	0.12***	0.02
Hispanic	0.08**	0.08***	0.03*
Asian or PI	-0.03	0.32***	-0.02
Native American	-0.02	-0.07*	0.01
Multiple races	0.05	-0.26***	0.26***
Male	0.09***	-0.10***	0.05***
Sibling count	0.02	-0.01	-0.00
Mom no diploma	0.24***	-0.33***	0.01
Mom HS diploma	0.21***	-0.24***	0.02
Mom some college	0.04	-0.12***	-0.00
Family shocks	0.03**	-0.01	0.02***
Victimization	0.05***	-0.02*	0.03***
Constant	0.13**	0.92***	0.06***
Adjusted R^2	0.08	0.13	0.10
Observations	1202	1036	1038

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Regressions of an indicator for leaving college without a bachelor's degree after enrolled (Dropout), the NLSY97 subjective probability of earning a bachelor's degree (Exp Coll), and the average subjective probability of future shocks including pregnancy, arrest, and death (Exp Shocks) on various covariates. Indicators of past shocks are summed to arrive at two summary measures, "family shocks" (such as parental incarceration or unemployment or a death in the family) and "victimization" (such as seeing a shooting or being the victim of a crime). In columns 2, 4, and 6 individual shock indicators are included as covariates. All estimation is weighted using NLSY97 sampling weights.

Table C8: Black Subsample: LPM for Bachelor's Degree, Given Enrollment

	(1)	(2)	(3)	(4)	(5)
Male	-0.11***	-0.10***	-0.10***	-0.08*	-0.07*
Sibling count	-0.04***	-0.04***	-0.03***	-0.04***	-0.03***
Low income	-0.14**	-0.11*	-0.11*	-0.13**	-0.08
Mid income	-0.03	-0.01	-0.01	-0.04	0.00
Mom no diploma	-0.34***	-0.32***	-0.28***	-0.33***	-0.27***
Mom HS diploma	-0.28***	-0.27***	-0.25***	-0.29***	-0.24***
Mom some college	-0.17**	-0.17**	-0.14*	-0.19**	-0.15**
Family shocks		-0.02			-0.02
Victimization		-0.05***			-0.05***
Coll exp 25-50			0.04		0.07
Coll exp 50-75			0.04		0.04
Coll exp 75-100			0.21***		0.20***
Exp: crime victim				-0.00	0.05
Exp: arrest				-0.18*	-0.11
Exp: death				0.06	0.05
Exp: pregnancy				-0.16**	-0.11
Exp: get drunk				-0.11	-0.08
Constant	0.67***	0.71***	0.46***	0.70***	0.52***
Adjusted R^2	0.14	0.15	0.18	0.15	0.19
Observations	617	617	617	617	617

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Linear probability model with earning a bachelor's degree as the outcome. "Coll exp X-Y" are indicators for the individual's subjective probability of earning a bachelor's degree being between X and Y percent. The other "Exp" controls represent the subjective probabilities placed on the specified adverse future events. All estimation is weighted using NLSY97 sampling weights.

Table C9: Low-Income Subsample: LPM for Bachelor's Degree, Given Enrollment

	(1)	(2)	(3)	(4)	(5)
Black	0.01	0.03	-0.02	0.02	-0.00
Hispanic	0.01	0.01	0.00	0.02	0.00
Asian or PI	0.25	0.22	0.17	0.24	0.14
Native American	0.06	0.03	0.12	0.06	0.09
Multiple races	-0.18***	-0.13**	-0.10***	-0.08	-0.01
Male	-0.07**	-0.06**	-0.04	-0.04	-0.02
Sibling count	-0.00	-0.01	-0.00	-0.00	-0.00
Mom no diploma	-0.26***	-0.25***	-0.18***	-0.25***	-0.17***
Mom HS diploma	-0.22***	-0.21***	-0.15**	-0.21***	-0.15**
Mom some college	-0.07	-0.05	-0.03	-0.06	-0.02
Family shocks		-0.03**			-0.03**
Victimization		-0.05***			-0.05***
Coll exp 25-50			0.02		0.01
Coll exp 50-75			0.09**		0.07*
Coll exp 75-100			0.19***		0.17***
Exp: crime victim				-0.08	-0.04
Exp: arrest				-0.15***	-0.07
Exp: death				-0.01	-0.02
Exp: pregnancy				-0.09**	-0.04
Exp: get drunk				-0.02	-0.03
Constant	0.37***	0.45***	0.20***	0.40***	0.30***
Adjusted R^2	0.07	0.09	0.11	0.08	0.14
Observations	982	982	982	982	982

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Linear probability model with earning a bachelor's degree as the outcome. "Coll exp X-Y" are indicators for the individual's subjective probability of earning a bachelor's degree being between X and Y percent. The other "Exp" controls represent the subjective probabilities placed on the specified adverse future events. All estimation is weighted using NLSY97 sampling weights.

Table C10: LPM for Starting at a Four-Year (Not For-Profit) Program, Given Enrollment

	(1)	(2)	(3)	(4)	(5)
Black	-0.03	0.01	-0.06**	-0.01	-0.01
Hispanic	-0.11***	-0.11***	-0.10***	-0.09***	-0.11***
Asian or PI	0.10	0.08	0.06	0.10	0.04
Native American	-0.26***	-0.17*	-0.26**	-0.28***	-0.19**
Multiple races	-0.15	-0.08	-0.12	-0.10	-0.07
Male	-0.08***	-0.08***	-0.04**	-0.07***	-0.04**
Sibling count	-0.01	-0.01	-0.00	-0.01	-0.01
Low income	-0.26***	-0.18***	-0.19***	-0.24***	-0.13***
Mid income	-0.11***	-0.08***	-0.08***	-0.10***	-0.06**
Mom no diploma	-0.36***	-0.33***	-0.26***	-0.35***	-0.24***
Mom HS diploma	-0.30***	-0.29***	-0.23***	-0.30***	-0.23***
Mom some college	-0.20***	-0.19***	-0.16***	-0.20***	-0.15***
No father in HH		-0.07***			-0.05**
Changed schools		-0.09***			-0.07***
Parent died		-0.08			-0.07
Other family died		0.00			-0.00
Parent hospitalized		-0.02			-0.05
Parent jailed		-0.11*			-0.06
Parents divorced		-0.05			-0.05
Parent unemp		0.00			0.00
Break-in		-0.04			-0.04
Bullied		-0.08***			-0.08***
Seen shooting		-0.07**			-0.04
Feels unsafe		-0.11***			-0.08***
Victim of crime		-0.02			-0.01
Ever homeless		-0.11**			-0.10*
Coll exp 25-50			0.02		0.01
Coll exp 50-75			0.18***		0.15***
Coll exp 75-100			0.34***		0.28***
Exp: crime victim				-0.00	0.09*
Exp: arrest				-0.14**	-0.04
Exp: death				-0.15***	-0.14***
Exp: pregnancy				-0.21***	-0.10*
Exp: get drunk				-0.03	-0.04
Constant	0.80***	1.00***	0.46***	0.84***	0.70***
Adjusted R^2	0.17	0.21	0.24	0.19	0.28
Observations	2511	2511	2511	2511	2511

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Linear probability model with choice of a four-year public or private non-profit school, given some postsecondary enrollment, as the outcome. "Coll exp X-Y" are indicators for the individual's subjective probability of earning a bachelor's degree being between X and Y percent. The other "Exp" controls represent the subjective probabilities placed on the specified adverse future events. All estimation is weighted using NLSY97 sampling weights.

Table C11: Black Subsample: LPM for Starting at a Four-Year (Not For-Profit) Program, Given Enrollment

	(1)	(2)	(3)	(4)	(5)
Male	-0.07*	-0.06*	-0.06*	-0.05	-0.05
Sibling count	-0.02	-0.02	-0.01	-0.02	-0.01
Low income	-0.10	-0.09	-0.07	-0.09	-0.07
Mid income	0.05	0.07	0.08	0.04	0.07
Mom no diploma	-0.38***	-0.39***	-0.32***	-0.38***	-0.34***
Mom HS diploma	-0.30***	-0.30***	-0.26***	-0.30***	-0.27***
Mom some college	-0.20**	-0.21**	-0.17**	-0.22***	-0.18**
Family shocks		0.01			0.01
Victimization		-0.03*			-0.02
Coll exp 25-50			0.00		0.01
Coll exp 50-75			0.03		0.03
Coll exp 75-100			0.21***		0.19***
Exp: crime victim				0.03	0.03
Exp: arrest				-0.13	-0.05
Exp: death				-0.07	-0.06
Exp: pregnancy				-0.12	-0.08
Exp: get drunk				-0.14*	-0.12*
Constant	0.64***	0.64***	0.43***	0.69***	0.49***
Adjusted R^2	0.13	0.13	0.17	0.14	0.17
Observations	620	620	620	620	620

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Linear probability model with choice of a four-year public or private non-profit school, given some postsecondary enrollment, as the outcome. "Coll exp X-Y" are indicators for the individual's subjective probability of earning a bachelor's degree being between X and Y percent. The other "Exp" controls represent the subjective probabilities placed on the specified adverse future events. All estimation is weighted using NLSY97 sampling weights.

Table C12: Low-Income Subsample: LPM for Starting at a Four-Year (Not For-Profit) Program, Given Enrollment

	(1)	(2)	(3)	(4)	(5)
Black	0.00	0.02	-0.03	0.01	-0.02
Hispanic	-0.01	-0.02	-0.02	-0.00	-0.02
Asian or PI	0.09	0.06	-0.02	0.08	-0.04
Native American	-0.25***	-0.28***	-0.18***	-0.25***	-0.21***
Multiple races	-0.20***	-0.15***	-0.10***	-0.08	0.00
Male	-0.06**	-0.06**	-0.03	-0.04	-0.01
Sibling count	0.00	-0.00	0.00	0.00	0.00
Mom no diploma	-0.33***	-0.32***	-0.23***	-0.32***	-0.22***
Mom HS diploma	-0.28***	-0.27***	-0.19***	-0.27***	-0.19***
Mom some college	-0.19***	-0.18**	-0.15**	-0.19***	-0.14**
Family shocks		-0.04***			-0.03**
Victimization		-0.05***			-0.04***
Coll exp 25-50			-0.00		-0.01
Coll exp 50-75			0.12***		0.11**
Coll exp 75-100			0.24***		0.22***
Exp: crime victim				0.01	0.06
Exp: arrest				-0.21***	-0.11*
Exp: death				-0.04	-0.05
Exp: pregnancy				-0.11*	-0.04
Exp: get drunk				-0.02	-0.04
Constant	0.47***	0.55***	0.26***	0.50***	0.37***
Adjusted R^2	0.06	0.08	0.12	0.07	0.15
Observations	986	986	986	986	986

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Linear probability model with choice of a four-year public or private non-profit school, given some postsecondary enrollment, as the outcome. "Coll exp X-Y" are indicators for the individual's subjective probability of earning a bachelor's degree being between X and Y percent. The other "Exp" controls represent the subjective probabilities placed on the specified adverse future events. All estimation is weighted using NLSY97 sampling weights.

Appendix D Additional Structural Model Features and Results

In this appendix we report on methods used to derive candidate noncompletion probabilities $\alpha^s(X_i)$ from the NLSY97 data, though these are superseded by those used in the main specification based solely on on-time completion rates in each group. We also write the likelihood function, describe how we compute standard errors for our utility parameters, and provide tables containing various parameter and outcome values we use or estimate.

Appendix D.1 Construction of Candidate Noncompletion Probabilities

Let n be the number of years a student enrolls to earn a degree, m be the number of years an "on-time" student would need to complete to earn that degree, and $x = n - m$ (that is, the deterministic number of years students must not have "completed" while enrolled). If π is the proportion of enrollees who earned their degree after n years of enrollment, we can calculate an implied rate of continuous-enrollment noncompletion p among these students using the formula

$$\pi = \frac{(n-1)!}{(n-1-x)!x!} \times p^x(1-p)^m. \tag{7}$$

For example, among Group 1 students, the proportion of bachelor's program enrollees in the NLSY97 who take exactly 6 years to get their degree is 7.2 percent. In this case, $n = 6$, $m = 4$, $x = 2$, and $\pi = .072$. This generates the expression:

$$.072 = \frac{5!}{3!2!} \times p^2(1-p)^4. \tag{8}$$

Essentially, a noncompletion must have happened twice in the first five years of enrollment, since the sixth results in graduation and therefore must have been completed. The first term in the formula determines the number of permutations by which this could happen (here, ten). Then, the latter terms express the probability of two noncompletions and four successfully completed years occurring. Solving for p, this formula has multiple solutions, but the only feasible noncompletion probability[32] among them in this specific case is $p = 0.106$.

These implied noncompletion probabilities differ for different values of n, since in the data the probability is not actually constant. Moreover, to calculate $\alpha^s(X_i)$ values they must be combined with dropout rates, since both types of incident represent educational disruptions or derailment. However, as noted in the main text, the on-time graduation rate suffices to capture all this information. We calculated values of p using (π, n, m, x) values for multiple years and groups, took multiple approaches to finding "central" or average values for each group, and combined these with group-specific dropout probabilities to get values

[32] Other solutions are infeasibly large values.

of $\alpha^s(X_i)$, but always found results quite similar to the derailment probabilities implied by on-time graduation rates.

Appendix D.2 Likelihood Function

Given our assumption that the idiosyncratic ε_{itd} are drawn from a Type 1 Extreme Value distribution, we can derive the following closed-form expression for agent i's probability of choosing an alternative d^* at age t for a candidate vector of utility parameters, denoted Θ:

$$P(d_{it} = d^*|Z_{it};\Theta) = \frac{exp\left[\bar{v_{d^*}}(Z_{it})\right]}{\sum_{d=0}^{2} exp\left[\bar{v_d}(Z_{it})\right]}.$$

This probability is calculated for each annual enrollment choice made by each agent in the data, and is the contribution of agent i at age t to the likelihood function, given the current parameter guesses. If there are N total agents, and each true decision outcome is expressed $\hat{d_{it}}$, the log-likelihood function can be expressed as

$$\mathcal{L} = \sum_{i=1}^{N}\sum_{t=1}^{T}\left[log\left(P(d_{it} = \hat{d_{it}}|Z_{it};\Theta)\right)\right].$$

Appendix D.3 Computation of Standard Errors

We compute standard errors in the estimation of structural utility parameters by constructing the Hessian of the likelihood function using the outer product measure. We calculate a numerical derivative of the likelihood for each estimated parameter (u_1 and u_2) by perturbing each parameter, solving for choice probabilities using the perturbed value, and computing a new likelihood.

Appendix D.4 Tables

The rest of this appendix contains tables reporting dollar-value translations of the utility parameters estimated by the model, and the calculated enrollment rates underlying Figures 1 and 2.

Table D13: Dollar Value of Education Utility

Group	1	2	3	4	5	6	7	8
URM	No	Yes	No	Yes	No	Yes	No	Yes
Low-income	No	No	Yes	Yes	No	No	Yes	Yes
Shocks	No	No	No	No	Yes	Yes	Yes	Yes
Panel A: Rational consideration of noncompletion probability								
Two-year	-3	0	-22	-1	-1	0	-17	-2
Four-year	-610	-435	-493	-394	-848	-200	-583	-299
Panel B: No consideration of noncompletion probability								
Two-year	-1173	-1843	-4697	-3552	-1936	-2161	-4710	-4278
Four-year	-5538	-8597	-11783	-13636	-8136	-9151	-14127	-13515

Estimated annual dollar value of utility in each program type – two-year (associate's) or four-year (bachelor's) – for various demographic groups, rounded to the dollar. In Panel A, individuals rationally consider probabilities of noncompletion; in Panel B, we assume they ignore these probabilities. Columns represent subsamples of respondents who had certain characteristics or not as indicated by the top three rows: individuals from URM (underrepresented minority) groups; those from low-income households (total less than $35,000); and those who experienced at least two of our recorded adverse shocks in childhood.

Table D14: Enrollment Probability at Age 18, Subsidized vs. Unsubsidized

Group	1	2	3	4	5	6	7	8
URM	No	Yes	No	Yes	No	Yes	No	Yes
Low-income	No	No	Yes	Yes	No	No	Yes	Yes
Shocks	No	No	No	No	Yes	Yes	Yes	Yes
Panel A: Rational consideration of noncompletion probability								
Two-year	0.16	0.24	0.22	0.25	0.21	0.23	0.24	0.22
Two-year, Subsidy	0.17	0.24	0.22	0.27	0.21	0.24	0.25	0.24
Four-year	0.28	0.17	0.14	0.08	0.20	0.16	0.08	0.08
Four-year, Subsidy	0.35	0.23	0.21	0.12	0.27	0.23	0.13	0.14
Panel B: No consideration of noncompletion probability								
Two-year	0.17	0.22	0.22	0.25	0.20	0.22	0.24	0.25
Two-year, Subsidy	0.15	0.21	0.22	0.24	0.19	0.22	0.24	0.24
Four-year	0.24	0.14	0.12	0.06	0.18	0.12	0.07	0.06
Four-year, Subsidy	0.29	0.17	0.14	0.08	0.21	0.15	0.09	0.08

Predicted choice probabilities for enrollment in two-year and four-year programs at age 18 by demographic group, based on model parameter estimates. In Panel A, individuals rationally consider probabilities of noncompletion; in Panel B, we assume they ignore these probabilities. "Subsidy" rows consider a $1,000 payment to students who enroll in any type of school. Columns represent subsamples of respondents who had certain characteristics or not as indicated by the top three rows: individuals from URM (underrepresented minority) groups; those from low-income households (total less than $35,000); and those who experienced at least two of our recorded adverse shocks in childhood.