Estimating the Perceived Returns to College*

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Abstract

The primary determinant of an individual's college attendance is their perceived lifetime return to college. I develop a method for inferring agents' perceived returns by exploiting the dollar-for-dollar relationship between perceived returns and tuition costs in a binary choice model of college attendance. This method has the advantage of estimating perceived returns in terms of compensating variation without assuming rational expectations on actual returns. Estimating the model using both maximum likelihood and moment inequalities, I find that the scale of the distribution of perceived returns is an order of magnitude lower than past work has found when assuming rational expectations on income returns. The low variance I find in perceived returns implies high responses to financial aid. I predict a 2.6 percentage point increase in college attendance from a $1,000 universal annual tuition subsidy, which is consistent with quasi-experimental estimates of the effects of tuition assistance on college attendance. Because I estimate the complete distribution of perceived returns, my results can be used to predict heterogeneous effects of counterfactual financial aid policies.

JEL Codes: C31, D84, I21

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1 Introduction

The existence of government financial aid for college suggests a concern that some individuals may make suboptimal choices about attending college. This concern is substantiated by studies such as Cunha, Heckman, and Navarro (2005) that find positive potential returns to college for many individuals who do not attend.[1] Because the actual returns to college are large for many people, errors in this decision will have economically significant effects on income and other outcomes. In order to inform policies that seek to affect individuals' college attendance decisions, it is not enough to estimate their actual returns to college; it is also necessary to estimate their perceived returns to college. Policies that cause perceived returns to look more like actual returns, either by providing information or introducing subsidies, will cause more efficient allocations of individuals into college.

In this paper I develop and implement a methodology for estimating the distribution of perceived returns to college. Using my method, I predict heterogeneous effects across the population on attendance for any given counterfactual change in well-publicized tuition subsidies regardless of whether the policy is applied uniformly across the population or is applied heterogeneously according to individuals' observed characteristics.[2] The primary contribution of this paper is that it is the first to estimate the distribution of perceived returns to college without depending on estimates of actual returns or assumptions regarding agents' knowledge of components of these returns other than pecuniary costs. I do this by estimating the causal effect of tuition on college attendance and comparing this to estimated relationships between individual characteristics and college attendance. I find that my estimates of perceived returns are consistent with the effects of tuition subsidies on attendance that previous studies of natural experiments have found, suggesting that this method can be used to successfully forecast the effects of counterfactual policies on college attendance.

The policy problem at hand is that while the socially optimal allocation of individuals into college requires assignment of individuals based on their actual social returns to college, individuals' actual attendance decisions are determined instead by their perceived private returns to college (and perceived ability to pay). If perceived and actual returns are different in sign or if individuals believe they are credit constrained, policy interventions that alter individuals'

[1]There is also evidence of negative returns for some individuals who do attend college.

[2]The caveat that any such policy must be well-publicized arises from the intuition that individuals will only respond to a policy if they are aware of its effects.

college attendance decisions can be welfare-improving. Information frictions interfere with optimal allocations of individuals into college most obviously by driving a wedge between perceived private returns and actual private returns, but also through interactions with other frictions. Specifically, information frictions interact with externalities if individuals are at all altruistic and have imperfect information about other individuals' preferences, and information frictions interact with credit constraints if perceived credit constraints are different from actual credit constraints.

It follows that in order to fully inform policy, we require estimates of both perceived private utility returns and actual social returns. The social return is comprised of actual private pecuniary returns, actual private nonpecuniary returns, and public returns associated with college attendance. Examples of work on these individual elements include Carneiro, Heckman, and Vytlacil (2011) who find that college attendance is strongly associated with private pecuniary returns to college, Oreopoulos and Salvanes (2011) who find that average nonpecuniary returns to college are potentially even larger than pecuniary returns, and Iranzo and Peri (2009) who find that pecuniary externalities from college are comparable in magnitude to typical estimates of private pecuniary returns. Estimates of perceived returns as obtained in this paper thus contribute a necessary piece of this policy puzzle.

A major advantage of the methodology employed in this paper is that because I do not rely on estimates of actual returns to infer perceived returns, I do not need to parse out the individual contributions of private pecuniary returns, private nonpecuniary returns, and externalities (insofar as they are internalized through altruism) to perceived returns. This allows me to avoid the difficulties involved in estimating these objects as well as the potentially greater difficulties involved in confidently establishing relationships between them and perceived returns.[3] Because the method I use relies on revealed preference arguments regarding observed college attendance, it naturally obtains estimates in terms of the underlying variable that drives attendance, namely, perceived utility returns. The conversion of these utility returns into a dollar scale is accomplished with a straightforward assumption on the perceived marginal cost to students of each dollar of tuition.

Existing research regarding agents' perceived returns to education relies on elicitation or

[3]For instance, because this method does not rely on earnings data, it is immune to selection bias from unobserved earnings for individuals who are not in the workforce. As a result, I have no need to take steps to correct for it such as excluding women from my sample (as is sometimes done in the literature on returns to education because of their low labor force participation relative to men).

estimation (or some combination thereof) of beliefs. Each of these present the researcher with substantial challenges. Elicitation can suffer from a lack of availability, as common data sources infrequently contain responses regarding beliefs about all of the objects of interest to researchers, and can suffer from a lack of reliability, as individuals' survey responses to questions about their beliefs may not correspond to the notion of beliefs used by the researcher.[4] These concerns are reduced for common experimental applications in which availability can be addressed by the experimental design, and reliability is improved both by increased researcher control over question framing and weaker required assumptions about the relationship between respondents' responses to questions and their actual beliefs.[5] In contrast, estimation of beliefs has the benefit that it is based on agents' observed choices rather than potentially unreliable survey responses, but has the disadvantage that beliefs and preferences cannot be jointly estimated, so assumptions must be made about agent preferences to estimate beliefs.[6] These approaches can be blended together by using elicited information on the subset of agent beliefs for which such information is available and reliable and using revealed preference to estimate other beliefs. A more comprehensive discussion of elicitation and estimation of beliefs can be found in Manski (2004).

Because of the lack of availability of reliable elicited information on perceived returns to college in known data sources, I will rely on estimation of beliefs by revealed preference.[7] Cunha and Heckman (2007) provide a valuable overview of related work which estimates heterogeneous ex ante and ex post returns to various education levels in a variety of environments.[8] The method used in these papers (referred to as the CHN method, after Cunha, Heckman, and Navarro) relies on estimates of the distribution of ex post (actual) returns to estimate ex ante (perceived) returns. The main assumption here is that if agents act in accordance with a given component

[4]Individuals' responses regarding beliefs may differ from the beliefs sought by the researcher if they are confused about the question, if demand effects are present, or if interpretation is required to translate responses from the form in which they are provided by respondents to the form in which they are relevant to the economic model. The existence of the experimental literature on how best to elicit beliefs such as Trautmann and Van De Kuilen (2015), further suggests the salience of these concerns.

[5]Jensen (2010), Zafar (2011), and Wiswall and Zafar (2015) are good examples of experimental research in which beliefs are elicited and these concerns are minimal. Because these papers use beliefs as predictors of heterogeneous treatment effects, it is not required that elicited beliefs correspond directly to actual beliefs, but only that they are a valid proxy for actual beliefs, a much weaker assumption.

[6]The problems with jointly estimating beliefs and preferences are described in more detail in Manski (1993).

[7]I am aware of no data source which elicits beliefs about individuals' net present value lifetime returns to college, the object of interest regarding college attendance. Even if such a data source existed, the reliability of responses would be suspect if respondents could conceivably vary in their interpretation of the question. For instance, if respondents differ in whether they incorporate beliefs about nonpecuniary costs into their responses about lifetime returns, the resulting distribution of elicited returns would lack a consistent interpretation.

[8]This includes Carneiro, Hansen, and Heckman (2001, 2003); Cunha and Heckman (2006); Cunha, Heckman, and Navarro (2005, 2006); Navarro (2005); and Heckman and Navarro (2007).

of their real returns (such as the component associated with cognitive ability), they have full information on that component of returns.[9]

The estimation of perceived returns to college in this paper relies on the same revealed preference intuition, but uses estimates of the effect of tuition on attendance from both maximum likelihood and moment inequalities developed by Dickstein and Morales (2015) (henceforth, DM) to identify the scale of perceived returns rather than using estimates of real returns. These methods require the specification of a known relationship only between tuition and perceived returns to college which results in an estimated distribution of perceived returns with minimal dependence by construction on real returns.[10] This improvement occurs because the methods in this paper provide estimates of perceived returns conditional on agent characteristics without requiring that the researcher take a stance on whether these characteristics or their effects on returns are strictly known or unknown to agents, allowing for the possibility that agents have partial knowledge or even biased beliefs about the associated components of returns to college.[11] Allowing for partial knowledge of each component of returns allows for the estimated distributions of perceived returns and actual returns to differ in scale, while allowing for biased beliefs on each component of returns allows the distributions to differ in position.

The plan of the rest of this paper is as follows. Section 2 introduces the empirical model. Section 3 describes the econometric strategy and the assumptions required for identification. Section 4 discusses the data used in estimation of the model. Section 5 provides the results and discusses their implications. Section 6 concludes.

2 Model

The generalized Roy model (1951) provides a helpful framework for considering selection based on potential outcomes. I define Y_{1i} as agent i's perceived present value of lifetime income associated with attending college and Y_{0i} as their perceived present value of lifetime income if

[9]CHN assume rational expectations when identifying ex ante returns. Specifically, they assume that individuals' beliefs about known components of returns are equal to the components' actual individual-specific true values and that beliefs about unknown components of returns are equal to their average values. The first of these assumptions can mistake the scale of perceived returns if agents act on partial information about certain components of returns, while the second restricts unknown components of real returns from having an effect on perceived returns, effectively ruling out systemic bias in perceived returns.

[10]Rational expectations is one example of the assumption on beliefs about tuition. Some assumed dependence between perceived returns and actual returns is retained by the assumption that agents' expectations of tuition can be defined in terms of actual tuition.

[11]In brief, the methods used in the current paper rely on an accurate assumption about the perceived cost to students of one dollar of tuition, while the CHN method relies on an accurate assumption about the mappings from real returns to perceived returns for components of returns depending on whether they are known or unknown.

they were to only complete high school. I further define C_i as their perceived cost of attending college, which includes psychic costs of attending college as well as their preferences over any other outcomes associated with their education decision (spousal income, health outcomes, etc.). Given some forecasting variables X, I can express the perceived potential outcomes and costs for individual i with the following linear-in-parameters production functions:

$$\begin{aligned} Y_{1i} &= X_i\beta_1 + \epsilon_{1i} \\ Y_{0i} &= X_i\beta_0 + \epsilon_{0i} \\ C_i &= X_i\beta_C + \widetilde{Tuition}_i\gamma + \epsilon_{Ci}, \end{aligned} \tag{1}$$

where agent i's expected tuition, $\widetilde{Tuition}_i$, contributes only to the perceived pecuniary cost of college at known marginal rate γ (the marginal percentage of tuition costs actually borne by students) and ϵ_{0i}, ϵ_{1i}, and ϵ_{Ci} are mean zero error terms.[12] In standard applications of the Roy Model, an identification issue arises because potential outcomes are only observed for individuals who make the associated choice, which generates assorted challenges for estimating the marginal effects $\{\beta, \gamma\}$ as well as the covariances between error terms in counterfactual states and the cost function. In this setting, because we cannot observe agent beliefs about earnings or costs for anyone in the sample, none of these parameters can be identified. I will instead focus my attention entirely on the agents' discrete choice problem.

Assuming that agents' utilities are additively separable in inputs, they choose whether to attend college in order to maximize expected net utility such that:

$$S_i = \begin{cases} 1 \text{ if } u(Y_{1i} - C_i) - u(Y_{0i}) \geq 0 \\ 0 \text{ otherwise,} \end{cases} \tag{2}$$

where S_i is an indicator of an agent choosing to attend college. Assuming further that utility is monotonically increasing, it follows that

$$S_i = \begin{cases} 1 \text{ if } Y_{1i} - Y_{0i} - C_i \geq 0 \\ 0 \text{ otherwise.} \end{cases} \tag{3}$$

[12] In general, a variable playing the role of tuition can be included in any of the equations so long as its marginal effect on perceived returns is known to the researcher. It is not necessary for any of the methods used in this paper that this variable satisfy the commonly invoked exclusion restriction of only affecting costs and not potential earnings.

is necessary and sufficient for the condition in equation (2) to hold.[13] This allows me to write the agent's decision equation in terms of compensating variation. This is useful because perceived returns in terms of compensating variation are linear in tuition and tuition subsidies, which I will rely on both in the estimation of perceived returns and in evaluation of policy counterfactuals. Explicitly defining the perceived return $Y_i = Y_{1i} - Y_{0i} - C_i$, as well as net marginal effects $\beta = \beta_1 - \beta_0 - \beta_C$ and $\epsilon_i = \epsilon_{1i} - \epsilon_{0i} - \epsilon_{Ci}$, we can write the perceived return to college in terms of explanatory variables

$$Y_i = X_i\beta - \widetilde{Tuition}_i\gamma + \epsilon_i, \tag{4}$$

which provides us with a standard latent variable equation for the college attendance decision. The empirical goal of this paper is thus to obtain estimates of the distribution of the unobserved perceived return Y by obtaining information about β, γ, $\widetilde{Tuition}$, and the distribution of ϵ.

3 Empirical Strategy

It follows from the model that given X, the distribution of Y can be fully described with accurate values of $\{\beta, \gamma, \widetilde{Tuition}, \epsilon\}$. There are several challenges in obtaining estimates of these objects. First, I note that either of the individual-specific objects $\{\widetilde{Tuition}, \epsilon\}$ have the potential to fully explain all observed behavior, leaving the model underidentified if they are left unrestricted.

To address this issue for $\widetilde{Tuition}$, I will assume tuition is a linear function of agent beliefs,

$$Tuition_i = \frac{\widetilde{Tuition}_i}{\lambda} + \nu_i, \tag{5}$$

in which λ captures agents' systematic and proportional mistakes in estimation of tuition and ν is a mean-zero error term independent of actual tuition that describes any part of actual tuition costs that agents are unaware of when they decide whether to attend college.[14] When $\lambda = 1$, this is a rational expectations assumption on tuition. To address the underidentification issue

[13] In the language of price theory, we can describe $\{\beta_1, \beta_0\}$ as prices on agent characteristics X in the college sector and non-college sector, respectively. Then, the perceived return estimated is the compensating variation for an agent for the change in prices from the college sector to the non-college sector given switching costs given by $\{\epsilon_{1i}, \epsilon_{0i}, C_i\}$. Because the compensating variation is by definition linear in dollars, it provides a conceptual framework that is vital to the identification strategy (which relies on a constant effect of tuition on perceived returns) while also directly addressing the relevant policy issue of the tuition subsidy or tax required to alter individuals' attendance decisions.

[14] This restriction nests that of Dickstein and Morales (2015) that $Tuition$ must be a mean-preserving spread of $\widetilde{Tuition}$ under the assumption $\lambda = 1$. It also nests CHN's assumption that either $Tuition_i = \mathbb{E}[Tuition]$ or $Tuition_i = \widetilde{Tuition}_i$. Note that the assumption that $\mathbb{E}[\nu_i] = 0$ is purely for convenience and has no substantive effect on the estimation of the model. While I can't separately identify any common systematic additive error in agent expectations over tuition, it will be captured by the constant in the perceived returns equation if it exists.

from idiosyncratic ϵ_i, I follow the common binary choice assumption that it is drawn from a normal distribution:

$$\epsilon_i|(X_i, Tuition_i) \sim \mathcal{N}(0, \sigma^2). \tag{6}$$

These assumptions are sufficient to secure estimates of a utility measure of perceived returns across the population, $Y^* = \frac{Y}{\sigma}$ by estimating $\{\beta^*, \gamma^*\} = \{\frac{\beta}{\sigma}, \frac{\gamma}{\sigma}\}$ by maximum likelihood, but will fail to price perceived returns in dollars as is necessary to determine the effects of tuition subsidies or taxes on attendance. This is due to reliance on binary choice outcomes rather than directly observing agents' forecasts of potential outcomes.[15] Given my assumptions that actual tuition affects perceived tuition at constant marginal rate λ and that perceived tuition affects perceived returns at constant marginal rate γ, I secure estimates of perceived returns scaled in dollars by estimating a value for γ and assuming $\lambda = 1$ (rational expectations on tuition), which imply values for the residual parameter vector $\{\beta, \sigma\}$.[16] Note that I do not need to make any assumption on the mean of ν, as this will be absorbed by the model constant in the perceived returns equation. Intuitively, if individuals are additively mistaken about the cost of college, this is indistinguishable from a shift in the distribution of perceived returns. The simple assumption $\lambda = \gamma = 1$ implies that a dollar increase in tuition is perceived by agents to cost them a dollar.[17] Finally, as this is fundamentally a forecasting model, in general it is not necessary that any of the parameters have a causal interpretation, but rather than the chosen value of any one parameter within $\{\beta, \gamma\lambda, \sigma\}$ corresponds to the hypothetical value it would take on in the forecasting equation of the latent variable:

$$Y_i = X_i\beta - Tuition_i\gamma\lambda + \epsilon_i. \tag{7}$$

In practice, I will need causal first stage estimates of the effect of tuition on attendance because the values of λ and γ that I use have causal interpretations. I choose $\lambda = 1$ with a rational expectations assumption on tuition (but not on the component of the error term that is corre-

[15] This problem arises because of the commonly known issue of binary choice models being underidentified by one parameter. This can be addressed by the normalizing assumption $\sigma = 1$ if the scale of the latent variable Y is irrelevant, as is the case for applications relating to the causes or prediction of choice outcomes. In these cases, it is common to work exclusively with the scale-invariant version of the latent variable, $Y^* = \frac{Y}{\sigma}$.

[16] In other words, if the relationship between tuition and perceived returns in dollars is known, then the ratio of the marginal effects of X on attendance and marginal effects of tuition on attendance provides the relationship between X and perceived returns in dollars. Mathematically speaking, $\frac{\partial Y^*}{\partial X} / \frac{\partial Y^*}{\partial Tuition} = \frac{\partial Y}{\partial X} / \frac{\partial Y}{\partial Tuition}$. Given the left-hand side of this equation provided by the first stage estimates of the discrete choice model and the term $\frac{\partial Y}{\partial Tuition} = \gamma\lambda$ where γ and λ are exogenous to the model, the term $\frac{\partial Y}{\partial X}$ is provided by simple algebra.

[17] If agents' beliefs are multiplicatively biased, $\lambda \neq 1$ and if they do not bear the full brunt of tuition costs, $\gamma \neq 1$. The estimation of γ is covered in Appendix D.

lated with tuition), and I estimate γ from the proportion of tuition costs paid by parents and other relatives as reported in my data.

3.1 Full Information with Exogenous Tuition

It is helpful to begin by describing how one could estimate the model if agents had perfect foresight over tuition and tuition were independent of the error term in the decision equation. Formally, this amounts to assuming that $\widetilde{Tuition}_i = Tuition_i\ \forall i$, which amounts to assuming that $\lambda = 1$ such that there is no systematic bias in beliefs about tuition, and that $\nu_i = 0\ \forall i$ such that there is no random error in agents' beliefs about tuition. If this assumption holds, I can directly replace the otherwise unobserved object of interest $\widetilde{Tuition}_i$ with data on tuition. The additional assumption that tuition is independent of ϵ will be violated if individuals with higher than expected perceived returns go to more expensive colleges or receive larger scholarships. If these assumptions hold, I can interpret the estimated relationship between tuition and attendance as causal such that it is consistent with my calibrated value for the effect of tuition on perceived returns. In this case, the decision rule is

$$S_i = \begin{cases} 1 \text{ if } X_i\beta - Tuition_i\gamma + \epsilon_i \geq 0 \\ 0 \text{ otherwise.} \end{cases} \tag{8}$$

The assumption of normally distributed errors allows me to write the probability of selection into college as

$$Pr(S_i = 1 | X_i, Tuition_i) = \Phi\Big(\frac{X_i\beta - Tuition_i\gamma}{\sigma}\Big), \tag{9}$$

where $\Phi(\cdot)$ denotes the standard normal cdf. We can thus estimate the parameters $\psi^* = \{\beta^*, \gamma^*\} = \{\frac{\beta}{\sigma}, \frac{\gamma}{\sigma}\}$ as the values that maximize the log-likelihood:

$$\begin{gathered} \mathcal{L}(\beta^*, \gamma^* | X, Tuition) = \\ \sum_i S_i \log\left(\Phi\Big(X_i\beta^* - Tuition_i\gamma^*\Big)\right) + (1 - S_i)\log\left(1 - \Phi\Big(X_i\beta^* - Tuition_i\gamma^*\Big)\right). \end{gathered} \tag{10}$$

Importantly, the assumption that agents know the exact values of the observed (by the researcher) tuition allows us to take it as given from the data. In general, the estimates we obtain are of the marginal effect of increasing tuition in the dataset, which will only be the same as the effect of increasing expected tuition if there is perfect information.[18] Maximum likelihood estimation of this model will produce estimates of $\{\beta^*, \gamma^*\}$ rather than that parameters of interest, $\{\beta, \sigma\}$. I convert estimates $\{\hat{\beta}^*, \hat{\gamma}^*\}$ into estimates $\{\hat{\beta}, \hat{\sigma}\}$ by assuming a known value for γ. Specifically:

$$\begin{aligned} \hat{\sigma} &= \frac{\gamma}{\hat{\gamma}^*}; \\ \hat{\beta} &= \hat{\sigma}\hat{\beta}^*. \end{aligned} \tag{11}$$

To be clear, if my distributional assumption on ϵ is accurate, the estimates obtained by maximum likelihood can be used to consistently forecast selection into college regardless of whether agents perfectly know $Tuition$ or whether $Tuition \perp\!\!\!\perp \epsilon$. This is the reason agents' beliefs are not relevant in common applications that seek only to describe the relationships between agents' characteristics and the probability of making a given choice. In this application, I want to not only forecast selection but to uncover the distribution of the latent variable (the perceived return to college) in dollars, so I am relying on the accuracy of the scale assumption on γ to avoid the standard assumption $\sigma = 1$. Insofar as these assumptions rely on the argument that an increase in tuition of one dollar causes agents to believe their net present value lifetime return is reduced by a known amount, it will only hold if our estimate of the effect of tuition on selection is causal. In the naive analysis I just described, I have assumed away two major threats to the causal interpretation, dependence between tuition and ϵ, and imperfect information on tuition. In the two succeeding subsections, I will address each of these threats and provide solutions to the problem of identification in the context in which these threats are present.

3.2 Partial Information & Endogeneity on Tuition: Instrumental Variables MLE

There is reason to think that agents do not have perfect information on tuition. For one, tuition costs for years beyond the first are not necessarily known even to colleges at the time of potential students' attendance decisions, and are thus unlikely to be perfectly forecast by potential students. Additionally, past work finds substantial inaccuracy and variance in individuals' elicited beliefs regarding tuition costs (for example Bettinger, Long, Oreopoulos, and Sanbonmatsu (2012)). I maintain the assumption of a constant known effect of tuition on perceived returns, but I will relax the assumption that agents have perfect information on tuition. Addi-

[18] Even with i.i.d. errors ϵ_i and ν_i, assuming $\lambda = 1$ will bias the scale of perceived returns by a factor of λ while assuming $\nu_i = 0\ \forall i$ will introduce attenuation bias in first stage estimates of γ^* if $Var(\nu) > 0$.

tionally, I will allow for correlation between tuition and the error term in perceived earnings as high unobserved ability individuals may pay higher net tuition due to attending higher quality colleges, or may pay lower net tuition due to the effect of merit-based scholarships, which would bias the standard maximum likelihood estimate of the effect of tuition on attendance upwards and downwards, respectively.

It is impossible to characterize the bias in estimates that will result from wrongly assuming perfect information on tuition without making restrictions on the relationship between agents' beliefs and reality. The bias that will arise from assuming $\widetilde{Tuition}_i = Tuition_i$ depends on the true relationship $Tuition_i = f(\widetilde{Tuition}_i)$, where $f(\cdot)$ provides the mapping from agents' actual beliefs to the data on tuition. However, when ν_i is a mean zero error term and λ is a constant as in (5), it is straightforward to characterize the bias in first stage estimates of γ^* from assuming perfect information. Considering first the extreme case in which $\nu_i = 0\ \forall i$, it is clear from considering (5) and (10) that we would not obtain first stage estimates of γ^*, but rather $\gamma^*\lambda$. In this case, making the correct assumption on the value of λ will be necessary and sufficient to secure unbiased estimates of γ^*. Considering the case when $Var(\nu_i) \neq 0$, the simplest way to describe the bias is to realize that if $\lambda = 1$, tuition contains classical measurement error if used as a measurement of $\widetilde{Tuition}_i$. This will result in attenuation bias in first stage estimates of γ^* if I use tuition in place of $\widetilde{Tuition}$ in the estimation. Because I obtain estimates of σ by applying the normalization given in (11), the attenuation bias in estimates of γ^* will result in bias away from zero in estimates σ, which will similarly cause bias away from zero in estimates of β.

In this section, I describe how to address both the issue of endogeneity in tuition and measurement error in tuition as a measurement of beliefs about tuition using maximum likelihood with instrumental variables. The model is given by the assumption on selection given by (3) and the characterization of agents' beliefs in (4) with the addition of the following description of the relationship between the determinants of perceived tuition and the instruments Z,

$$\begin{aligned} \widetilde{Tuition}_i &= Z_i\delta + u_i \\ Tuition_i = \frac{\widetilde{Tuition}_i}{\lambda} + \nu_i &= \frac{Z_i\delta + u_i}{\lambda} + \nu_i. \end{aligned} \tag{12}$$

If the instrument Z is uncorrelated with both ϵ and ν (where it is uncorrelated with u by construction), then it is a valid instrument for beliefs about tuition insofar as it is a valid instrument for tuition. The error terms $\{\epsilon, u, \nu\}$ can be freely interdependent if Z is a valid instrument for beliefs about tuition.[19] The key result under these assumptions is

$$\widehat{\widetilde{Tuition}}_i = \lambda \widehat{Tuition}_i = Z_i \hat{\hat{\delta}}, \tag{13}$$

which allows me to use the first stage estimates of the effect of Z on tuition to obtain an estimate of beliefs about tuition, $\widehat{\widetilde{Tuition}}_i$, that contains neither the endogenous error u nor the measurement error ν.

I assume that ϵ_i and u_i are distributed according to an i.i.d. multivariate normal

$$(\epsilon_i, u_i)|(X_i, Z_i) \sim \mathcal{N}(0, \Sigma), \tag{14}$$

where the covariance matrix Σ is given by:

$$\Sigma \equiv \begin{bmatrix} \sigma^2 & \sigma_{u\epsilon} \\ \sigma_{u\epsilon} & \sigma_u^2 \end{bmatrix}. \tag{15}$$

Under these assumptions, it is convenient to replace $\widetilde{Tuition}_i$ in terms of the instrument Z in the perceived returns equation as follows:

$$Y_i = X_i\beta - Z_i\delta\gamma - u_i\gamma + \epsilon_i, \tag{16}$$

where the assumption in (15) implies

$$(\epsilon_i - u_i\gamma)|(X_i, Z_i) \sim \mathcal{N}(0, \sigma^2).^{20} \tag{17}$$

Then, I can follow Rivers and Vuong (1988) in writing the log-likelihood as:

$$\begin{gathered} \mathcal{L}(\beta^*, \gamma^*|X, Z) = \\ \sum_i S_i \log \Big[\Phi(X_i\beta^* - Z_i\delta\gamma^*)\Big] + (1 - S_i) \log \Big[1 - \Phi(X_i\beta^* - Z_i\delta\gamma^*)\Big]. \end{gathered} \tag{18}$$

[19] The composite error term $\frac{u_i}{\lambda} + \nu_i$ will play the same role as the error term in a standard instrumental variables first stage equation.

[20] I denote $Var(\epsilon_i - u_i\gamma) = \sigma^2$ in the IV Probit model while also denoting $Var(\epsilon_i) = \sigma^2$ in the Probit model by recognizing that $u_i\gamma = 0$ by construction in the Probit model (tuition effectively serves as an instrument for itself, such that $u_i = 0\ \forall i$). This allows for notational simplicity in the comparison of the variance of the unobserved error in perceived returns across specifications.

Noting the absence of the problematic terms u_i and ν_i, it follows that the IV Probit estimates $\{\hat{\beta}^*_{IVP}, \hat{\gamma}^*_{IVP}\}$ will be consistent estimates of the true $\{\beta^*, \gamma^*\}$ if Z is a valid instrument and the assumption on the error terms u_i and ϵ_i are correct. With the assumption on the distribution of the error term, I obtain estimates of the distribution of perceived returns to college by plugging these estimates into the latent variable equation:

$$Y_i|(X_i, Z_i) \sim \mathcal{N}(X_i\hat{\beta} - Z_i\hat{\delta}\gamma, \hat{\sigma}^2). \tag{19}$$

3.3 Partial Information & Endogeneity on Tuition: Moment Inequalities

With valid instruments Z, the instrumental variables Probit described in the last section will provide consistent estimates of the true parameters $\{\beta^*, \gamma^*\}$ under an accurate specification of the first stage (12) if the assumption of joint normality stated in (15) is correct. If the first stage is misspecified the estimation will have the same problems as those associated with weak instruments. If the error term u_i is sufficiently non-normal, the estimates $\{\beta^*, \gamma^*\}$ will be biased away from their true values according to the shape of the actual distribution of u_i.

Because the actual beliefs about tuition are never observed, it is impossible to formally test either the strength of the first stage or the distribution of the error term in the first stage (in addition to the standard untestability of the validity of the instrument). I repeat the first stage from the IV Probit here for reference:

$$Tuition_i = \frac{\widetilde{Tuition}_i}{\lambda} + \nu_i = \frac{Z_i\delta + u_i}{\lambda} + \nu_i. \tag{20}$$

Because I use Z as an instrument for $Tuition$ as a work-around to instrumenting for $\widetilde{Tuition}_i$, any test of the strength of the first stage will relate to the relationship between Z and $Tuition$ rather than $\widetilde{Tuition}$. If agents have incomplete information on tuition even conditional on Z, such a test will overstate the strength of the instrument. As such, any related test statistic should be viewed as an upper bound measure of the strength of the instrument. It is thus valid to reject a sufficiently weak instrument, but a high test statistic is insufficient to establish the strength of the instrument for predicting $\widetilde{Tuition}$.

Regarding the distribution of the first stage error, it is apparent from the above equation that I cannot estimate u_i directly. The best I can do is to estimate $\frac{u_i}{\lambda} + \nu_i$ from the difference between $Tuition$ and its predicted value given Z. Rejecting normality in this composite error term is neither necessary nor sufficient to reject the normality assumption on u.

Fortunately, the moment inequalities described by Dickstein and Morales (2015) will find consistent estimates of $\{\beta^*, \gamma^*\}$ when agents have partial knowledge of tuition as described in equation (20) without the need of functional form assumptions or error term assumptions on the first stage.[21] The first set of moment inequalities are based directly on revealed preference arguments and are similar to those used in Pakes (2010) and Pakes, Porter, Ho, and Ishii (2015). The second set are based on maximum likelihood. Both sets of inequalities rely on variation in Z to identify the effect of tuition, maintaining the assumption that Z is a valid instrument for beliefs about tuition and is uncorrelated with the part of tuition that is unknown to agents.[22] Because this method places weaker restrictions on the relationship between the instruments and agents' beliefs about tuition, it will provide a set of parameter values that satisfy the inequalities rather than point estimates of model parameters.

3.3.1 Revealed Preference Moment Inequalities

The conditional revealed preference moment inequalities are given by

$$\begin{aligned} &\mathbb{E}\left[-(1-S_i)(X_i\beta^* - Tuition_i\lambda\gamma^*) + S_i\frac{\phi(X_i\beta^* - Tuition_i\lambda\gamma^*)}{\Phi(X_i\beta^* - Tuition_i\lambda\gamma^*)}\middle| Z_i\right] \geq 0, \\ &\mathbb{E}\left[S_i(X_i\beta^* - Tuition_i\lambda\gamma^*) + (1-S_i)\frac{\phi(X_i\beta^* - Tuition_i\lambda\gamma^*)}{1-\Phi(X_i\beta^* - Tuition_i\lambda\gamma^*)}\middle| Z_i\right] \geq 0. \end{aligned} \tag{21}$$

where Z is a valid instrument for perceived tuition. These inequalities are consistent with the revealed preference argument that perceived returns are positive for those who select into college and negative for those who do not. The formal proof of the revealed preference inequalities can be found in Dickstein and Morales (2015), but I will provide a sketch of the intuition here.

Consider an agent that chooses to enroll in college such that $S_i = 1$. Following the standard revealed preference arguments articulated in (3), it must be the case that such an individual's

[21] DM do not explicitly account for λ in their methodology, but its inclusion is a trivial extension. Any estimate of γ^* made under the normalizing assumption $\lambda = 1$ can be converted into an estimate under a different assumption on λ by simply multiplying it by λ.

[22] Dickstein and Morales describe this assumption as agents knowing Z. Technically, it is only necessary that agents know predicted tuition given Z, not Z itself. This weaker assumption allows for the inclusion of instruments in Z that agents may not consciously know as long as the distribution of agent beliefs about tuition conditional on Z is degenerate. This means that even though agents likely do not consciously know the average tuition in their county of residence at age 17, this instrument still passes the information test if agents' beliefs about tuition vary with it as much as actual tuition varies with it. Additionally, because I will include X in Z as is standard for instrumental variables, I do not need to assume that agents know anything about X with respect to their perceived returns to college, but only that they know about their tuition conditional on X.

perceived return to college is positive such that

$$S_i(X_i\beta - \widetilde{Tuition}_i\gamma + \epsilon_i) \geq 0. \tag{22}$$

We do not observe ϵ_i for anyone, but this condition should hold on average if it holds for individuals. Taking the expectation across individuals conditional on X, the unobserved $\widetilde{Tuition}_i$, and the observed college choice yields

$$\mathbb{E}\left[S_i(X_i\beta^* - \widetilde{Tuition}_i\gamma^*) + (1-S_i)\frac{\phi(X_i\beta^* - \widetilde{Tuition}_i\gamma^*)}{1-\Phi(X_i\beta^* - \widetilde{Tuition}_i\gamma^*)}\middle| X, \widetilde{Tuition}_i\right] \geq 0. \tag{23}$$

The second moment inequality above is thus obtained by replacing the unobserved $\widetilde{Tuition}_i$ with $Tuition_i\lambda$ and conditioning on Z. The inequality is maintained after the this substitution by Jensen's inequality as long as $Tuition_i\lambda$ is a mean-preserving spread of $Tuition$ because the expectation of the error term is convex.[23] As long as Z is a valid instrument for perceived tuition, the inequalities are maintained conditional on Z by law of iterated expectations. The first inequality follows from the same intuition applied to individuals who do not select into college.

3.3.2 Odds-Based Moment Inequalities

The conditional odds-based moment inequalities are given by

$$\begin{aligned}
&\mathbb{E}\left[\left(S_i\frac{1-\Phi(X_i\beta^* - Tuition_i\lambda\gamma^*)}{\Phi(X_i\beta^* - Tuition_i\lambda\gamma^*)} - (1-S_i)\right)\middle| Z_i\right] \geq 0, \\
&\mathbb{E}\left[\left((1-S_i)\frac{\Phi(X_i\beta^* - Tuition_i\lambda\gamma^*)}{1-\Phi(X_i\beta^* - Tuition_i\lambda\gamma^*)} - S_i\right)\middle| Z_i\right] \geq 0.
\end{aligned} \tag{24}$$

Proofs of these inequalities are available in Dickstein and Morales (2015), but I include here an overview of the intuition. First note that the log-likelihood conditional on $\{X, \widetilde{Tuition}_i\}$ is

$$\begin{aligned}
&\mathcal{L}(S_i|X, \widetilde{Tuition}_i; \beta^*, \gamma^*) = \\
&\mathbb{E}\left[S_i \log\left(\Phi(X_i\beta^* - \widetilde{Tuition}_i\gamma^*)\right) + (1-S_i)\log\left(1-\Phi(X_i\beta^* - \widetilde{Tuition}_i\gamma^*)\right)\middle| X, \widetilde{Tuition}_i\right],
\end{aligned} \tag{25}$$

[23]The restriction of beliefs given by (5) is sufficient for the application of Jensen's inequality for any error distribution with a convex inverse-mills ratio, such as the Normal and the Logistic distributions.

for which the score equation is given by

$$\mathbb{E}\left[S_i \frac{\phi(X_i\beta^* - \widetilde{Tuition_i}\gamma^*)}{\Phi(X_i\beta^* - \widetilde{Tuition_i}\gamma^*)} - (1-S_i)\frac{\phi(X_i\beta^* - \widetilde{Tuition_i}\gamma^*)}{1-\Phi(X_i\beta^* - \widetilde{Tuition_i}\gamma^*)}\middle| X, \widetilde{Tuition_i}\right] = 0. \tag{26}$$

The intuition of the odds-based moment inequalities is fundamentally the same as that of the conditional score function, which essentially describes the way a marginal change in the value of a parameter within $\{\beta^*, \gamma^*\}$ will affect the model's accuracy in predicting selection ($S_i = 1$) and nonselection ($1 - S_i = 1$). The score function assigns higher weights to model failure than to model success, so that marginal changes in parameters that improve very bad predictions will be prioritized over those that improve slightly bad predictions.[24]

The fundamental goal is to replace the unobserved $\widetilde{Tuition}$ with $Tuition$ and to predict the effect of this on the score equation. Dickstein and Morales (2015) show how to achieve this by transforming the score function into two convex functions by normalizing the weights on selection and nonselection respectively to unity. The resulting transformations of the score function,

$$\begin{aligned}
&\mathbb{E}\left[\left(S_i \frac{1-\Phi(X_i\beta^* - \widetilde{Tuition_i}\gamma^*)}{\Phi(X_i\beta^* - \widetilde{Tuition_i}\gamma^*)} - (1-S_i)\right)\middle| X, \widetilde{Tuition_i}\right] = 0,\\
&\mathbb{E}\left[\left((1-S_i) \frac{\Phi(X_i\beta^* - \widetilde{Tuition_i}\gamma^*)}{1-\Phi(X_i\beta^* - \widetilde{Tuition_i}\gamma^*)} - S_i\right)\middle| X, \widetilde{Tuition_i}\right] = 0.
\end{aligned} \tag{27}$$

are globally convex in $\widetilde{Tuition_i}$. This allows us to apply Jensen's inequality to predict the direction of the inequality when replacing $\widetilde{Tuition_i}$ with $Tuition\lambda$ as long as $Tuition\lambda$ is a mean-preserving spread of $Tuition$ as assumed in (5). As with the revealed preference inequalities, these inequalities still hold conditional on Z as long as agents know tuition insofar as it is predicted by Z by law of iterated expectations, leading to the odds-based moment inequalities in (24).

It may seem like the two moment inequalities in (24) would be redundant as they are both

[24]To see this clearly, recall that

$$\lim_{x\to-\infty}\frac{\phi(x)}{\Phi(x)} = |x|,\ \lim_{x\to\infty}\frac{\phi(x)}{\Phi(x)} = 0;$$
$$\lim_{x\to-\infty}\frac{\phi(x)}{1-\Phi(x)} = 0,\ \lim_{x\to\infty}\frac{\phi(x)}{1-\Phi(x)} = |x|.$$

Thus when chosen parameters predict that an individual is very likely to select into college such that $X_i\beta^* - \widetilde{Tuition_i}\gamma^*$ is large, this individual's contribution to the score will be small if they actually do attend college and large if they do not.

derived from normalizations on the score function. The key point, however, is that $\widetilde{Tuition_i}$ is replaced with $Tuition_i\lambda$ after this normalization, so the resulting inequalities are not simply transformations of one another. The easiest way to see this is to imagine the case in which the constant $\beta_0^* \to \infty$ with all other parameters remaining at their true values such that the terms inside the cdfs become arbitrarily large and positive. It can be seen in this case that the first inequality would approach $\mathbb{E}[-(1-S_i)|Z_i] \geq 0$, violating the inequality, while the second would become unboundedly large, satisfying the inequality. A sufficiently low value for β_0^* will violate the second constraint for similar reasons. In this way, the two inequalities provide bounds on the parameters. A further discussion of the intuition behind these inequalities is available in Dickstein and Morales (2015).

3.3.3 Estimation Using Moment Inequalities

Under the information assumptions provided, the true parameter $\psi^* = \{\beta^*, \gamma^*\}$ will be contained within the set of parameters that satisfy the inequalities, which I define as Ψ_0^*. First, because it is computationally expensive to compute the inequalities conditional on Z, I will instead use unconditional inequalities that are consistent with the conditional inequalities described above. Additionally, in small samples it is possible that the true parameters will not strictly satisfy these inequalities, so it is necessary to construct a test of the hypothesis that a given value $\psi_p^* = \{\beta_p^*, \gamma_p^*\}$ is consistent with the inequalities. To do this I employ the modified method of moments procedure described by Andrews and Soares (2010). A description of this procedure is available in Appendix B.

4 Data

The primary dataset used is the Geocode file of the 1979 National Longitudinal Survey of Youth (NLSY79). This data source provides a wide variety of information on individuals who were between the ages of 14 and 22 in 1979. Vitally, it provides information on the college(s) that individuals attended if they attended college as well as loans and financial aid received during college. Because the Geocode file provides detailed geographic information, it can also be combined with other datasets to obtain average tuition for both local colleges in individuals' counties of residence at age 17 and actual tuition for the college that they attended. The geographic information is also useful for obtaining information on local labor market characteristics. This dataset also includes a rich set of information on individuals' academic abilities and family characteristics that are predictive of college attendance, including information about the percentage of college costs that individuals pay themselves. As a final advantage, this dataset has been used extensively in the related literatures on ex ante returns such as Cunha, Heckman, and Navarro (2005) and Cunha and Heckman (2016) and the effects of policy interventions on college attendance such as Dynarski (2003) so that the relationships between this paper's results and those of existing work can be readily attributed to differences in methodology rather than differences across datasets. I merge this dataset with data on colleges from the Integrated Postsecondary Education Data System (IPEDS), and data on local and state labor markets from the Bureau of Economic Analysis (BEA) and the Bureau of Labor Statistics (BLS).

Other than dropping 41 individuals who reported graduating from college without ever attending college, I do not impose any limitations on the sample. Notably, because I do not use actual income to infer perceived returns, there is no reason to exclude women due to fertility and labor force participation concerns as is common in the literature.[25] The initial sample of 12,686 is reduced to 5,492 due to missing observations for variables of interest. A description of the data is provided in Table 1.[26]

I choose college attendance as the decision of interest.[27] This assumes that individuals who attend college do so because they perceive the return to completing a 4-year degree to be positive. If any individuals begin college intending to drop out because their perceived returns to fewer than 4 years of college are positive but their perceived returns to 4 years of college are negative, I will overestimate their perceived returns to college by using attendance as the relevant decision. I expect that such individuals are rare. I find that approximately 57% of my sample attended college after high school. This rate is somewhat lower in my data than the current average because college enrollment was lower in the early 1980's (when the individuals in my sample were attending college) and because the NLSY79 contains oversamples of poor whites and minorities who are less likely to attend college than average. I code an individual

[25] I will include some results for white males purely for comparability to the literature.

[26] The transformation of ASVAB scores to have positive support is required because a cancellation that takes place in the derivation of the moment inequalities requires that each variable's support in the data have a common sign. This transformation has no substantive effect on the estimation as the constant in the model will adjust to offset it. Average county wages come from the Bureau of Economic Analysis, and state unemployment rates come from the Bureau of Labor Statistics. These are matched to the primary dataset using the NLSY79's geographic information.

[27] The same estimation procedure could be performed on graduation, but would somewhat complicate the interpretation as dropping out suggests dynamic changes in information. Extensions of the estimation strategy that allow for ordered decisions and information dynamics would be well suited to investigating differences between attendance and completion and are left to future research.

Table 1: Description of the Primary Variables

	Overall mean	High School Graduates mean	College Attendees mean
Mother Education	11.194	10.263	11.899
Father Education	11.198	9.860	12.214
Number of Siblings	3.611	4.160	3.195
ASVAB Score Subtest 3	0.071	-0.120	0.216
ASVAB Score Subtest 4	0.061	-0.167	0.234
ASVAB Score Subtest 5	0.073	-0.155	0.246
ASVAB Score Subtest 6	0.079	-0.154	0.257
ASVAB Score Subtest 7	0.073	-0.098	0.202
ASVAB Score Subtest 8	0.072	-0.070	0.180
ASVAB Score Subtest 9	0.068	0.040	0.090
ASVAB Score Subtest 10	0.064	-0.249	0.302
ASVAB Score Subtest 11	0.064	-0.037	0.140
ASVAB Score Subtest 12	0.064	-0.040	0.144
High School GPA	2.357	1.943	2.671
Broken Home	0.323	0.366	0.291
Urban Residence at Age 14	0.779	0.750	0.801
Average County Wage at Age 17	10.579	10.532	10.614
State Unemp Rate at Age 17	7.135	7.148	7.126
Tuition	13,662	9,267	16,995
Effective Tuition	7,343	5,776	8,532
Observations	5492	2369	3123

Notes: Means are of all NPSY79 samples. Parents' education is in years. High school GPA is out of a maximum value of 4. All dollar values are adjusted to 2018 values using a 3% interest rate. Each ASVAB test score is transformed to have unit variance and zero mean. Broken home indicates the absence of either biological parent in the home for any year from birth to age 18.

as having attended college if they explicitly report having received a college degree by age 23 or if they report a highest grade attended above 12 by age 23.

Because I focus on a single decision at a single point in time, I do not convert the NLSY79 dataset into panel data. I instead use the longitudinal data to obtain information about the timing of college attendance, college tuition, and scholarships in years prior to receipt of a bachelor's degree and to obtain retrospective information that influences the college attendance decision. I use four times the average present value (in 2018 terms, using a 3% interest rate) of tuition in all years prior to receipt of a bachelors degree to construct a total present value tuition measure for individuals who complete a 4-year degree. I use the information on tuition for individuals who complete college and attend 4-year colleges to impute counterfactual 4-year tuition for individuals who did not attend college.

Noting that I only observe tuition for individuals that attend college and that individuals only attend college if their perceived return to college is positive, I impute tuition in a manner that is consistent with the model of college attendance described above. I control for variables

X_T while accounting for selection with the system:

$$Tuition_i = \begin{cases} X_{iT}\alpha_T + Local\_Tuition\_17_i\alpha_{LT} + \xi_{iT} & \text{if } S_i = 1 \\ . & \text{otherwise,} \end{cases} \tag{28}$$

$$S_i = \begin{cases} 1 \text{ if } Z_{iT}\alpha_S - Local\_Tuition\_17_i\alpha_{LS} + \xi_{iS} > 0 \\ 0 \text{ otherwise,} \end{cases} \tag{29}$$

in which a variable within Z_T satisfies the exclusion restriction that it is not included in X_T. Because I do not observe tuition for people who do not attend college (the very problem I seek to address), I use local tuition at age 17 (the instrument for tuition) in these equations instead of actual tuition. Secondly, I argue that distance from college at age 14 provides variation in selection that does not otherwise affect tuition, such that I can exclude it from X_T while including it in Z_T.

Using distance to college as an instrument for educational attainment was introduced by Card (1993) to estimate the effect of education on earnings. Its use is similar here in predicting college attendance, but the identification here relies on it having no effect on tuition conditional on other controls, while making no assumption on its effect on earnings. An additional concern specific to tuition is that distance to college may be associated with college prices, for instance if more rural areas are more likely to have small community colleges than urban areas. I address this concern by controlling for local tuition in county of residence at age 17 as well as including an indicator variable for living in an urban county. Conditional on AFQT, local tuition at age 17, urbanicity of residence, and the other controls in X_T, I argue that distance to college only contributes a measure of the potential costs associated with housing and transportation associated with college attendance, which should predict attendance without otherwise affecting tuition.

Relatedly, use of average local tuition at age 17 as an instrument for the effect of college attendance on earnings was introduced by Kane and Rouse (1995). I include this as a control for the imputation of tuition while using it as an instrument in estimation of perceived returns. For individuals who live in a county with a college, I use the enrollment-weighted average tuition of public 4-year colleges in their county. For individuals who do not live in a county with a college, I use the state-level enrollment-weighted average. Instead of relying on this instrument affecting selection without otherwise affecting earnings as it has primarily been used in the past, I rely on it affecting tuition without otherwise affecting selection.

One concern with the use of distance to college to instrument for selection into college is that it has been shown to be correlated with AFQT, a measure of ability. To address this concern, I include each ASVAB subtest, from which the AFQT score is computed, as controls in all estimated equations. Hansen, Heckman, and Mullen (2004) show that years of schooling at the time of testing affects AFQT scores, so rather than using raw ASVAB scores, I use the residual of each test score after controlling for years of education. I make no other adjustments to any of the variables in the data.

At first glance, the imputation of tuition and the estimation of the model may seem circular because I estimate a selection equation to impute tuition and then use imputed tuition to estimate a very similar selection equation for the main results. A succinct chronological ordering of each step in the estimation procedure is helpful for dispelling this potential confusion. First, I estimate the selection equation (29) using variables that are observed for everyone in my sample. Because I only use these estimates to control for selection, I am uninterested in the scale of the latent variable of this equation as well as causal effects of any variables on the latent variable. Second, I use these estimates to impute tuition with (28) while controlling for selection from (29) with the exclusion restriction that distance to college affects attendance but not potential tuition. Third, I instrument for this imputed tuition with local tuition at age 17 in (12). Fourth, I use the instrumented value of tuition to estimate the causal effect of tuition on selection.[28] Finally, I apply the normalization assumption that tuition affects perceived returns at known marginal rate γ. Table 2 shows the variables that are and are not included in each estimated equation both for the tuition imputation and for the main results.

I estimate a value for γ using data from the NLSY79 on the proportion of college tuition paid for by the student. This data is only available in 1979, so I impute a value for the proportion of costs paid using ordinary least squares. In practice, I will use this $\hat{\gamma}(X_i)$ when estimating perceived returns, such that each individual is allowed to differ in the amounts of pecuniary costs they bear. The estimation of $\gamma(X)$ is described in detail in Appendix D.

Finally, Because the moment inequalities are estimated using a grid search, they are highly computationally expensive. For this reason, I use principal components to reduce the parameter space to a constant, a coefficient on tuition, a coefficient on the first principal component of

[28] For the moment inequalities, steps 3 and 4 are integrated into one step.

Table 2: List of Variables Included and Excluded in Each System

Variable Name	Tuition (Observation) (Z_T)	Tuition (Imputation) (X_T)	Return IVs (Z)	Return (X)
Imputed Tuition	·	·	·	✓
Local Tuition, Age 17	✓	✓	✓	·
ASVAB (All Tests)	✓	✓	✓	✓
Mother's Education	✓	✓	✓	✓
Mother's Education Squared	✓	✓	✓	✓
Father's Education	✓	✓	✓	✓
Father's Education Squared	✓	✓	✓	✓
Number of Siblings	✓	✓	✓	✓
Number of Siblings Squared	✓	✓	✓	✓
Urban at Age 14	✓	✓	✓	✓
High School GPA	✓	✓	✓	✓
High School GPA Squared	✓	✓	✓	✓
Broken Home	✓	✓	✓	✓
Average County Wage, Age 17	✓	✓	✓	✓
State Unemployment, Age 17	✓	✓	✓	✓
Distance to College	✓	·	·	·

Notes: I rely on distance to college affecting attendance without directly tuition. I further rely on local tuition at age 17 affecting tuition without otherwise affecting perceived returns, conditional on the other controls. I do not include distance to college in the main equation because tuition is imputed from this variable and all other objects in X_T, such that including it in the main equation would produce perfect collinearity on imputed tuition.

variables associated with individuals' general ability, and a coefficient on the first principal component of variables associated with individuals' local geographic characteristics.[29] The details of the principal component analysis are presented in Appendix C.

5 Results

Table 3 shows estimates of the model parameters ($\{\beta, \sigma\}$) of perceived returns to college for the Probit, IV Probit, and moment inequalities using principal components. The bias in the Probit specification is evident in the insensible negative estimate of the standard deviation. Recalling the normalization in (11), the estimate of the standard deviation will be negative when expected tuition is positively associated with college attendance, i.e. individuals who are likely to attend college are also likely to attend expensive colleges. The negative standard deviation affects the signs of the other coefficients because the estimates from the discrete choice model are multiplied by $\hat{\sigma}$ to convert them into dollar terms. Graphs of the implied distribution of perceived returns for the IV Probit and moment inequalities are shown in figures 1 and 2, respectively.

[29] It takes approximately 16 hours to estimate this 4-parameter model. Because the primary time cost is in the grid search, adding any additional variables can be expected to increase the computation time required exponentially.

Table 3: Perceived Returns Estimates, 2018 Dollars, Principal Components

	(1) Probit	(2) IV Probit	(3) Moment Inequalities
Constant	23.425	-29.644	[-72.587, 0.712]
	(1.789)	(1.736)	N/A
PC1(Ability)	-7.940	12.069	[3.097, 24.894]]
	(0.501)	(0.607)	N/A
PC2(Location)	1.485	1.301	[-2.435, 5.113]
	(0.427)	(0.477)	N/A
σ	-22.422	21.064	[1.282, 42.809]
	(2.401)	(4.634)	N/A
Observations	5492	5492	5492

Notes: Standard errors in parentheses. Parameters are marginal effects of the variable on perceived returns to college in thousands of dollars. The coefficient on tuition is assumed to be equal to $\lambda\gamma(X)$. Estimates are from equation (4) with the details varying by estimation method. See text for details.

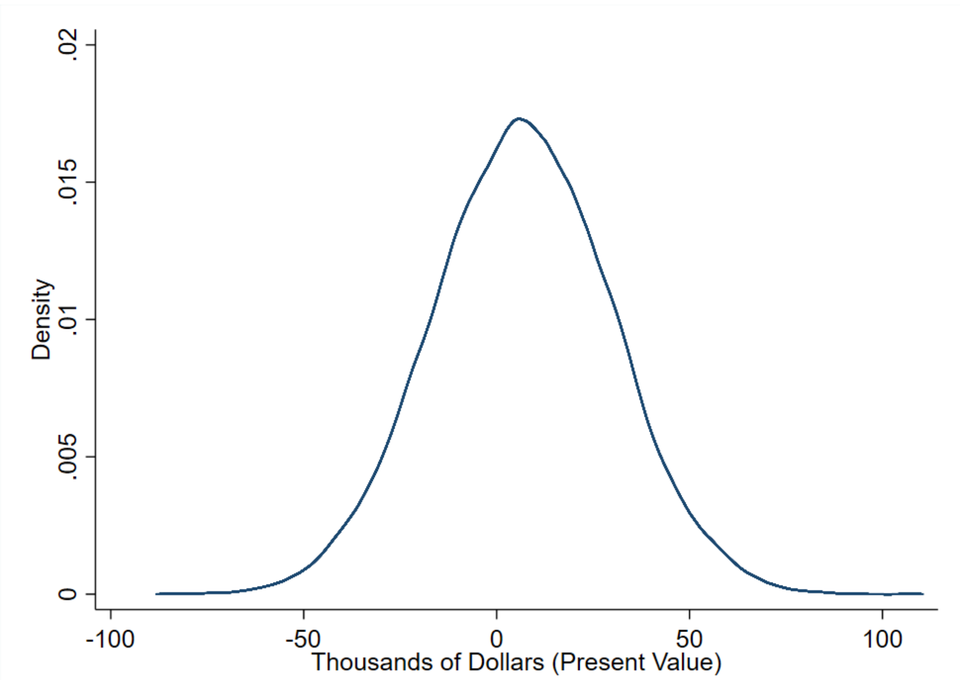

Figure 1: Perceived Returns to College, IV Probit, Principal Components

Notes: Perceived returns across the population, weighted by 1988 sample weights, using principal components. The distribution is given by $Y = X\hat{\beta} - Z\hat{\delta}\lambda\hat{\gamma}(X) + \mathcal{N}(0, \hat{\sigma}^2)$.

The results in Table 3 are scaled using the estimated $\gamma(X)$ described in Appendix D and the rational expectations assumption on tuition ($\lambda = 1$). The unscaled results are presented in Table 4. It is worth noting that the moment inequality bounds in Table 4 (and consequently Table 3) fail to completely characterize the confidence set of parameters that satisfy the moment inequalities. The hyper-rectangle implied by the upper and lower bound on each parameter is larger than the actual confidence set of parameters that satisfy the moment inequalities. The resulting distributions of beliefs about returns to college are obtained for each point in this confidence set. Two and three-dimensional cuts of the confidence set of $\{\hat{\beta}^*_{MI}, \hat{\gamma}^*_{MI}\}$ are shown in Figures 3 and 4, respectively, for illustrative purposes. The first stage for the IV Probit is provided in Appendix F.[30]

Table 4: Perceived Returns Estimates, Unscaled, Principal Components

	(1) Probit	(2) IV Probit	(3) Moment Inequalities
Constant	-1.045	-1.407	[-11.331, 0.111]
	(0.080)	(0.082)	N/A
PC1(Ability)	0.354	0.573	[0.483, 4.443]
	(0.022)	(0.029)	N/A
PC2(Location)	-0.066	0.062	[-0.333, 1.661]
	(0.019)	(0.023)	N/A
Tuition	0.045	-0.047	[-0.476, -0.014]
	(0.005)	(0.010)	N/A
Observations	5492	5492	5492

Notes: Standard errors in parentheses. Parameters are marginal effects of the variable on perceived returns to college in standard deviations. For these results, I assume $\sigma = 1$. Estimates are from equation (4) with the details varying by estimation method. See text for details.

Turning to the comparison between the IV Probit and the moment inequalities, I note that the IV Probit point estimates fall close to the middle of the moment inequality confidence sets, suggesting that the assumptions that perceived tuition is linear in local tuition at age 17 and that the error term in beliefs about tuition is normally distributed are not particularly harmful to the estimation.[31] I further note that the bounds on the moment inequalities parameters are quite large, suggesting, for instance, that the standard deviation of perceived returns to college is somewhere between $1,200 and $43,000. Because of the wide bounds on the moment inequalities and the suggestive evidence of the validity of the IV Probit for the purpose of this paper, I will focus on the IV Probit estimates for subsequent results and counterfactuals.

[30] Recall that the moment inequalities make use of the instruments without estimating a first stage.

[31] Recall that these are the assumptions the IV Probit makes that the moment inequality estimation procedure does not.

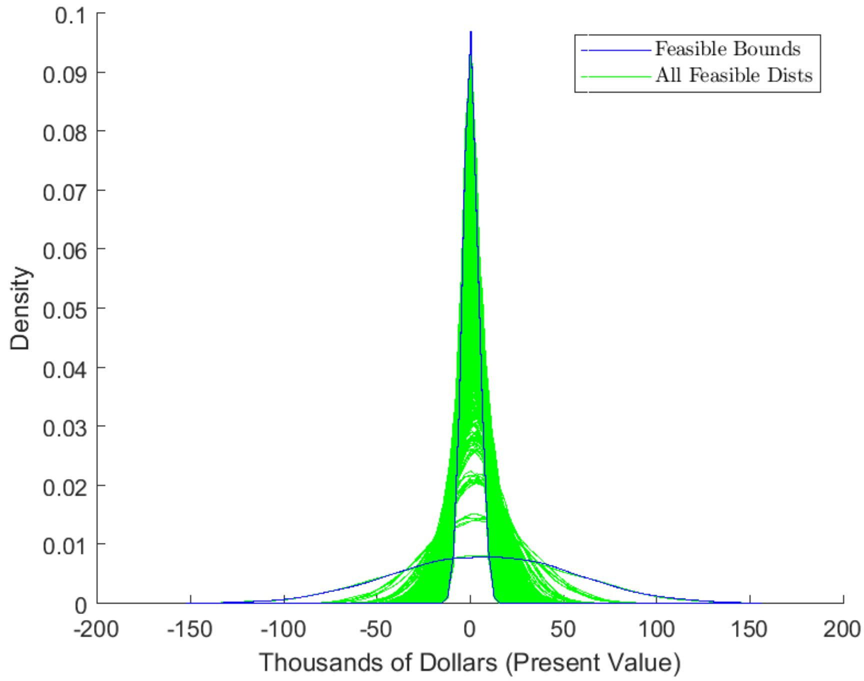

Figure 2: Perceived Returns to College, Moment Inequalities, Principal Components

Notes: Perceived returns across the population, weighted by 1988 sample weights, using principal components. Each point $\{\hat{\beta}_p, \hat{\sigma}_p\}$ in the confidence set (partially shown in figures 3 and 4) implies an entire distribution of beliefs about returns given by $X\hat{\beta}_p - Tuition\lambda\hat{\gamma}(X) + \mathcal{N}(0, \hat{\sigma}_p^2)$. I am unable to reject any of these implied distributions with 95% confidence. The distributions in blue are those with the lowest and highest values of $\hat{\sigma}$.

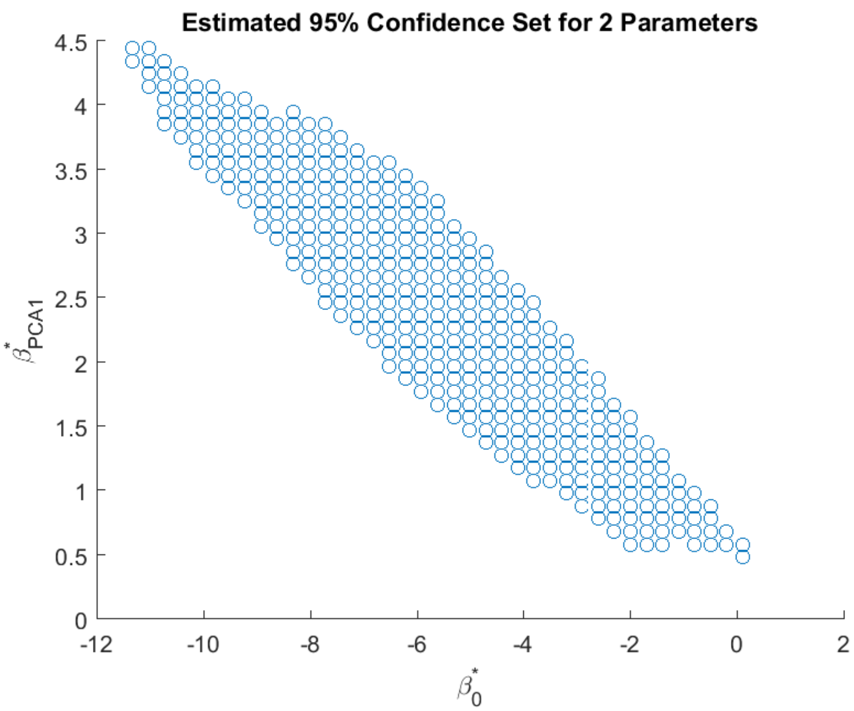

Figure 3: Unscaled Confidence Set for 2 Parameters, Moment Inequalities

Notes: The confidence set contains all combinations of parameter values that I cannot reject satisfy the moment inequalities in the unscaled discrete choice model. Note that the limits of the x and y axes correspond to the results in Table 4, while the 95% confidence set is a subset of the rectangle represented by these limits. The complete 95% confidence set is a 4-dimensional object. The normalizations in (11) are performed on each point in the confidence set to obtain the results in Table 3.

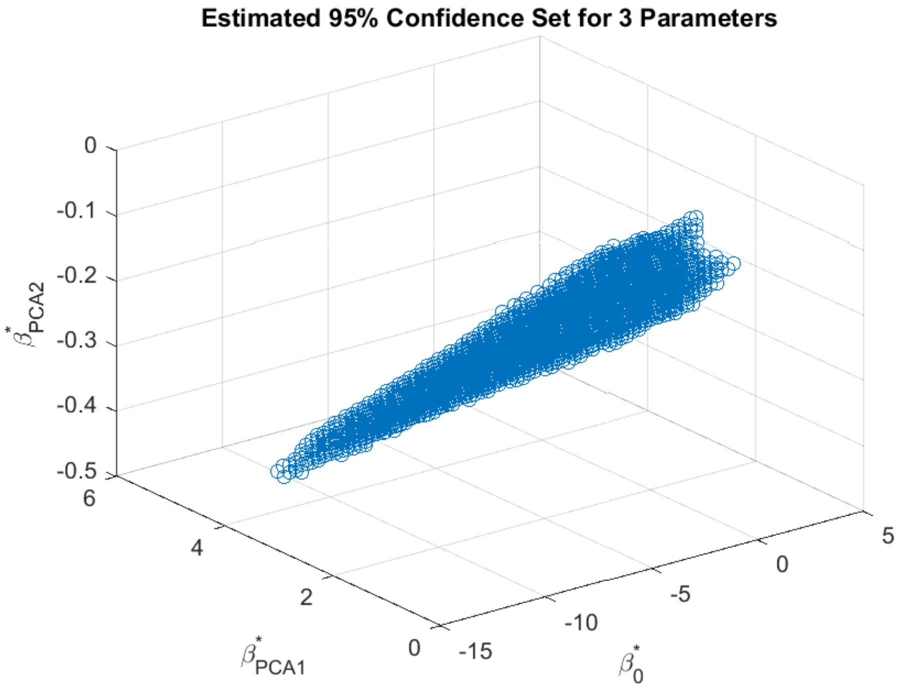

Figure 4: Unscaled Confidence Set for 3 Parameters, Moment Inequalities

Notes: The confidence set contains all combinations of parameter values that satisfy all of the moment inequalities in the unscaled discrete choice model. Note that the limits of the x, y, and z axes correspond to the results in Table 4, while the 95% confidence set is a subset of the 3-dimensional orthotope represented by these limits. The complete 95% confidence set is a 4-dimensional object. The normalizations in (11) are performed on each point in the confidence set to obtain the results in Table 3.

Because I find in this application that the IV Probit estimates are broadly consistent with the moment inequality estimates, I will use the full set of controls for the remaining analysis rather than the principal components. This is of interest for more clearly identifying the sources of variation in perceived returns to college. The IV Probit results when including all controls are presented in Table 6, with the corresponding visual representation of the distribution of perceived returns shown in Figure 5. The first stage and and unscaled estimates are provided in Appendix F.

I note first that the estimates of σ in the principal component specification and the full controls specification are statistically indistinguishable, suggesting that the two specifications give qualitatively similar results. The specification with full controls gives insight into which characteristics are associated with higher perceived returns as well as providing insight into the curvature of these characteristics. Recall that none of these coefficients have a causal interpretation; the ultimate goal is to forecast policy effects conditional on observed characteristics, so the relationship between characteristics and perceived returns should exploit all of the explanatory power of any variable, not just the causal relationship. The results suggest that individuals

Table 5: Perceived Returns Estimates, 2018 Dollars, All Controls

	(1) Probit	(2) Std. Error	(3) IV Probit	(4) Std. Error
Constant	17.730	(2.355)	14.170	(2.007)
Mother Education	-7.191	(1.143)	-4.799	(0.766)
Mother Education Squared	0.460	(0.059)	0.306	(0.039)
Father Education	-1.436	(0.880)	-0.777	(0.599)
Father Education Squared	0.192	(0.042)	0.120	(0.029)
Number of Siblings	-3.424	(0.857)	-2.045	(0.592)
Number of Siblings Squared	0.208	(0.074)	0.125	(0.050)
ASVAB Score Subtest 3	0.804	(1.311)	0.562	(0.879)
ASVAB Score Subtest 3 Squared	1.146	(0.971)	0.780	(0.650)
ASVAB Score Subtest 4	-1.012	(1.281)	-0.673	(0.859)
ASVAB Score Subtest 4 Squared	4.562	(1.007)	3.346	(0.692)
ASVAB Score Subtest 5	1.504	(1.432)	1.040	(0.961)
ASVAB Score Subtest 5 Squared	-5.380	(1.101)	-3.849	(0.749)
ASVAB Score Subtest 6	2.067	(1.199)	1.576	(0.811)
ASVAB Score Subtest 6 Squared	-4.569	(0.946)	-3.193	(0.638)
ASVAB Score Subtest 7	-0.595	(1.057)	-0.274	(0.713)
ASVAB Score Subtest 7 Squared	-2.869	(0.921)	-1.994	(0.619)
ASVAB Score Subtest 8	-3.099	(1.000)	-2.130	(0.671)
ASVAB Score Subtest 8 Squared	-1.851	(0.884)	-1.207	(0.593)
ASVAB Score Subtest 9	-4.606	(1.245)	-3.271	(0.841)
ASVAB Score Subtest 9 Squared	-1.693	(0.935)	-0.972	(0.634)
ASVAB Score Subtest 10	5.780	(1.238)	4.214	(0.850)
ASVAB Score Subtest 10 Squared	6.983	(0.973)	4.744	(0.652)
ASVAB Score Subtest 11	-3.585	(1.233)	-2.550	(0.831)
ASVAB Score Subtest 11 Squared	-0.364	(0.929)	-0.322	(0.625)
ASVAB Score Subtest 12	-1.883	(1.243)	-0.998	(0.847)
ASVAB Score Subtest 12 Squared	4.211	(0.932)	2.956	(0.629)
High School GPA	24.402	(4.379)	17.964	(3.058)
High School GPA Squared	-0.446	(0.975)	-0.556	(0.668)
Broken Home	-0.464	(1.632)	0.441	(1.173)
Urban Residence at Age 14	6.698	(1.800)	4.541	(1.208)
Average County Wage at Age 17	0.800	(0.327)	0.709	(0.239)
State Unemp Rate at Age 17	0.084	(0.382)	0.063	(0.257)
σ	37.337	(10.811)	25.077	(6.656)
Observations	5492	5492	5492	5492

Notes: All non-categorical variables are demeaned such that the constant gives the mean for white males. Parameters are marginal effects of the variable on perceived returns to college in thousands of dollars. The coefficient on tuition is assumed to be equal to $\lambda\hat{\gamma}(X)$. Estimates are from equation (4) with the details varying by estimation method. See text for details.

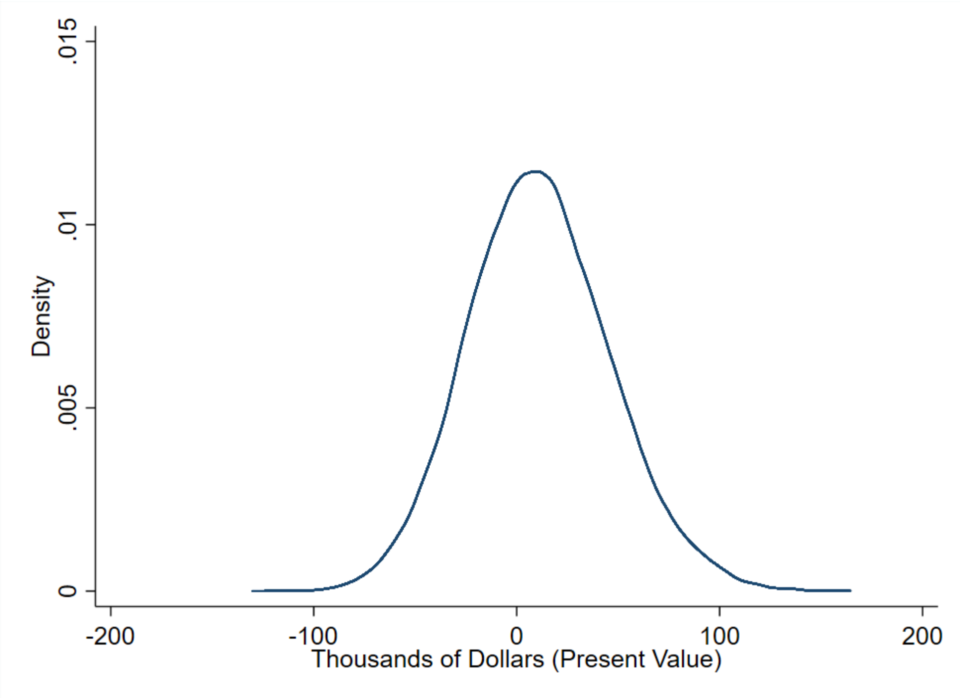

Figure 5: Perceived Returns to College, IV Probit, All Controls

Notes: Perceived returns across the population, weighted by 1988 sample weights, for the full controls specification. The distribution is are given by $Y = X\hat{\beta} - Z\hat{\delta}\lambda\hat{\gamma}(X) + \mathcal{N}(0, \hat{\sigma}^2)$.

with college-educated parents have about \$30,000 higher perceived returns on average than those with parents who only completed high school(holding other variables at their means).[32]

The relationships between GPA and the various ASVAB scores are of further interest, as they are consistent with selection on gains in college attendance. For instance, GPA and the the first two ASVAB subtests on science and arithmetic predict high perceived returns. Meanwhile, ASVAB scores associated with nonacademic ability (such as subtests 7 and 9 on auto and shop information and mechanical comprehension) are associated with low perceived returns to college.[33] The negative relationship between subtests 5 and 6 (which measure word knowledge and paragraph comprehension) and perceived returns are also interesting in light of past findings of a negative relationship between verbal skills and wages, such as in Sanders (2015).

If my estimates of perceived returns are biased, it is likely that they overestimate the variance of the distribution. First, if local tuition at age 17 is associated with the unobserved component of perceived returns, it is likely to produce positive bias in estimates of the effect of tuition on attendance. This will happen if high local tuition is associated with higher perceived returns (i.e. people who live near elite universities expect their returns to college to be high, conditional

[32]Recall that the point at which a variable and its quadratic of opposite sign cross zero is given by $\beta_1 x + \beta_2 x^2 = 0 \implies x = \frac{-\beta_1}{\beta_2}$.

[33]Recall that the ASVAB tests have all been transformed to have unit variance and positive support.

on their other characteristics). I have attempted to account for this by including indicators of local labor market health. Second, If there is predictive power for actual tuition in local tuition at age 17 that is unknown to agents, estimates of the effect of tuition on attendance (the unscaled IV Probit or moment inequality estimates) will be biased toward zero. This is similar to the problems with assuming people know tuition perfectly, the predicted value for tuition will contain classical measurement error insofar as it is a measure of beliefs about tuition. Because the causal effect of perceived tuition on perceived returns should be negative, this bias moves the estimate of the effect of tuition on attendance in the positive direction.

Thus both likely sources of bias are positive, which would move the estimate of the effect of tuition on attendance closer to zero. Then applying the normalization in (11) will produce upward bias in estimates of σ. In other words, this bias would cause me to conclude that tuition has a small effect relative to other factors, which would imply (because tuition is valued in dollars) that other factors have large effects in dollars. The effect of this is to blow up the distribution of perceived returns and to thus underestimate the effect of tuition subsidies/taxes on attendance.

6 External Validation and Policy Counterfactuals

Estimates of perceived returns are of interest to policymakers for identifying how many and what type of individuals value college at various levels. With this knowledge, it is possible to predict the number and type of individuals who will and will not attend college in the presence or absence of tuition subsidies or taxes. In this section, I will test the validity of the methodology of this paper by comparing the predicted effects of tuition subsidies on attendance from my estimates with those found in a natural experiment on Social Security Student Benefits studied by Dynarski (2003). Then, I will investigate the costs and effects of additional counterfactual policies.

6.1 Social Security Student Benefit

The Social Security Student Benefit was a policy from 1965 to 1982 that provided income assistance to children of deceased, disabled, or retired parents if they attended college. The financial reward was based on parental earnings, and was on average roughly $11,400 (2018 dollars) per year. This was sufficient to completely offset tuition costs for public institutions and to nearly do so even for many private institutions. Because this policy ended right as the individuals in the NLSY79 were deciding whether to attend college, this dataset was chosen by Dynarski (2003) to estimate the effects of the policy on educational outcomes including college attendance rates using differences in differences. I compare the implied effect of tuition aid on college attendance from the perceived returns I estimate to the results from her paper.

The primary result I attempt to match from Dynarski (2003) is the effect of the policy on attendance probabilities by age 23. Dynarski finds that the termination of this policy caused a 24.3% decrease in college attendance for the affected group, though these estimates were not significantly different from zero.[34] Assuming a linear effect of tuition on enrollment, she finds that a $1000 yearly subsidy caused a 3.6% increase in college attendance in year 2000 dollars.[35]

The validation exercise is thus to determine whether my estimates of perceived returns predict a 24.3% increase in enrollment from an $45,600 ($11,400/year x 4 years) subsidy. Because I use the same basic dataset to estimate perceived returns as Dynarski used to estimate the effects of the SSA Student Benefit, the results should be roughly comparable. Because there was variation in benefits received, applying the $45,600 uniformly across the population may somewhat misstate the policy effect according to the association between paternal death and perceived returns to college.[36] Finally, because Dynarski identifies the effect of student aid off of individuals with deceased fathers, my estimates of the effect of aid on the entire population will exceed hers if her treated group has lower responses to aid than average. The distribution of perceived returns implied by the estimates in Table 4 are shown in Figure 6 along with a counterfactual distribution showing the effect of a uniform $45,600 subsidy to all potential college students. The predicted effect of the policy on attendance is given by the difference in the mass to the right of zero between the distributions. This effect is 26.0%, which is very close to the effect of 24.3% found by Dynarski (2003).

An advantage of the methodology employed in this paper is that by obtaining the complete distribution of perceived returns, I do not rely on an assumption of a linear (or other) effect of tuition on attendance when computing effects of other counterfactual policies. For instance, the difference in differences methodology employed by Dynarski clearly identifies the effect of

[34]Dynarski focused on the difference in attendance between children of deceased fathers before and after termination of the program. Fewer than 200 individuals in her data had deceased fathers, which likely contributed to the lack of significance despite the substantial point estimates.

[35]This amounts to a 2.1% increase in 2018 dollars using a 3% discount rate.

[36]The NLSY79 does not have benefit amounts received, only parental mortality status. Dynarski used average benefits and data on parent mortality to infer the effect of benefit amounts.

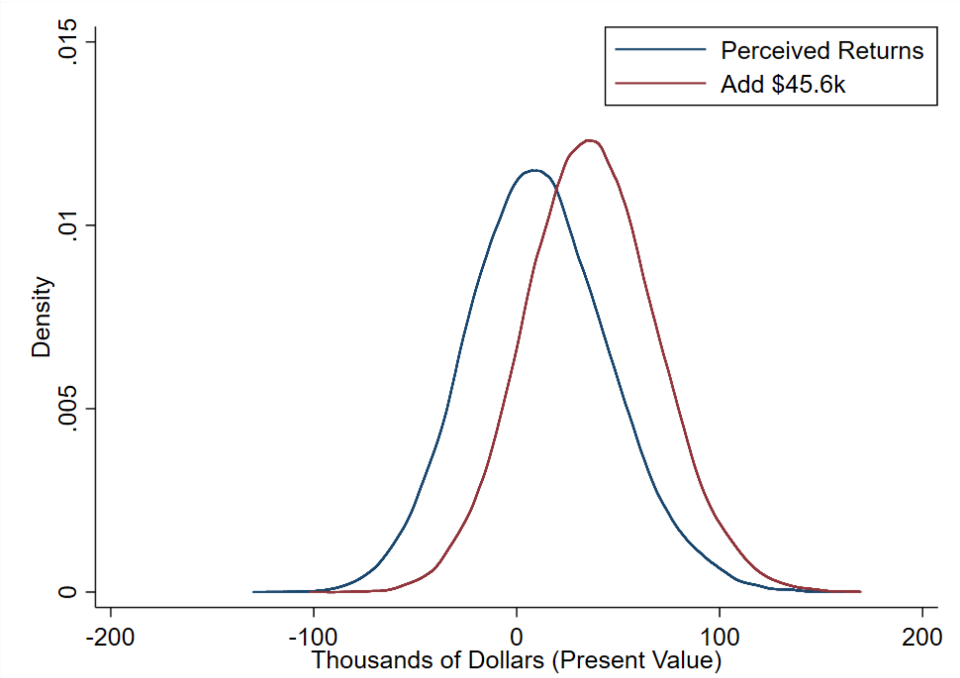

Figure 6: Effect of Universally Applied Aid Equivalent to Social Security Student Benefit

Notes: The shift in the presence of the policy comes from adding $45,600 dollars to everyone, which is assumed to be well-publicized such that we have new perceived effective tuition for individual i given by $\widetilde{Tuition_i}\hat{\gamma}(X_i) = \widetilde{Tuition_i}\hat{\gamma}(X_i) + \$45,600\hat{\gamma}(X_i)$. The increase in mass just to the right of zero is the result of individuals with lower perceived returns paying a higher percentage (given by $\hat{\gamma}(X_i)$) of tuition than those with higher perceived returns, such that the tuition aid shifts them relatively further to the right. The shift visually looks smaller than $45,600 because the average $\hat{\gamma}(X) = 0.61$.

the \$11,400 annual tuition subsidy, but relies on a linear assumption on the effect of tuition is made to infer the effect of a \$1000 annual subsidy. Thus, while Dynarski infers a 2.1% effect of \$1,000 dollars (3.6% in year 2000 dollars), the predicted effect of a \$1,000 annual subsidy using the methodology employed in this paper is 2.6%. This larger effect is found because the average mass of the distribution of perceived returns is higher between \$0 and -\$4,000 than it is between \$0 and -\$45,600 dollars, such that the marginal effect of aid falls as aid rises.[37] I argue that the ability of the methodology described in this paper to closely match the results from a cleanly identified natural experiment bodes extremely well for its validity and predictions for a wide variety of potential policies.

6.2 Attendance Target with Cost-Minimization

Given the external validity of the results as demonstrated above, it is possible to use my estimates of perceived returns to predict the effects of other potential policies. Here I describe the cost-minimizing policy that reaches a given attendance target, given the results above.[38] In the interest of comparability to the Social Security Benefit, I choose $A = 87.3\%$ as the target level of college attendance because that is the attendance level predicted by the preceding counterfactual (Social Security Student Benefit applied universally).

The cost-minimizing schedule of student aid conditional only on observables is shown in Figure 7. To derive it, I begin by noting the attendance probability for individual i, conditional on observables and financial aid offer a_i, is given by

$$Pr\left(S_i = 1|\hat{Y}_i, a_i\right) = \Phi\left(\frac{\hat{Y}_i + a_i\hat{\gamma}_i}{\hat{\sigma}}\right), \tag{30}$$

where $\hat{Y}_i = \mathbb{E}[Y_i|X_i, Tuition_i]$.[39] The expected cost to the government for this financial aid offer is then given by

$$\mathbb{E}[C_i|\hat{Y}_i, a_i] = a_i\Phi\left(\frac{\hat{Y}_i + a_i\hat{\gamma}_i}{\hat{\sigma}}\right), \tag{31}$$

where a_i is spent by the government on individual i only if they choose to attend college. Note that the government must pay a_i to person i even if they would have gone to college in the absence of the policy. Avoiding aid for individuals who are likely to go to college in the absence

[37]It is worth noting that Dynarski (2003) suggested this exact possibility.

[38]Defining such a concrete target may be appealing to policymakers. For instance, President Obama specifically stated a goal of the U.S. having the highest proportion of college graduates in the world.

[39]Note that while the government spends a_i on individual i, the individual's return to college increases by $a_i\gamma_i$ because they pay γ_i proportion of their schooling costs.

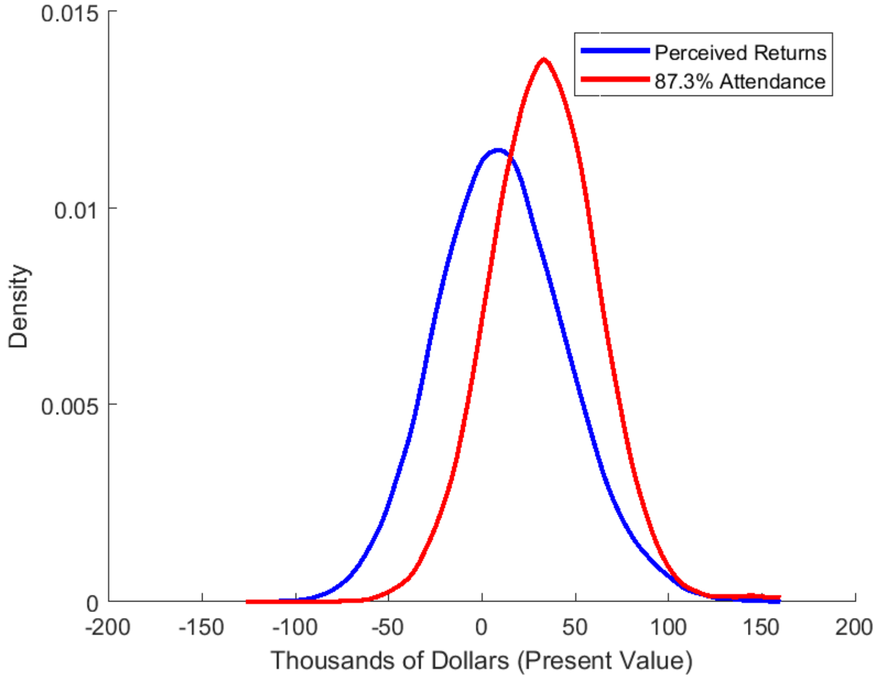

Figure 7: Cost-Minimizing Aid for Attendance Target

Notes: The red line shows perceived returns to college in the presence of the cost-minimizing policy that achieves the attendance target of 87.3%. This is the same proportion of the population that I predict will attend in the preceding section with the universally-applied subsidy of the same magnitude as the Social Security Student Benefit. The average cost per individual for that policy is $39,800, while the average cost in the cost-minimizing policy shown here is $29,400. Visual comparison of Figure 6 and Figure 7 show that the cost-minimizing policy shifts perceived returns to college less for individuals with high perceived returns than for those with low perceived returns.

of aid will play an important role in the cost-minimization.

The attendance target implies that the government receives a constant marginal benefit, b, from any individual attending college.[40] Choosing a_i to set expected marginal benefit equal to expected marginal costs gives

$$b = \frac{\frac{\Phi(\hat{Y}_i^*(a_i))}{\phi_i(\hat{Y}_i^*(a_i))}\hat{\sigma} + a_i\hat{\gamma}_i}{\hat{\gamma}_i}, \tag{32}$$

wherein $\hat{Y}_i^*(a_i) = \frac{\hat{Y}_i + a_i\hat{\gamma}_i}{\hat{\sigma}}$ is the expected perceived return to college for individual i accounting for the financial aid offer and observables. I assume the government is constrained to use subsidies and not taxes ($a_i \geq 0\ \forall i$), which leads to the solution (given b) being the set $\{a_1\}_i$ that satisfies[41]

$$b_{1i} = \begin{cases} b & \text{if } b_{0i} < b, \\ b_{0i} & \text{if } b_{0i} \geq b. \end{cases} \tag{33}$$

where b_{1i} gives expected marginal cost per expected attendance for person i in the presence of the policy and b_{0i} is the same in the absence of the policy:

$$b_{0i} = \frac{\frac{\Phi(\hat{Y}_i^*(0))}{\phi_i(\hat{Y}_i^*(0))}\hat{\sigma}}{\hat{\gamma}_i}. \tag{34}$$

Essentially, this condition is that aid will be extended to those who respond most per cost for any attendance target above the initial attendance proportion. Note that b_{1i} is monotonically increasing in a_i, which implies that the single cutoff b will define marginal costs per marginal attendance for the treated group.[42]

The above gives the cost-minimizing idiosyncratic aid for each individual, $a_i(b)$, given an arbitrary cutoff value b. To reach attendance target A, all that remains is to find the value b^* that satisfies

$$\mathbb{E}\left[\Phi\left(\frac{\hat{Y}_i + a_i(b^*)\hat{\gamma}_i}{\hat{\sigma}}\right)\right] = A. \tag{35}$$

Then the cost-minimizing idiosyncratic aid is given by the a_i that solves (33).

The cost-minimizing financial aid solution has several interesting features. First, it focuses aid on individuals with low perceived returns. This happens because marginal increases in

[40] This formulation of the problem will generalize nicely to the case where the government has an idiosyncratic benefit, b_i, from individual i attending college, obtained for instance from estimates of lifetime returns to college.

[41] If the government can use taxes, the solution is is given by $b_{i1} = b\ \forall_i$.

[42] The condition that b_{1i} is monotonically increasing in a_i will be satisfied for any symmetric, log-concave distribution (such as the normal). This is a sufficient condition but not a necessary one, as $a_i\hat{\gamma}_i$ is increasing in a_i and will contribute to b_{1i} increasing in a_i.

aid increase attendance by $\phi(\hat{Y}^*(a_i))$ while costing $\Phi(\hat{Y}^*(a_i))$, and the latter is large for large values of $\hat{Y}$ while the former is not. In other words, tuition subsidies for individuals with low perceived returns cause the government to spend less money on subsidies for people who would have attended college anyway. Secondly, it focuses aid on individuals who pay high percentages of their schooling costs, $\hat{\gamma}_i$. This is because the government must spend a_i to increase perceived returns by $a_i\hat{\gamma}_i$, which will be higher for high values of $\hat{\gamma}_i$. Thirdly, I note that individuals who have low perceived returns also tend to pay a high fraction of their educational costs, so these two types of people are really only one type of person. Many of these individuals will not respond to financial aid (because their perceived return is still below zero even in the presence of aid), keeping costs low for the government. Finally, such individuals that do respond will do so because they have high draws from the error term in their perceived returns (selection) equation. Carneiro, Heckman, and Vytlacil (2011) find that such individuals with high unobserved preferences for college also have relatively high real returns. Because this policy targets low socioeconomic status individuals who are likely to have relatively high returns while minimizing costs, it can likely serve as a useful heuristic for the government if it seeks to both reduce inequality and induce selection on gains. I conclude discussion of this policy by noting that its solution can easily be modified to provide optimal idiosyncratic financial aid conditional on known actual returns to college or to provide optimal aid conditional on a binding total financial aid budget constraint for the government.

7 Conclusions

I obtain estimates of beliefs about returns to college based on observed selection into college. Importantly, I am able to obtain these estimates without assuming that agents perfectly observe any data object that is known to the econometrician, and I only assume agent knowledge of the effect of tuition on returns. Prior research has made stronger assumptions about the information held by agents. The results suggest that 2.6% of individuals would be induced to attend to college with an annual tuition subsidy of only $1000, which is consistent with the results from a host of studies of natural experiments.[43] Past estimates of the distribution of perceived returns such as those in Cunha, Heckman, and Navarro (2005) that are identified from assumptions on

[43] It is common in this literature to provide effects of $1,000 annual subsidies in year 2000 terms. This effect is 4.2%, while effects from 0%-6% are commonly found in studies of natural experiments, with the 0% estimates commonly attributed to administrative costs and/or information frictions associated with the policy. See Deming and Dynarski (2010) for a broad survey.

agents beliefs about real returns exhibit substantially higher variance and would be unable to predict the effects of tuition subsidies, though it is important to note that these authors do not claim to estimate compensating variation and do not claim to predict any such effects.

The methodology employed in this paper is especially well-suited to counterfactual policy analysis for multiple reasons. First, it avoids assuming that agents have rational expectations over returns to college. Second, it naturally identifies perceived returns in terms of compensating variation, which is directly applicable to policy questions. Third, if credit constraints are a factor, they will be seamlessly incorporated into the compensating variation specifically because they, like compensating variation, are linear in dollars where they exist. The effects of a tuition subsidy would then be to not only increase perceived returns at a constant marginal rate, but to reduce credit-constraints at a constant marginal rate. The predictions about which and how many individuals will be induced to attend college in the presence of any such policy will be identical whether we explicitly account for perceived credit constraints or not.

Past estimates of heterogeneous lifetime income returns to college commonly produce distributions of returns that have much higher mean and variance than the perceived return distribution that I estimate (See Cunha and Heckman (2007) for a survey of papers that estimate heterogeneous lifetime income returns). Cunha and Heckman (2016) more recently provides similar results for earnings from age 22 to 36 which are consistent with lifetime earnings that substantially exceed the perceived returns I estimate in both mean and variance. Average treatment effect estimates of wage returns to college are generally consistent with these estimates of lifetime earnings when making standard assumptions about hours worked per year and years worked.[44] The qualitative takeaway from this result is that individuals at best dramatically underestimate their returns to college while still making the attendance decision that will maximize their earnings (this will occur anytime the sign of an individual's actual return matches the sign of their perceived return, and at worst that they make a suboptimal decision due to underestimating the value of college relative to returns). Another way of describing the results is that individuals appear to dramatically overweight tuition costs relative to the other components of returns to college, an interpretation that appears consistent with reports in the popular press relating to concerns that the costs of college are considered prohibitively high for many individuals.

[44] See, for instance, Card (2001), Carneiro, Heckman, and Vytlacil (2011) and Heckman, Humphries, and Veramendi (2018)

The methodology employed in this paper is well-suited for extensions in a variety of education decisions. These estimates are of potential interest for comparison to the analogous model of actual lifetime returns to college. Using a compatible specification for estimation of actual returns, with the same controls, the same imputation of tuition, and the same instruments, will produce the same estimates as those of perceived returns if agents have perfect foresight of their actual returns conditional on these variables. A test of perfect foresight in such a model is a joint test of all parameters being equal in the actual returns equation and the perceived returns equation. Similarly, upon performing such an analysis, it would be possible to identify predictors of misinformation as those variables with more divergent coefficients across the two equations. A comparison of perceived returns and actual returns is beyond the scope of this paper and is left for future work. The difference in estimates of the marginal effects of determinants of returns on actual returns and perceived returns will describe optimal schedules of tuition subsidies to induce selection on financial gains, with the caveat that such an exercise would ignore nonpecuniary private returns, externalities from education, and general equilibrium effects. Additional fruitful areas for future research include extensions of the methods above to college major choice (in a multinomial choice setting) or years of education (in an ordered choice setting).

In addition to education applications, the method described in this paper is well-suited to the estimation of perceived benefits for any purchase in which there are information frictions in pricing. One potential example is fertility decisions, in which pecuniary medical costs associated with childbirth are one of many components of the net benefits to childbearing, and could be used to identify the perceived valuation of having children despite not likely being perfectly forecast at the time of the childbearing decision. Another potential application is the perceived value of home ownership, especially in the context of adjustable rate mortgages, wherein the price ultimately paid for the home is again unforecastable at the time of purchase. Finally, as evidenced by the use of similar methodology in Dickstein and Morales (2015), it is clear that this method can be used to determine profit expectations of firms for a wide variety of potential investments such as export decisions, R&D, plant openings, and others.

References

Ahn, H., and C. F. Manski (1993): "Distribution Theory for the Analysis of Binary Choice under Uncertainty with Nonparametric Estimation of Expectations," *Journal of Econometrics*, 56(3), 291–321.

Aiyagari, S. R., J. Greenwood, and A. Seshadri (2002): "Efficient Investment in Children," *Journal of Economic Theory*, 102(2), 290–321.

Andrews, D. W., and G. Soares (2010): "Inference for Parameters Defined by Moment Inequalities Using Generalized Moment Selection," *Econometrica*, 78(1), 119–157.

Arnott, R., and J. Rowse (1987): "Peer Group Effects and Educational Attainment," *Journal of Public Economics*, 32(3), 287–305.

Attanasio, O., and K. Kaufmann (2009): *Educational Choices, Subjective Expectations, and Credit Constraints. No. W15087.* National Bureau of Economic Research.

Becker, G. S. (1962): "Investment in Human Capital: a Theoretical Analysis," *Journal of Political Economy*, 70(5), 9–49.

Becker, G. S., and N. Tomes (1986): "Human Capital and the Rise and Fall of Families," *Journal of Labor Economics*, 4(3), S1–S39.

Bettinger, E. P., B. T. Long, P. Oreopoulos, and L. Sanbonmatsu (2012): "The Role of Application Assistance and Information in College Decisions: Results from the H&R Block Fafsa Experiment," *The Quarterly Journal of Economics*, 127(3), 1205–1242.

Black, D. a., and J. a. Smith (2006): "Estimating the Returns to College Quality with Multiple Proxies for Quality," *Journal of Labor Economics*, 24(3), 701–728.

Cameron, S. V., and C. Taber (2004): "Estimation of Educational Borrowing Constraints Using Returns to Schooling," *Journal of Political Economy*, 112(1), 132–182.

Card, D. (1993): "Using Geographic Variation in College Proximity to Estimate the Return to Schooling," Discussion paper, National Bureau of Economic Research.

——— (2001): "Estimating the Return to Schooling: Progress on Some Persistent Econometric Problems," *Econometrica*, 69(5), 1127–1160.

Carneiro, P., K. T. Hansen, and J. J. Heckman (2001): *Educational Attainment and Labor Market Outcomes: Estimating Distributions of the Returns to Educational Interventions.* Paper Presented As Klein Lecture, University of Pennsylvania, Philadelphia.

——— (2003): *Estimating Distributions of Treatment Effects with An Application to the Returns to Schooling and Measurement of the Effects of Uncertainty on College. No. W9546.* National Bureau of Economic Research.

Carneiro, P., and J. J. Heckman (2002): "The Evidence on Credit Constraints in Post-Secondary Schooling," *The Economic Journal*, 112(482), 705–734.

Carneiro, P., J. J. Heckman, and E. J. Vytlacil (2011): "Estimating Marginal Returns to Education," *American Economic Review*, 101(6), 2754–81.

Cunha, F., and J. Heckman (2006): *The Evolution of Labor Earnings Risk in the Us Economy.* in 2006 Meeting Papers, No. 665. Society for Economic Dynamics.

——— (2008): "a New Framework for the Analysis of Inequality," *Macroeconomic Dynamics*, 12(S2), 315–354.

——— (2016): "Decomposing Trends in Inequality in Earnings Into Forecastable and Uncertain Components," *Journal of Labor Economics*, 34(S2), S31–S65.

Cunha, F., J. Heckman, and S. Navarro (2005): "Separating Uncertainty from Heterogeneity in Life Cycle Earnings," *Oxford Economic Papers*, 57(2), 191–261.

Cunha, F., and J. J. Heckman (2007): "Identifying and Estimating the Distributions of Ex Post and Ex Ante Returns to Schooling," *Labour Economics*, 14(6), 870–893.

Cunha, F., J. J. Heckman, and S. Navarro (2006): "Counterfactual Analysis of Inequality and Social Mobility," *Mobility and Inequality: Frontiers of Research in Sociology and Economics :*, pp. 290–348.

De Fraja, G. (2002): "The Design of Optimal Education Policies," *The Review of Economic Studies*, 69(2), 437–466.

Dearden, L., L. Mcgranahan, and B. Sianesi (2004): "The Role of Credit Constraints in Educational Choices: Evidence from Ncds and Bcs70," *Cee Dp*, 48.

Deming, D., and S. Dynarski (2010): "College Aid," in *Targeting Investments in Children: Fighting Poverty When Resources Are Limited*, pp. 283–302. University of Chicago Press.

Dickstein, M. J., and E. Morales (2015): *What Do Exporters Know?. No. W21351.* National Bureau of Economic Research.

Dillon, E. W., and J. A. Smith (2017): "Determinants of the Match Between Student Ability and College Quality," *Journal of Labor Economics*, 35(1), 45–66.

Dominitz, J. (1998): "Earnings Expectations, Revisions, and Realizations," *Review of Economics and Statistics*, 80(3), 374–388.

Dynarski, S. M. (2003): "Does Aid Matter? Measuring the Effect of Student Aid on College Attendance and Completion," *American Economic Review*, 93(1), 279–288.

Grodsky, E., and M. T. Jones (2007): "Real and Imagined Barriers to College Entry: Perceptions of Cost," *Social Science Research*, 36(2), 745–766.

Hansen, K. T., J. J. Heckman, and K. J. Mullen (2004): "The Effect of Schooling and Ability on Achievement Test Scores," *Journal of Econometrics*, 121(1-2), 39–98.

Hartog, J. (2000): "Over-Education and Earnings: Where Are We, Where Should We Go?," *Economics of Education Review*, 19(2), 131–147.

Heckman, J. J. (1977): "Sample Selection Bias As a Specification Error (with An Application to the Estimation of Labor Supply Functions)," .

Heckman, J. J., J. E. Humphries, S. Urzua, and G. Veramendi (2011): "The Effects of Educational Choices on Labor Market, Health, and Social Outcomes," Unpublished Manuscript, University of Chicago, Department of Economics.

Heckman, J. J., J. E. Humphries, and G. Veramendi (2018): "Returns to Education: the Causal Effects of Education on Earnings, Health, and Smoking," *Journal of Political Economy*, 126(S1), S197–S246.

Heckman, J. J., and S. Navarro (2007): "Dynamic Discrete Choice and Dynamic Treatment Effects," *Journal of Econometrics*, 136(2), 341–396.

Hogan, V., and I. Walker (2007): "Education Choice under Uncertainty: Implications for Public Policy," *Labour Economics*, 14(6), 894–912.

Hoxby, C., S. Turner, and Others (2013): "Expanding College Opportunities for High-Achieving, Low Income Students," *Stanford Institute for Economic Policy Research Discussion Paper*, (12-014).

Hoxby, C. M. (2010): "The Effects of Class Size and Composition on Student Achievement: New Evidence from Natural Population Variation. No. W6869," *National Bureau of Economic Research*, 1998.

Iranzo, S., and G. Peri (2009): "Schooling Externalities, Technology, and Productivity: Theory and Evidence from Us States," *The Review of Economics and Statistics*, 91(2), 420–431.

Jensen, R. (2010): "The (Perceived) Returns to Education and the Demand for Schooling," *The Quarterly Journal of Economics*, 125(2), 515–548.

Kane, T. J., and C. E. Rouse (1995): "Labor-Market Returns to Two-and Four-Year College," *The American Economic Review*, 85(3), 600–614.

Keane, M. P., and K. I. Wolpin (1997): "The Career Decisions of Young Men," *Journal of Political Economy*, 105(3), 473–522.

Kohn, M. G., C. F. Mansk, and D. S. Mundel (1976): "An Empirical Investigation of Factors Which Influence College-Going Behavior," *in Annals of Economic and Social Measurement*, 5, 391–419.

Lochner, L., and A. Monge-Naranjo (2011): *Credit Constraints in Education. No. W17435*. National Bureau of Economic Research.

Lucas, R. E. (1988): "on the Mechanics of Economic Development," *Journal of Monetary Economics*, 22(1), 3–42.

Manski, C. (1991): "Nonparametric Estimation of Expectations in the Analysis of Discrete Choice under Uncertainty," *Nonparametric and Semiparametric Methods in Econometrics and Statistics :*, pp. 259–275.

Manski, C. F. (1993): "Adolescent Econometricians: How Do Youth Infer the Returns to Schooling?," in *Studies of Supply and Demand in Higher Education, . University of Press*, pp. 43–60.

Manski, C. F. (2004): "Measuring Expectations," *Econometrica*, 72(5), 1329–1376.

Miyagiwa, K. (1991): "Scale Economies in Education and the Brain Drain Problem," *International Economic Review :*, pp. 743–759.

Navarro, S. (2005): "Understanding Schooling: Using Observed Choices to Infer Agent's Information in a Dynamic Model of Schooling Choice When Consumption Allocation is Subject to Borrowing Constraints.'," Ph.D. thesis, University of Chicago Ph. D. Thesis.

Nguyen, T. (2008): "Information, Role Models and Perceived Returns to Education: Experimental Evidence from Madagascar," Unpublished Manuscript 6.

Oreopoulos, P., and K. G. Salvanes (2011): "Priceless: The Nonpecuniary Benefits of Schooling," *Journal of Economic Perspectives*, 25(1), 159–84.

Pakes, A. (2010): "Alternative Models for Moment Inequalities," *Econometrica*, 78(6), 1783–1822.

Pakes, A., J. Porter, K. Ho, and J. Ishii (2015): "Moment Inequalities and Their Application," *Econometrica*, 83(1), 315–334.

Rivers, D., and Q. H. Vuong (1988): "Limited Information Estimators and Exogeneity Tests for Simultaneous Probit Models," *Journal of Econometrics*, 39(3), 347–366.

Roy, A. D. (1951): "Some Thoughts on the Distribution of Earnings," *Oxford Economic Papers*, 3(2), 135–146.

Sanders, C. (2015): "Reading Skills and Earnings: Why Do Doing Words Good Hurt You're Wages," Discussion paper, Working Paper.

Trautmann, S. T., and G. Van De Kuilen (2015): "Belief Elicitation: a Horse Race Among Truth Serums," *The Economic Journal*, 125(589), 2116–2135.

Willis, R. J., and S. Rosen (1979): "Education and Self-Selection," *Journal of Political Economy*, 87(5), S7–S36.

Wiswall, M., and B. Zafar (2015): "How Do College Students Respond to Public Information about Earnings?," *Journal of Human Capital*, 9(2), 117–169.

Zafar, B. (2011): "How Do College Students Form Expectations?," *Journal of Labor Economics*, 29(2), 301–348.

A Moment Inequality Intuition

In this section I provide more discussion of the intuition of the moment inequalities used in this paper in the context of a simple example with simulated data. Suppose we have a simple discrete choice model wherein individuals select under decision rule (3)

$$S = 1 \iff Y \geq 0; \text{ else } S = 0 \tag{36}$$

and as in section 2 the perceived return Y is generated by a linear-in-parameters production function

$$Y = -2.5 + \tilde{x}_1\beta_1 + \epsilon_i, \tag{37}$$

which we assume for simplicity is a function of agent beliefs about a single variable x_1. With simulated data, we can clearly investigate what a standard Probit is able to achieve, what its limitations are, and how moment inequalities can improve upon it when there is imperfect information.

I generate data as follows, wherein $\beta_1 = -0.1$:

$$\begin{bmatrix} \tilde{x}_1 \\ z_1 \\ \epsilon_i \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} 1 \\ .5 \\ 0 \end{bmatrix}, \begin{bmatrix} 4 & 3.8 & 0 \\ 3.8 & 4 & 0 \\ 0 & 0 & 1 \end{bmatrix} \right).$$

Importantly, I generate the variable observed by the econometrician x_1 as a mean-preserving spread of the agents' expectations of it:

$$x_1 = \tilde{x}_1 + \mathcal{N}(0, 1). \tag{38}$$

Finally, I normalize the data to ensure that each variable has positive support.

First, we consider the realistically impossible setting in which we have access to the agent's information set such that we can make use of $\tilde{x}_1$ in our estimation procedure. When we run a simple Probit using

$$Pr(S_i = 1) = \Phi(\sigma^{-1}\tilde{x}_1\beta_1). \tag{39}$$

in which we include the agent's belief about x_1 in the estimation procedure, we unsurprisingly obtain an unbiased estimate $\widehat{\mathbb{E}[\beta_1} = 0.1957$. No normalization is required because the standard deviation of the error term has been set to 1. In this case the values of β_1 for which both inequalities are satisfied will be the exact parameter value identified by MLE, as seen in Figure 8.

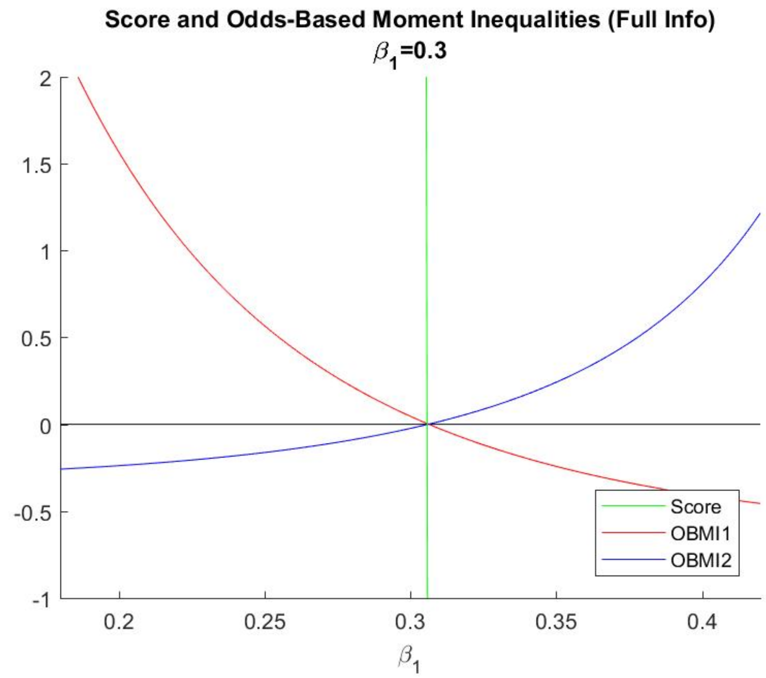

Figure 8: The score function from the MLE estimation perfectly intersects both of the odds-based moment inequalities, which are simply algebraic transformations of the score when we assume agents have perfect information on x_1. The point identified by MLE such that the score is equal to zero corresponds to the knife edge region in which both odds-based moment inequalities are satisfied only in the case of full information.

In the realistic setting in which we only observe x_1 and not $\tilde{x}_1$, the Probit will fail even in the absence of endogeneity. As discussed in section 2, we will essentially underestimate how elastic agents are to changes in x_1 because we will assume they are reacting to all of its variation when in reality they may only be reacting (more strongly) to only some of its variation. Erroneously performing a simple Probit

$$Pr(S_i = 1) = \Phi(\sigma^{-1} x_1 \beta_1) \tag{40}$$

produces the biased estimate $\hat{\beta}_1 = 0.0936$. If we use the moment inequality functions without conditioning on Z (such that they are equivalent to the score function) they still provide no additional benefit. However, when we condition on z_1, we essentially see both inequality curves from figure 1 shift upward such that a purple region emerges in which both inequalities are satisfied. This purple region contains the true parameter value $\beta_1 = 0.3$. This occurs because the distribution chosen is log-concave such that it has a convex odds-ratio. In other words, the

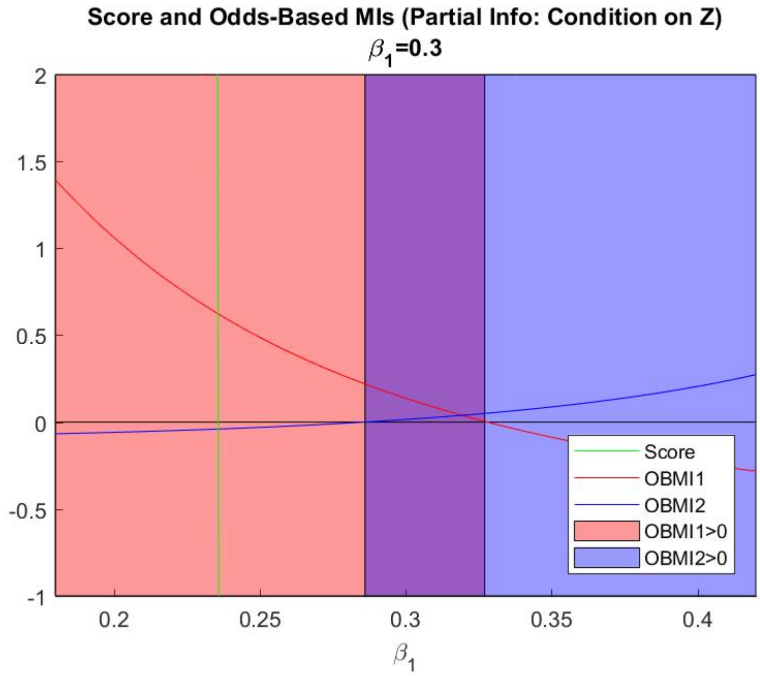

Figure 9: The estimates from MLE with a full information assumption (where the score function is equal to zero) suffers from attenuation bias. The red region designates the area where the first moment inequality is satisfied while the blue designates the area where the second inequality is satisfied. The overlapping region (purple) shows the area where both are satisfied and contains the true parameter value $\beta_1 = 0.3$.

noise in x_1 that is not contained in $\tilde{x}_1$ causes half of the $x_1 > \tilde{x}_1$ and the other half $x_1 < \tilde{x}_1$. Because of the shape of the normal distribution, the mean of $\frac{\Phi(x_1\beta_1)}{1-|phi(x_1\beta_1)}$ will be dominated by the values of x_1 that are greater than $\tilde{x}_1$.

B Estimation of Moment Inequality Confidence Sets

I primarily follow Appendix A.5 and A.7 in Dickstein and Morales (2015) to estimate the moment inequality model. My method of evaluating a given point, also described in Andrews and Soares (2010), is the same that of Dickstein and Morales (2015). The primary difference arises in the grid search. I begin by briefly describing the intuition of the evaluation of parameters when estimating the moment inequality confidence sets.

Defining an error in this context as the deviation of a data moment from satisfaction of its inequality, the essential goal is to compare the sum of squared errors of the unconditional sample moments to what it would be under the null hypothesis that a given parameter vector is asymptotically consistent with the set of moment inequalities. This yields an intuitive test statistic that measures the the degree of violation of the ℓ moment inequalities for a given parameter vector:

$$Q(\psi_p^*) = \sum_\ell [min(\sqrt{N}\frac{\bar{m}_\ell(\psi_p^*)}{\hat{\sigma}_\ell}, 0)]^2, \tag{41}$$

where $\bar{m}_\ell(\psi_p^*)$ is the sample mean of the ℓth unconditional moment evaluated at ψ_p^*, and $\hat{\sigma}_\ell/\sqrt{N}$ is the estimated standard deviation of the ℓth unconditional moment.

Define $Q_a^n(\psi_p^*)$ as the asymptotic distribution of $Q(\psi_p^*)$ under the null hypothesis that $\mathbb{E}[m_\ell] = 0 \; \forall \; \ell$. If the value of $Q(\psi_p^*)$ obtained is less than the critical value defined at the αth percentile of $Q_a^n(\psi_p^*)$, then we will fail to reject that $\psi_p^* \in \Psi_0^*$. The distribution $Q_a^n(\psi_p^*)$ is thus sufficient to test this hypothesis. It is clear that distribution of the normalized moments at a given parameter vector is a multivariate normal with mean $\sqrt{N}\frac{\mathbb{E}[m(\psi_0^*)]}{\sigma_\ell}$ and variance $\Sigma_\psi(\psi_p^*)$ by central limit theorem. However, because the distribution of $Q_a^n(\psi_p^*)$ is that of the sum of ℓ squared truncated normals, it does not follow a known distribution. We can however obtain a simulated distribution $\hat{Q}_a^n(\psi_p^*)$ by generating R draws from the null distribution of normal moments with mean 0 and variance $\hat{\Sigma}_\psi(\psi_p^*)$. Each draw from this simulated distribution of moments provides a test statistic $Q_{ar}^n(\psi_p^*)$ resulting in a simulated distribution $\hat{Q}_a^n(\psi_p^*)$. Define the critical value at confidence level α $cv_\alpha(\psi_p^*)$ as the αth percentile of the simulated distribution $\hat{Q}_a^n(\psi_p^*)$. If the calculated test statistic in our sample $Q(\psi_p^*)$ is less than the critical value $cv_\alpha(\psi_p^*)$, the we fail to reject that the parameter vector ψ_p^* is within Ψ_0.

Regarding the algorithm for determining which points are within the confidence set, I will focus primary on distinctions between my estimation algorithm and those of DM. DM perform a brute force grid search on 3 parameters with a grid fineness of 40, producing $40^3 = 64,000$ points to evaluate. Because I evaluate 4 parameters when estimating the moment inequalities, I would need to evaluate $40^4 = 2,560,000$ points, dramatically more than DM. Initial attempts to achieve convergence with this method were unsuccessful. I augment the grid search algorithm in two ways. First, after making an initial grid to search in (by following the method DM use), I order these points in terms of their distance from the analogous IV Probit estimates. Because the intuition for these two methods is very similar, I expect them to produce similar results. Second, once I find a feasible point, I abandon the grid search of all points and search locally around the successful point.

This second alteration essentially makes use of the continuity of the moment inequalities to avoid checking points that will not succeed. For instance, ceteris paribus, if the moment inequalities are satisfied at $\beta_0^* = 1$ and are not satisfied at $\beta_0^* = 2$, then this algorithm avoids checking $\beta_0^* = 3$. This essentially turns one extremely large grid search into a set of very small grid searches. When in the course of performing the grid search described by DM, a point in k-dimensional space space is found that cannot be rejected as satisfying the inequalities, I abandon the initial grid and instead form check the k-dimensional hyper-rectangle defined by grid points that are 1 unit away from the unrejected point. I then repeat this procedure for all points that I fail to reject, and not for rejected points. This procedure allows me to find all unrejected points that are adjacent to other unrejected points, in a fraction of the time of searching the entire grid.

C Principal Component Analysis

Here I provide estimates related to the principal component analysis mentioned in Section 4. The purpose of the principal component analysis is to reduce the parameter space sufficiently for the estimation algorithm described in Appendix B to converge in a timely fashion. I condense the controls listed in Table 2 into principal components according to the categorization in Table 6.

Table 6: List of Variables Included and Excluded in Principal Component Analysis

Variable Name	PC1 (Ability)	PC2 (Location)
ASVAB (All Tests)	✓	·
Mother's Education	✓	·
Mother's Education Squared	✓	·
Father's Education	✓	·
Father's Education Squared	✓	·
Number of Siblings	✓	·
Number of Siblings Squared	✓	·
High School GPA	✓	·
High School GPA Squared	✓	·
Bio Parents Home	✓	·
Urban at Age 14	·	✓
Average County Wage, Age 17	·	✓
State Unemployment, Age 17	·	✓

The loadings from the first principal component of each set of controls are provided in Table 7.

Table 7: Principal Component Loadings

	(1) PC1 (Ability)	(2) PC2 (Location)
Mother Education	0.192	
Mother Education Squared	0.193	
Father Education	0.206	
Father Education Squared	0.203	
Number of Siblings	-0.159	
Number of Siblings Squared	-0.149	
ASVAB Score Subtest 3	0.288	
ASVAB Score Subtest 3 Squared	0.021	
ASVAB Score Subtest 4	0.286	
ASVAB Score Subtest 4 Squared	0.088	
ASVAB Score Subtest 5	0.291	
ASVAB Score Subtest 5 Squared	-0.081	
ASVAB Score Subtest 6	0.264	
ASVAB Score Subtest 6 Squared	-0.089	
ASVAB Score Subtest 7	0.203	
ASVAB Score Subtest 7 Squared	-0.048	
ASVAB Score Subtest 8	0.175	
ASVAB Score Subtest 8 Squared	-0.039	
ASVAB Score Subtest 9	0.230	
ASVAB Score Subtest 9 Squared	0.061	
ASVAB Score Subtest 10	0.279	
ASVAB Score Subtest 10 Squared	0.103	
ASVAB Score Subtest 11	0.262	
ASVAB Score Subtest 11 Squared	0.093	
ASVAB Score Subtest 12	0.264	
ASVAB Score Subtest 12 Squared	0.058	
High School GPA	0.200	
High School GPA Squared	0.205	
Broken Home	-0.027	
Average County Wage at Age 17		0.707
State Unemp Rate at Age 17		0.566
Urban Residence at Age 14		0.424
Observations	5492	5492

Notes: Estimates are for the full NLSY79 sample. I use the first principal component from each set of variables in Table 6 to construct a measure of ability and local geographic characteristics.

D Estimation of γ

In order to estimate $\hat{\gamma}(X)$ to obtain the perceived returns scaled in dollars, I use data from the NLSY79 on the percentage of college costs that students pay themselves. This information is only available in 1979. The raw data for observed values of γ are provide in Figure 9. Individual responses take one of four values. Students may report that they pay all, over half, less than half, or none of their educational expenses. I assign a value of 0.25% to those who report paying less than half, and a value of 0.75% to those who report paying more than half.

I estimate the following regression:

$$\gamma(X_i) = \frac{Tuition\_Paid_i}{Tuition_i} = X\beta_\gamma + \frac{X}{Tuition_i}\beta_{\gamma T}. \tag{42}$$

The terms divided by $Tuition_i$ will provide the effect of that component of X on the percentage of tuition paid, $\gamma(X)$. The terms that are not divided by $Tuition_i$ will provide the effect of that component of X on raw tuition. If for instance an individual's parents contribute $\$A + \$Tuition_i B$, the A will be caught by the terms not divided by zero, and should not be included in γ. Results from this regression are shown in Table 8. The imputed values for $\gamma(X)$ across the full sample are provided in Figure 10. Note that a few of these values exceed 1, which is conceptually interpretable as parents paying more than 100% of marginal tuition costs (parents provide in-kind benefits in excess of tuition, potentially as a reward for choosing a high quality, expensive college).

E Imputation of Tuition

I impute tuition as described in section 4. I impute sticker price at college and scholarships separately and then combine them to produce net tuition. The results from the imputation are presented in Tables 9 and 10. I impute across all time periods in which I observe individuals because I use multiple years of tuition for single individuals to impute tuition conditional on observed characteristics.

F Auxiliary Results

The unscaled results with all controls are provided in Table 11. The first stage for the IV Probit is provided in Table 12. Recall that the F-stat on local tuition at age 17 should be viewed as a

Table 8: Effect on Percentage of Tuition Paid

	(1) Coef.	
inv_tuition	-68.58	(-1.35)
Mother Education	-0.00855	(-0.34)
Mother Education Squared	-0.000486	(-0.48)
Father Education	0.00793	(0.44)
Father Education Squared	-0.000827	(-1.18)
Number of Siblings	0.0821***	(4.84)
Number of Siblings Squared	-0.00427*	(-2.54)
ASVAB Score Subtest 3	-0.00553	(-0.21)
ASVAB Score Subtest 3 Squared	-0.0112	(-0.54)
ASVAB Score Subtest 4	-0.00822	(-0.35)
ASVAB Score Subtest 4 Squared	0.0149	(0.80)
ASVAB Score Subtest 5	-0.0614	(-1.72)
ASVAB Score Subtest 5 Squared	0.00409	(0.14)
ASVAB Score Subtest 6	0.0154	(0.48)
ASVAB Score Subtest 6 Squared	-0.0259	(-0.98)
ASVAB Score Subtest 7	0.0382	(1.75)
ASVAB Score Subtest 7 Squared	0.00391	(0.19)
ASVAB Score Subtest 8	-0.0240	(-1.28)
ASVAB Score Subtest 8 Squared	-0.00867	(-0.56)
ASVAB Score Subtest 9	0.00596	(0.28)
ASVAB Score Subtest 9 Squared	0.0127	(0.77)
ASVAB Score Subtest 10	0.00363	(0.16)
ASVAB Score Subtest 10 Squared	-0.0144	(-0.77)
ASVAB Score Subtest 11	-0.0306	(-1.38)
ASVAB Score Subtest 11 Squared	0.0121	(0.65)
ASVAB Score Subtest 12	0.0582*	(2.34)
ASVAB Score Subtest 12 Squared	0.0136	(0.75)
High School GPA	-0.0434	(-0.39)
High School GPA Squared	0.00926	(0.45)
Broken Home	0.179***	(5.72)
T_div_mhgc	5.655	(1.15)
T_div_mhgc2	-0.198	(-0.93)
T_div_fhgc	-0.0404	(-0.01)
T_div_fhgc2	0.00216	(0.01)
T_div_numsibs	-1.523	(-0.36)
T_div_numsibs_sq	-0.0777	(-0.18)
T_div_asvab3	2.681	(0.39)
T_div_asvab3_sq	-1.599	(-0.29)
T_div_asvab4	2.022	(0.56)
T_div_asvab4_sq	-1.125	(-0.22)
T_div_asvab5	8.127	(1.25)
T_div_asvab5_sq	6.543	(0.91)
T_div_asvab6	-6.804	(-1.27)
T_div_asvab6_sq	2.046	(0.57)
T_div_asvab7	0.841	(0.21)
T_div_asvab7_sq	-2.876	(-0.70)
T_div_asvab8	-2.670	(-0.72)
T_div_asvab8_sq	8.866*	(2.02)
T_div_asvab9	-5.246	(-1.35)
T_div_asvab9_sq	5.687	(1.89)
T_div_asvab10	-4.271	(-0.97)
T_div_asvab10_sq	-0.188	(-0.05)
T_div_asvab11	5.663	(1.23)
T_div_asvab11_sq	-3.355	(-0.84)
T_div_asvab12	0.613	(0.10)
T_div_asvab12_sq	-1.272	(-0.35)
T_div_GPA	29.60	(1.26)
T_div_GPA_sq	-5.105	(-1.29)
T_div_Broken_Home	-7.677	(-1.13)
Constant	0.568**	(2.85)
Observations	1113	

Notes: Standard errors are in parentheses. Estimates are for the part of the NLSY79 sample who attended college in 1979 and provided tuition and tuition paid information.

Table 9: Tuition Imputation

	(1) Coef.	
sticker_		
mhgc	-1936.1***	(-28.45)
mhgc2	116.4***	(35.40)
fhgc	-257.7***	(-4.93)
fhgc2	34.65***	(15.72)
numsibs	-1013.1***	(-19.83)
numsibs Squared	67.54***	(13.90)
asvab3	276.3***	(15.78)
asvab3 Squared	42.57***	(19.05)
asvab4	-84.28***	(-6.81)
asvab4 Squared	32.72***	(26.39)
asvab5	219.6***	(17.14)
asvab5 Squared	-14.40***	(-12.26)
asvab6	291.4***	(12.01)
asvab6 Squared	-37.87***	(-7.07)
asvab7	13.35*	(2.09)
asvab7 Squared	-9.771***	(-21.23)
asvab8	-11.90**	(-2.85)
asvab8 Squared	1.147***	(6.88)
asvab9	-304.5***	(-21.06)
asvab9 Squared	5.887***	(3.48)
asvab10	346.9***	(23.35)
asvab10 Squared	65.26***	(38.42)
asvab11	-6.806	(-0.45)
asvab11 Squared	-22.31***	(-12.12)
asvab12	-109.0***	(-5.82)
asvab12 Squared	17.92***	(6.21)
urban	657.7***	(5.48)
GPA	4307.5***	(10.77)
GPA Squared	-125.3	(-1.90)
c_wage_per_employed_age_17	1256.9***	(76.41)
unemployment_age_17	-298.0***	(-12.94)
local_tuition_17	7.613***	(77.89)
Constant	-9589.1***	(-9.75)
select		
College_age_14	0.182***	(28.30)
mhgc	-0.165***	(-44.67)
mhgc2	0.0108***	(57.28)
fhgc	-0.0228***	(-8.03)
fhgc2	0.00401***	(29.84)
numsibs	-0.0293***	(-27.45)
asvab3	0.00167	(1.73)
asvab3 Squared	0.000838***	(6.72)
asvab4	-0.0129***	(-18.90)
asvab4 Squared	0.00240***	(35.15)
asvab5	0.00335***	(5.00)
asvab5 Squared	-0.00186***	(-33.55)
asvab6	0.0205***	(16.33)
asvab6 Squared	-0.00924***	(-37.46)
asvab7	0.00138***	(3.91)
asvab7 Squared	-0.000467***	(-19.78)
asvab8	-0.00664***	(-29.24)
asvab8 Squared	-0.000127***	(-13.05)
asvab9	-0.0169***	(-21.49)
asvab9 Squared	-0.00115***	(-12.02)
asvab10	0.0232***	(29.98)
asvab10 Squared	0.00398***	(42.66)
asvab11	-0.0126***	(-15.20)
asvab11 Squared	0.000729***	(6.91)
asvab12	-0.0124***	(-11.95)
asvab12 Squared	0.00429***	(26.30)
urban	0.191***	(31.29)
GPA	0.599***	(168.74)
c_wage_per_employed_age_17	-0.00919***	(-9.65)
unemployment_age_17	0.0101***	(7.69)
local_tuition_17	-0.000112***	(-21.17)
Constant	-1.182***	(-50.34)
/mills		
lambda	11064.7***	(25.71)
Observations	352933	

Notes: Standard errors in parentheses. Parameters are marginal effects of the variable on college sticker price. See section 4 for details.

Table 10: Scholarship Imputation

	(1) Coef.	
NPV_scholarship_		
mhgc	-2409.9***	(-15.64)
mhgc2	116.0***	(14.76)
fhgc	1541.9***	(16.84)
fhgc2	-49.95***	(-13.74)
numsibs	554.6***	(9.32)
numsibs Squared	-30.59***	(-5.83)
asvab3	104.0***	(3.99)
asvab3 Squared	49.81***	(14.79)
asvab4	-351.2***	(-20.00)
asvab4 Squared	21.55***	(10.53)
asvab5	88.77***	(5.31)
asvab5 Squared	-3.781	(-1.81)
asvab6	354.4***	(9.80)
asvab6 Squared	-169.1***	(-13.75)
asvab7	70.91***	(8.17)
asvab7 Squared	-11.43***	(-17.72)
asvab8	-121.6***	(-15.95)
asvab8 Squared	-2.422***	(-8.58)
asvab9	-441.4***	(-11.08)
asvab9 Squared	-40.76***	(-15.65)
asvab10	122.3***	(6.22)
asvab10 Squared	63.24***	(13.61)
asvab11	-172.1***	(-6.10)
asvab11 Squared	28.30***	(11.05)
asvab12	-27.14	(-1.07)
asvab12 Squared	68.04***	(9.41)
urban	2303.7***	(13.57)
GPA	2144.5*	(2.56)
GPA Squared	1100.3***	(14.84)
c_wage_per_employed_age_17	195.3***	(8.28)
unemployment_age_17	-30.34	(-0.98)
local_tuition_17	1.674***	(12.97)
Constant	-28077.8***	(-8.02)
select		
College_age_14	0.0536***	(8.49)
mhgc	-0.119***	(-35.29)
mhgc2	0.00630***	(39.25)
fhgc	0.0502***	(18.44)
fhgc2	-0.00170***	(-14.16)
numsibs	0.00761***	(7.17)
asvab3	0.00977***	(10.35)
asvab3 Squared	0.00161***	(13.47)
asvab4	-0.00527***	(-8.01)
asvab4 Squared	0.00120***	(18.80)
asvab5	0.000356	(0.54)
asvab5 Squared	-0.00137***	(-24.66)
asvab6	0.0143***	(11.48)
asvab6 Squared	-0.00868***	(-34.52)
asvab7	-0.00120***	(-3.52)
asvab7 Squared	-0.000209***	(-8.96)
asvab8	-0.00479***	(-22.00)
asvab8 Squared	-0.000170***	(-18.60)
asvab9	-0.0302***	(-39.72)
asvab9 Squared	-0.00112***	(-12.08)
asvab10	0.00449***	(5.95)
asvab10 Squared	0.00373***	(43.27)
asvab11	-0.0177***	(-22.14)
asvab11 Squared	0.000764***	(7.59)
asvab12	0.00603***	(6.02)
asvab12 Squared	0.00562***	(36.46)
urban	0.0683***	(11.37)
GPA	0.502***	(142.33)
c_wage_per_employed_age_17	-0.00962***	(-10.39)
unemployment_age_17	-0.000505	(-0.40)
local_tuition_17	0.00000553	(1.08)
Constant	-1.580***	(-68.24)
/mills		
lambda	22726.9***	(13.44)
Observations	352933	

Notes: Standard errors in parentheses. Parameters are marginal effects of the variable on college sticker price. See section 4 for details.

lower bound on the strength of the instrument, as explained in Section 5. This value is 4629.13.

Table 11: Perceived Returns Estimates, Unscaled, All Controls

	(1) Probit	(2) Std. Error	(3) IV Probit	(4) Std. Error
Constant	0.475	(0.063)	0.565	(0.080)
Mother Education	-0.193	(0.031)	-0.191	(0.031)
Mother Education Squared	0.012	(0.002)	0.012	(0.002)
Father Education	-0.038	(0.024)	-0.031	(0.024)
Father Education Squared	0.005	(0.001)	0.005	(0.001)
Number of Siblings	-0.092	(0.023)	-0.082	(0.024)
Number of Siblings Squared	0.006	(0.002)	0.005	(0.002)
ASVAB Score Subtest 3	0.022	(0.035)	0.022	(0.035)
ASVAB Score Subtest 3 Squared	0.031	(0.026)	0.031	(0.026)
ASVAB Score Subtest 4	-0.027	(0.034)	-0.027	(0.034)
ASVAB Score Subtest 4 Squared	0.122	(0.027)	0.133	(0.028)
ASVAB Score Subtest 5	0.040	(0.038)	0.041	(0.038)
ASVAB Score Subtest 5 Squared	-0.144	(0.029)	-0.153	(0.030)
ASVAB Score Subtest 6	0.055	(0.032)	0.063	(0.032)
ASVAB Score Subtest 6 Squared	-0.122	(0.025)	-0.127	(0.025)
ASVAB Score Subtest 7	-0.016	(0.028)	-0.011	(0.028)
ASVAB Score Subtest 7 Squared	-0.077	(0.025)	-0.079	(0.025)
ASVAB Score Subtest 8	-0.083	(0.027)	-0.085	(0.027)
ASVAB Score Subtest 8 Squared	-0.050	(0.024)	-0.048	(0.024)
ASVAB Score Subtest 9	-0.123	(0.033)	-0.130	(0.034)
ASVAB Score Subtest 9 Squared	-0.045	(0.025)	-0.039	(0.025)
ASVAB Score Subtest 10	0.155	(0.033)	0.168	(0.034)
ASVAB Score Subtest 10 Squared	0.187	(0.026)	0.189	(0.026)
ASVAB Score Subtest 11	-0.096	(0.033)	-0.102	(0.033)
ASVAB Score Subtest 11 Squared	-0.010	(0.025)	-0.013	(0.025)
ASVAB Score Subtest 12	-0.050	(0.033)	-0.040	(0.034)
ASVAB Score Subtest 12 Squared	0.113	(0.025)	0.118	(0.025)
High School GPA	0.654	(0.117)	0.716	(0.122)
High School GPA Squared	-0.012	(0.026)	-0.022	(0.027)
Broken Home	-0.012	(0.044)	0.018	(0.047)
Urban Residence at Age 14	0.179	(0.048)	0.181	(0.048)
Average County Wage at Age 17	0.021	(0.009)	0.028	(0.010)
State Unemp Rate at Age 17	0.002	(0.010)	0.003	(0.010)
Tuition	-0.027	(0.008)	-0.040	(0.011)
Observations	5492	5492	5492	5492

Notes: Standard errors in parentheses. Parameters are marginal effects of the variable on perceived returns to college in thousands of dollars. The value for σ is assumed to be 1. Estimates are from equation (4) with the details varying by estimation method. See text for details.

Table 12: First Stage Estimates, Effect of Instruments on Tuition

	(1)	
	Coef.	
Mother Education	-0.529***	(-13.37)
Mother Education Squared	0.0225***	(11.88)
Father Education	0.255***	(8.28)
Father Education Squared	-0.00964***	(-6.94)
Number of Siblings	0.578***	(18.45)
Number of Siblings Squared	-0.0304***	(-11.05)
ASVAB Score Subtest 3	0.348***	(7.17)
ASVAB Score Subtest 3 Squared	0.193***	(5.47)
ASVAB Score Subtest 4	-0.184***	(-3.85)
ASVAB Score Subtest 4 Squared	0.913***	(26.46)
ASVAB Score Subtest 5	0.133*	(2.48)
ASVAB Score Subtest 5 Squared	-0.669***	(-16.63)
ASVAB Score Subtest 6	0.587***	(13.19)
ASVAB Score Subtest 6 Squared	-0.363***	(-10.36)
ASVAB Score Subtest 7	0.476***	(12.20)
ASVAB Score Subtest 7 Squared	-0.322***	(-9.62)
ASVAB Score Subtest 8	-0.272***	(-7.37)
ASVAB Score Subtest 8 Squared	0.0794*	(2.51)
ASVAB Score Subtest 9	-0.571***	(-12.60)
ASVAB Score Subtest 9 Squared	0.403***	(11.81)
ASVAB Score Subtest 10	0.911***	(20.27)
ASVAB Score Subtest 10 Squared	0.600***	(17.66)
ASVAB Score Subtest 11	-0.323***	(-7.10)
ASVAB Score Subtest 11 Squared	-0.292***	(-8.64)
ASVAB Score Subtest 12	0.583***	(12.75)
ASVAB Score Subtest 12 Squared	0.433***	(12.96)
High School GPA	3.649***	(26.38)
High School GPA Squared	-0.430***	(-13.86)
Broken Home	2.296***	(39.64)
Average County Wage at Age 17	0.672***	(66.25)
State Unemp Rate at Age 17	-0.176***	(-12.17)
Urban Residence at Age 14	0.212**	(3.13)
Local Tuition	0.00405***	(68.04)
Constant	-15.39***	(-48.53)
Observations	5492	

Notes: Standard errors in parentheses. Parameters are marginal effects of the variable on thousands of dollars of effective tuition ($Tuition_i\hat{\gamma}(X)\lambda$).