ESSAYS IN LABOR ECONOMICS

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ABSTRACT

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This dissertation consists of three chapters regarding labor economics. The first chapter studies the relative preference men and women have for working with coworkers of the same or opposite sex. The second chapter develops a conceptual framework for estimating the distribution of perceived returns to investments conditional on observed characteristics. The third chapter applies the methods described in the second chapter to estimate perceived returns to college and discusses policy implications.

The first chapter analyzes the effect of occupational gender composition on job-specific labor supply for workers of each gender. I construct a static model of job selection wherein preferences regarding coworker gender composition produce gender-specific compensating differentials. I estimate the model to identify the underlying coworker gender preference parameters. Based on estimated compensating differentials, men's preference is highest for occupations that are 60% female and lowest for female-dominated occupations. Women prefer jobs that are female-dominated, and are least satisfied with jobs that are 25% male all else equal.

The second chapter describes a conceptual framework for inferring agents' perceived returns to college by exploiting the dollar-for-dollar relationship between perceived returns and tuition costs in a binary choice model of college attendance. This approach has four attractive features. First, it provides estimates of perceived returns in terms of compensating variation, which directly inform financial policies that

seek to (dis)incentivize the investment. Second, it provides very fine continuously-heterogeneous estimates conditional on a large set of observed characteristics, allowing for differential predictions for how selective, well-publicized policies are likely to affect different types of individuals. Third, because it obtains type-specific perceived returns distributions instead of point elasticities, it provides differential predictions for the effects of type-specific financial interventions depending on the magnitude of the intervention. Finally, the estimates are obtained assuming rational expectations only on prices (one component of returns) rather than on returns as a whole.

The third chapter applies the method described in the second chapter to estimate perceived returns to college using NLSY79 data. 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. Adapting the difference-in-difference estimation performed by Dynarski (2003) on the effect of the Social Security Student Benefit to the current setting, I find that the policy increased perceived returns to college by $23,800, compared to an average aid amount of $6,700 per year ($26,800 per four years) (year 2000 dollars). Using the estimated distribution of perceived returns, I perform a counterfactual policy experiment that induces a set percentage of the population to attend college at minimal cost to the government.

1. COWORKER GENDER PREFERENCES: EFFECTS ON GENDER GAPS IN OCCUPATIONAL SELECTION AND WAGES

1.1 Introduction

Occupational selection is a major factor in a wide array of differential outcomes for men and women. Not only is it a major factor in gaps in pay between men and women, but it also has implications for productivity and job satisfaction. Given these important implications, it is valuable to identify the various factors that drive men and women to choose different jobs. I contribute to this effort by investigating the role that the gender composition of an occupation plays in attracting workers of each gender. I obtain nonlinear preferences for men and women over the gender composition of jobs by estimating gender-specific compensating differentials for the share of a job that is female.

This question is of particular interest not only because it considers another factor that explains differential job satisfaction and selection by gender but because this factor produces externalities by necessity and therefore has serious implications for welfare. When a person selects an occupation due in part to its gender composition, they affect its gender composition. This necessarily affects the favorability of the job for themselves and all others in the job (except in the specific case where the job is already entirely dominated by their gender). The individual may take into account their own effect on the gender composition of the job when making their occupational decision, but will not generally internalize their impact on the attractiveness of the occupation to others.

Because I allow for preferences over the gender composition of jobs to vary nonlinearly and even nonmonotonically, my strategy allows for the possibility of multiple equilibria in the gender composition of jobs. For instance, I find that in male-dominated occupations, marginal increases in the female share of the occupation increase men's compensating differentials. This means that the firm's marginal cost of hiring a woman is not only given by her wage, but by the increase in men's equilibrium wages times the number of men currently working in the firm. Hiring a large number of women, however, reduces men's compensating differential while also reducing the number of men in the occupation, which causes a much smaller increase in firm costs per female hire. The policy implication of this is that firms may avoid marginal increases in female representation in jobs because they are at a local minimum of costs, and policies that shift large numbers of women into male-dominated jobs may achieve a different, and possibly welfare-improving, equilibrium. Any policy that induces such a shift would achieve its desired effect even if it is only temporary.

Differences between minority and nonminority workers in terms of employment and wages has previously been explored through various mechanisms, including the preferences of employers, consumers, and coworkers. These works present models that are generally applicable but are overwhelmingly implemented in the investigation of differences based on either race or gender (which we consider here). The seminal work on the subject is that of Becker (1957). In Becker, firms receive utility from profits and lose utility from hiring black workers. In order to be indifferent between hiring whites and blacks, the firm provides a lower wage to blacks with the differential being exactly equal to the disutility received from hiring the black worker. The model predicts that profit is decreasing in the strength of the racial prejudice and due to

Table 1.1.: Descriptive Statistics of Male and Female Wages

Share of Occupation Female	**variable**	**N**	**mean**	**sd**
0-25%	Share Female	49343	.1159596	.087984
	Mean Male Wage	44307	20.10564	11.25329
	Mean Female Wage	5036	20.99102	10.87163
25-50%	Share Female	143742	.357084	.0637713
	Mean Male Wage	97130	26.69123	11.55262
	Mean Female Wage	46612	19.7498	9.898433
50-75%	Share Female	27322	.6197304	.0769729
	Mean Male Wage	11534	21.92464	11.69915
	Mean Female Wage	15788	16.67704	8.212288
75-100%	Share Female	55772	.905058	.0705397
	Mean Male Wage	5892	19.23069	10.1875
	Mean Female Wage	49880	15.81967	6.902736
Total	Share Female	276179	.4506459	.2723732
	Mean Male Wage	158863	24.23173	11.85176
	Mean Female Wage	117316	17.71856	8.781421

Note: The unit of observation is an individual. Observations are on full-time, full-year workers with reported wages in job/state/year combinations with at least 50 observations from 1990-2015 in the Current Population Survey.

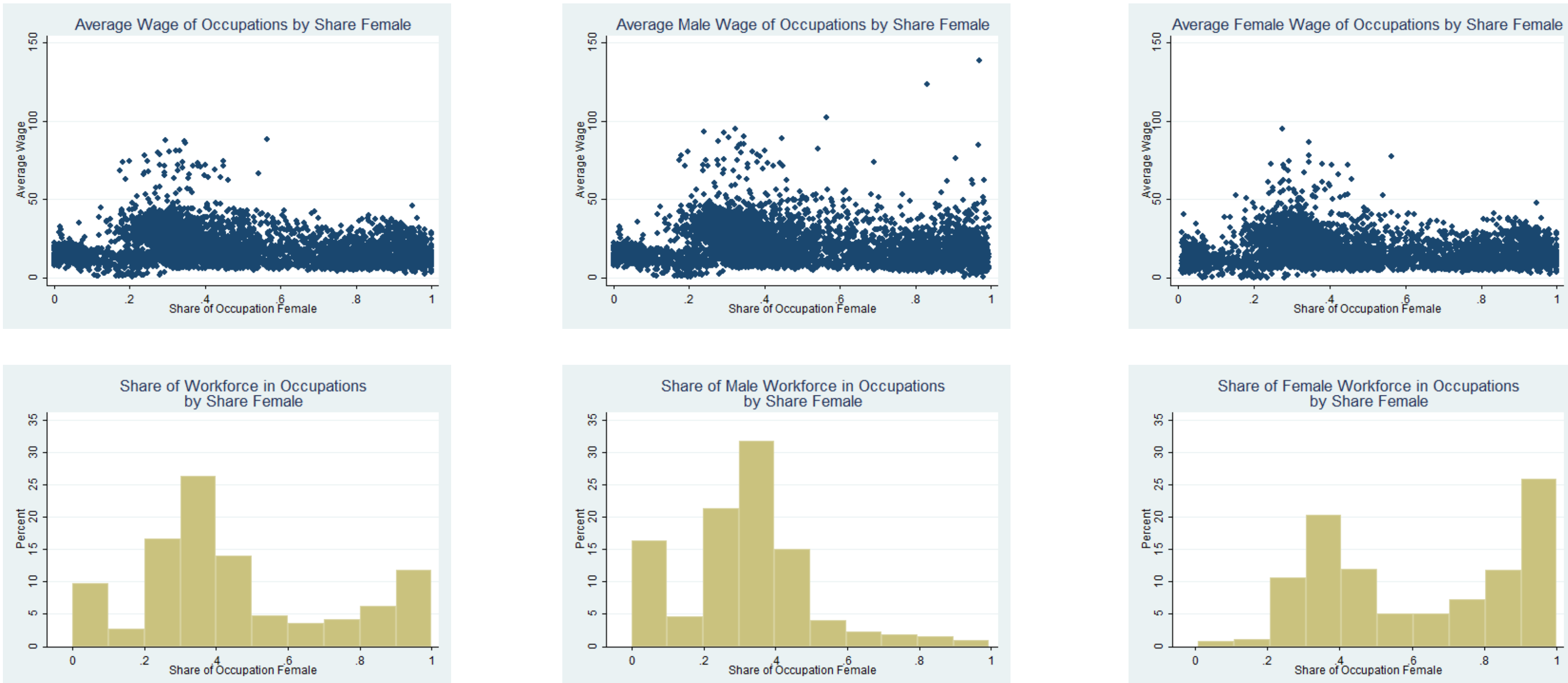

Figure 1.1.: Wages and Population Densities

Notes: Average wages and population densities by gender according to share of women in an occupation in a given state and year. Occupations are defined at the 3-digit occ1990 occupational coding scheme available in the census. This figure plots average wages for full-time, full-year workers in occupations with at least 50 individuals by the share of the occupation that is female as well as the distribution of the workforce by the share of the occupation that is female. All data is from the CPS, 1990-2015.

entry and exit, the long-run equilibrium allows for only the most productive prejudiced firms to survive (they will hire only whites) and non-prejudiced firms will hire whites and blacks with a single wage. More broadly speaking, if there is prejudicial distaste by some employers, consumers, or coworkers, the market should allow prejudiced firms, consumers, and workers to interact exclusively with white-only versions of each other, while the rest of the market (blacks and non-prejudiced whites) interacts only internally as well. The essential outcome is one of highly segregated markets with no wage differentials unless segregation is impossible due to the numbers of minorities and firms in the market (in which case a wage gap can persist).

In our formulation, we allow for the possibility of individuals still interacting with other types if their idiosyncratic taste for a particular job is sufficiently high. This allows for less extreme outcomes than are predicted by the Becker model; segregation will be incomplete and we can maintain wage gaps with widespread weak own-type preferences. Additionally, we frame individual preferences in terms of own-group vs. out-group preference rather than a strict majority on minority prejudice. This allows us to consider the effects not only of the majority having distaste for working with minorities, but vice versa (in either case due either to actual prejudice or homophily).

Along very similar lines to worker preferences regarding their coworkers, we have Goldin (2014), which refers to the possibility of a job being "polluted" by the presence of a particular type of worker. Here, workers receive utility both from some wage that they earn at a job and from a sense of prestige that is associated with the perceived difficulty of the job by society. The model proceeds in 2 stages. In the first stage, men are alone in the market and work various jobs. In stage 2, men stay in the same job and women enter the job market. Each job requires some amount of some trait C, such as physical strength, in order to work at a given firm, and the worker's pay is proportionate to their level of C. Importantly, at the beginning of stage 2 there is a random technology shock to firms where the amount of the trait required to work in the firm either decreases or does not. Jobs that had a high C in stage 1 may now have a low C, but will retain the prestige associated with the stage 1 value if society is unable to determine that the amount of the trait needed to succeed in the job has diminished. If women are believed by society to have lower average values of C than was required to work such a job in stage 1, and this job hires a sufficient number of women, society will infer that the technological change has occurred in this industry and the job is no longer as difficult as it once was (even if this has not happened). This reduces the prestige of the job for the incumbent male workers. Because of this, these men will demand a wage premium to compensate them for their lost prestige over the women (who are modeled as not caring about prestige). Alternatively, firms can create a “different” occupation for women that is effectively the same as that of men, allowing the men to retain their prestige while still hiring women. The first case produces a wage gap and the second produces occupational segregation.

It is important to consider the difference between this notion of occupational pollution and the type of coworker preferences we are investigating. Here, the two types of workers do not mind working with one another, they simply dislike having their prestige reduced. In the scenario we investigate, the two groups actually get disutility from interacting with one another (perhaps due to outright harassment or more mild mechanisms such as restrictions in what types of opinions are considered acceptable to voice, which plausibly varies by how much one type dominates the social setting). It is plausible that both mechanisms are in effect, but discerning the magnitude of each effect may be difficult. It is plausible that the pollution effects may matter more for occupational choice, while coworker preferences may more strongly affect selection into industries. Comparing industrial segregation to occupational segregation (accounting for the expected correlation between the two) may provide insight into the relative potency of each of these mechanisms.

A related paper by Pan (2015) examines male and female preferences for jobs in a framework which also borrows from literature on the tipping phenomenon in housing markets. She investigates occupations in the U.S. economy and is able to identify tipping points wherein after a certain proportion of an occupation's workers become female, male growth in the occupation becomes negative and the job becomes heavily female-dominated. She uses IPUMS from 1940-1990 and is able to analyze changes in occupations in terms of gender representation. She shows that firms with 25%-45% female labor forces begin to have negative net male employment growth in white collar occupations, while the tipping point varies from 13%-30% for blue collar occupations. Additionally, she finds that tipping occurs sooner in regions where men hold more sexist attitudes toward women. This may also explain the lower tipping points in blue collar occupations vs. white collar occupations if blue collar men have higher rates of such opinions than white collar men. Such an analysis of changes in male and female representation in jobs is obviously related to our question, though we will attempt to identify compensating differentials instead of tipping points.

Sasaki (1999) produces a search model that is qualitatively similar to mine in that coworker gender preferences are directly modeled within the utility function. Broadly speaking, this model's qualitative predictions under an assumption of male distaste for female coworkers mirror our own in finding increased female participation produces higher female wages and lower unemployment, while increased distaste for female coworkers among males reduces female earnings and employment. Notable differences are present as well. Sasaki imposes that men have distaste for women without providing the opportunity for women to have symmetric preferences. Additionally, this model is somewhat more extreme in assuming that the nature of males' preferences is that if a firm hires any women at all, the male get a constant disutility from working in that firm. Our formulation allows for a flexible utility term that allows for the utility for each additional other-typed coworker to be convex, concave, and/or nonmonotonic. This allows us to more closely match the data to explain the tipping behavior observed empirically in the proportion of male workers in occupations, as well as selection and gender gaps in jobs.

I model labor market outcomes with preferences regarding the distribution of coworkers in a Roy model. If an individual has to choose between occupations in which to work, their reservation wage in each occupation will depend in part on disutility from working with each type of worker. Thus, if an individual is otherwise indifferent between two firms, but one has an even slightly higher proportion of their own type of worker (through random chance or through systematic correlation of type and idiosyncratic job preference), this individual will strictly prefer this firm over the other if they prefer their own type. In equilibrium, this can be expected to predict substantial segregation due to shifts in job selection by workers away from the hypothetical equilibrium without any homophilic preferences.

1.2 Model

1.2.1 Workers

Throughout the following, the index i will refer to types of individuals (male or female) while j will refer to jobs $(1, ..., N)$. Workers receive linear utility from wages w_{ij}, the proportion of female coworkers in a job ψ_j according to type-specific tastes $g_i(\psi_j)$, and an i.i.d. random additive job-specific nonpecuniary benefit $\alpha_{ij} \sim F_{ij}(\alpha)$.

These are all common knowledge for all individuals and jobs. The utility function is thus given by:

$$u_{ij} = ln(w_{ij}) + g_i(\psi_j) + \alpha_{ij}, \quad i = m, f \quad \& \quad j = 1, 2, ..., N. \tag{1.1}$$

The condition for an individual of type i choosing job j over all other jobs is thus:

$$\begin{gathered} u_{ij} \geq u_{ik}, \quad \forall k \neq j \\ ln(w_{ij}) + g_i(\psi_j) + \alpha_{ij} \geq ln(w_{ik}) + g(\psi_k) + \alpha_{ik}, \quad \forall k \neq j \end{gathered} \tag{1.2}$$

Here we impose that each person of type i's draw of α_{ij} for each job comes from an i.i.d. Type I Extreme Value distribution with CDF:

$$F_{ij}(\alpha_1, ..., \alpha_N) = \exp\Big(- \sum_{j=1}^{N} e^{\mu_{ij} - \alpha_j} \Big). \tag{1.3}$$

The mode of the distribution, μ_{ij}, is allowed to vary both between firms and between types. This allows people to view a job more or less favorably based on their gender. For instance, if men have less distaste for particularly unpleasant jobs than women, $\mu_{mj} > \mu_{fj}$ will allow this to enter into the model. The Extreme Value distribution allows for an attractive analytical solution for the proportion of individuals of type i that will choose job j, which we will denote λ_{ij}. This proportion is given by:

$$\begin{aligned} \lambda_{ij} &= \Pr[ln(w_{ij}) + g_i(\psi_j) + \alpha_j > ln(w_{ik}) + g_i(\psi_k) + \alpha_k \quad \forall k \neq j] \\ &= \Pr[\alpha_k < ln(w_{ij}) - ln(w_{ik}) + g_i(\psi_j) - g_i(\psi_k) + \alpha_j \quad \forall k \neq j] \\ &= \int F_j[\alpha_j + \epsilon_1, ..., \alpha_j + \epsilon_N] d\alpha_j \end{aligned} \tag{1.4}$$

where $F_j(\cdot)$ is the derivative of the cdf with respect to it's jth term and $\epsilon_k \equiv w_{ij} - w_{ik} + g_i(\psi_j) - g_i(\psi_k)$. Evaluating this integral provides the following for the proportion of type i that will work in job j:

$$\lambda_{ij} = \frac{e^{ln(w_{ij}) + g_i(\psi_j) + \mu_{ij}}}{\sum_k e^{ln(w_{ik}) + g_i(\psi_k) + \mu_{ik}}} \tag{1.5}$$

Which we can rearrange to obtain the inverse labor supply:

$$ln(w_{ij}) = \ln\left(\frac{\lambda_{ij}}{1-\lambda_{ij}}\right) + \ln\left[\sum_{k\neq j} e^{ln(w_{ik})+g_i(\psi_k)+\mu_{ik}}\right] - \left[g_i(\psi_j) + \mu_{ij}\right] \tag{1.6}$$

Looking at each term sequentially, we can see that the wage is a function of the proportion of type i that the firm hires (upward-sloping supply), the attractiveness of other firms (the functional form emphasizes the most attractive alternative), and the compensating variation both for the individual's preference for their coworkers and for the mode of their random preference for the job.

It is worth noting here that $g_i(\cdot)$ could be any function (individuals have knowledge of it, but we do not). In applications, we want to parameterize it flexibly enough that it allows for several possibilities. If $g_i(\cdot)$ is convex, individuals are largely unaffected by a few individuals like themselves, but will be strongly affected by many. Concavity naturally suggests the opposite. Nonmonotonic $g_i(\cdot)$ is consistent with either preference for diversity ($g_i(\cdot)$ increases then decreases with $\psi_j \in [0,1]$) or a preference to avoid cross-type tensions ($g_i(\cdot)$ decreases then increases with $\psi_j \in [0,1]$). A mixture of these types of preferences would naturally lead to a complex functional form, and I know of nothing in the literature that would make any strong prediction between the above possibilities.

Depending on the functional form of $g_i(\cdot)$, there could be multiple solutions for $\{\psi_j\}$ in the model. In order to obtain unique solutions, we use a sequential entry concept where men start out in the labor force (in their preferred job given $\psi_{mj} = 1$ for all jobs in the labor market) while women start out in the domestic sector. Arbitrarily setting the domestic sector to be j=1 provides initial conditions for female job choice that $\psi_{f1} = 1$, and $\psi_{fk} = 0\ \forall k \neq 1$. The infinitesimal mass of women with the highest utility for jobs will enter those jobs first, and the value of ψ_{fj} will update accordingly for all jobs. This process is repeated until an equilibrium value for ψ_{fj}

is reached $\forall j$. Sequential entry implies that this first equilibrium will occur at the maximum value of the solution for ψ_{f1}, so this condition will designate the unique equilibrium. The potential for multiple equilibria provides a possible opportunity for welfare improvements in the event of a policy that can shift the allocation of labor to a new equilibrium with higher utility outcomes for workers.

1.2.2 Firms

Firms are perfectly competitive profit maximizers. Each firm j hires a mass η_{ij} of type i workers from a measure 1 mass of available workers, such that $\eta_j = \sum_i \eta_{ij}$ is the total mass of workers employed by firm j and $\sum_j \eta_j = 1$ is the total labor force. I assume that firms have CES production over male and female labor:

$$F_j(\eta_{mj}, \eta_{fj}) = \left(\gamma_{mj}\eta_{mj}^{\frac{\epsilon-1}{\epsilon}} + \gamma_{fj}\eta_{fj}^{\frac{\epsilon-1}{\epsilon}}\right)^{\frac{\epsilon}{\epsilon-1}} \tag{1.7}$$

where γ_{ij} governs occupation-gender-specific productivity and ϵ is the elasticity of substitution between male and female labor which is common to all firms. Their problem is then to maximize profit:

$$\pi_j = \max_{\eta_{mj},\eta_{fj}} (\gamma_{mj}\eta_{mj}^{1-\epsilon} + \gamma_{fj}\eta_{fj}^{1-\epsilon})^{\frac{1}{1-\epsilon}} - w_{mj}\eta_{mj} - w_{fj}\eta_{fj} \tag{1.8}$$

The first-order conditions from this problem provide the wage equation for type i at firm j as follows:

$$w_{ij} = \gamma_{ij}\eta_{ij}^{-\frac{1}{\epsilon}}\left(\gamma_{mj}\eta_{mj}^{\frac{\epsilon-1}{\epsilon}} + \gamma_{fj}\eta_{fj}^{\frac{\epsilon-1}{\epsilon}}\right) \quad \forall i = m, f \tag{1.9}$$

This provides a channel whereby the firm can offer different wages to different genders, which is necessary for the emergence of a compensating differential. We could produce such a channel with perfect substitution if we were to assume monopolistic competition among firms (wherein firms would internalize workers' gender composition preferences) but the CES-perfect competition assumption has the advantage of being both more intuitive and more tractable.

1.2.3 Equilibrium

Given prices $\{w_{ij}\}$, an equilibrium is an allocation $\{\eta_{ij}, \psi_j, \lambda_{ij}\}$ in which workers choose their preferred job, firms maximize profit, and markets clear[1] such that we have:

$$ln(w_{ij}) = \ln\left(\frac{\lambda_{ij}}{1-\lambda_{ij}}\right) + \ln\left[\sum_{k\neq j} e^{ln(w_{ik})+g_i(\psi_k)+\mu_{ik}}\right] - \left[g_i(\psi_j) + \mu_{ij}\right] \tag{1.10}$$

$$w_{ij} = \gamma_{ij}\eta_{ij}^{-\frac{1}{\epsilon}}\left(\gamma_{mj}\eta_{mj}^{\frac{\epsilon-1}{\epsilon}} + \gamma_{fj}\eta_{fj}^{\frac{\epsilon-1}{\epsilon}}\right) \tag{1.11}$$

$$\lambda_{fj} = \frac{\psi_j\eta_j}{S_f}, \quad \& \quad \lambda_{mj} = \frac{(1-\psi_j)\eta_j}{S_m} \tag{1.12}$$

where $S_i = \sum_j \eta_{ij}$ is the proportion of the population that is gender i. Furthermore, we make use of the following identities:

$$\eta_j \equiv \sum_i \eta_{ij}, \quad \sum_j \eta_j \equiv 1, \quad \& \quad \eta_{ij} = S_i\lambda_{ij} \tag{1.13}$$

which state, respectively, that the sum of workers of each gender in a job is equal to the total mass of labor in that job, that the sum of all workers in all jobs is equal to the total labor force, and that the mass of workers of type i in job j is equal to the proportion of type i in the labor force times the probability of a person of type i selecting job j.

We can solve the above system to obtain the percentage of each type that chooses each occupation $\{\lambda_{ij}\}$, the percentage of each occupation that is each type

[1] The market clearing equations are a simple application of Bayes' Rule where we use: $Pr(j|i) = \frac{Pr(i|j)Pr(j)}{Pr(i)}$.

$\{\psi_j\}$, wages by type by occupation $\{w_{ij}\}$, the proportion of each type that is in each occupation $\{\eta_{ij}\}$, and the proportion of the total population that is in each occupation $\{\eta_j\}$.

1.3 Data

We use data from the 2010-2015 U.S. Census available through IPUMS to determine the magnitude of gender-specific compensating differentials predicted by the model. Census data is ideal because it provides data over time and regions, allowing us to effectively control for differences by state and year while still using state-year-job variation for identification. Additionally, the large number of observations available in this data set allow us to precisely estimate higher ordered polynomials of the gender preferences, which is necessary to pick up important information about the shape of the gender-preference function.

There is a question regarding the correct designation of "jobs" in the data, depending on the exact nature of gender preferences. Preferences may manifest differently at the firm, occupation, and industry levels. Workers may care about how masculine or feminine a job is perceived to be, which likely would occur less at the firm level and more at the occupation or industry level. However, workers may also care about interactions with coworkers, in which case firm-level data may provide more insight (though occupations within firms may also determine the duration, intensity, and frequency of interactions, so occupation remains a factor). Workers may choose occupations based on their expected interactions in firms, but may not know the gender composition of particular firms. My primary analysis focuses on occupations since I expect individuals to exercise substantially more control over their choice of occupation than the industry, and I expect them to have more information about occupations than firms. We make use of 3 occupational classifications provided through the Census (with 7, 14, and 46 job categories, specifically). A 3-digit designation is available with 389 occupational designations, but this many occupations is computationally infeasible given my empirical strategy.

To obtain a consistent job classification across years, I construct an occupational designation variable using the occly variable available through IPUMS (which provides an individual's 3-digit occupation for the prior year). This variable does not use a consistent coding scheme across years, so I make use of a crosswalk provided by IPUMS to convert the occly variable into a consistent coding scheme for last year occupations that is analogous to the current year occ1990 classification provided by IPUMS. I additionally construct variables governing the proportion of own-type workers who select a given job (λ_{ij}) and the proportion of workers in a given job who are female (ψ_j). Both variables are constructed using weighted observations of each state-year-job combinations at each level of occupational aggregation (1-digit, 2-digit, and 3-digit).

Because my identification relies on the assumption of a stable preference function $g(\cdot)$, it is important to only include years where this assumption is likely to hold. Because attitudes about gender roles regarding the workforce are constantly evolving, I balance the need for cross-year variation with the need for a stable preference function by using data from 2010 to 2015.

1.4 Empirical Strategy

In order to identify the magnitude of gender preferences, I identify the compensating differentials obtained by each gender as a result of the gender composition of their job as predicted by the model. There are substantial challenges with this as the gender shares of occupations and industries are highly correlated with other aspects of the job such as physical, cognitive, and social demands, required education, hours worked, and so on. While prior research has documented that women make lower wages than men even within the same job (Blau and Kahn, 2016), there is room for serious consideration regarding the level of heterogeneity in the actual job content of the "same job" for different workers of that job, even for finely aggregated job classifications.

My empirical design avoids the pitfalls of comparing men and women in the same job category by splitting the sample by gender prior to the analysis. The relevant empirical distinction between this topic and much of the related literature is that here there is no need to compare women to men. I am only comparing people of each gender to other members of their own gender who work in the same job with different gender compositions. This means that if a particular job systematically pays women or men different wages for any reason (at any level of aggregation), I can control for this with a simple job fixed effect. This has the effect of disregarding a large amount of variation that is undoubtedly important for determining why men and women receive different wages in a given job, but is actually unrelated to the compensating differential for gender composition.

The equation I want to estimate is a parameterized version of equation (6) from the model:

$$ln(w_{ij}) = \ln\left(\frac{\lambda_{ij}}{1-\lambda_{ij}}\right) + \ln\left[\sum_{k\neq j}\theta_k e^{ln(w_{ik})+g_i(\psi_k)+\mu_{ik}\beta_k}\right] - g_i(\psi_j) - \mu_{ij}\beta_j \qquad (1.14)$$

I model $g_i(\psi)$ as a fourth-order polynomial, wherein ψ is defined at the state-year-job level. The error term μ is a set of controls including age, age-squared, full-time status, education, race, and fully-interacted state, year, and occupation fixed effects (with state-year-occupation fixed effects omitted to preserve identifying variation), and with β included as the vector of coefficients on these elements. For an individual's own job, their individual values are used in these controls while state-year specific occupational averages are used for other jobs. I vary the designation of jobs j and k by specification and weight outside option jobs by θ, which is consistent with the presence of multiple identical jobs in the more general model.[2]

The nonlinear nature of the equation of interest is problematic for direct estimation. We therefore estimate the following approximation[3]:

$$ln(w_{ij}) \approx \ln\left(\frac{\lambda_{ij}}{1-\lambda_{ij}}\right) + ln(w_{i\ell}) + g_i(\psi_\ell) + \mu_{i\ell}\beta_\ell + ln(\theta_\ell) - g_i(\psi_j) - \mu_{ij}\beta_j \quad (1.15)$$

where job ℓ is one other job. This approximation is exact when there are only two jobs in the economy and does well when job ℓ is the most relevant outside option, as measured by both attractiveness and prevalence in the economy. In practice, I designate this outside option as the most common job other than an individual's own job by gender, state, and year. This approximation will only bias my estimates of $g(\cdot)$ if traits of other outside options (which are now left in the error term) are correlated with both wages and own-job gender composition in a way that isn't captured by the included outside option or other controls. Results from this specification are in table 2, and a visual representation is provided in figure 2.

Table 2 shows that gender preferences have an insignificant effect on wages with economically relevant point estimates. It is possible that the inclusion of additional years in our dataset or the use of a finer occupational classification will produce findings that are significantly different from zero. Because the coefficients on the quartic polynomial are difficult to interpret, I provide a visual representation of the implied compensating differentials in figure 2.

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[2]This is easiest to see in equation 5. Imagine that among all jobs j, exactly θ_ℓ are type ℓ (and are identical). This would result in the denominator reading $\sum_{k\neq\ell} exp[w_{ik}+g_i(\psi_k)+\mu_{ik}]+\theta_\ell exp[w_{i\ell}+g_i(\psi_\ell)+\mu_{i\ell}]$.

[3]I use $ln(1+x) \approx x$ where $x = \frac{\sum_{k\neq j,\ell}\theta_k exp[w_{ik}+g_i(\psi_k)+\mu_{ik}\beta_k]}{\theta_\ell exp[w_{i\ell}+g_i(\psi_\ell)+\mu_{i\ell}\beta_\ell]} \approx 0$. It is clear that this term approaches zero when job ℓ is more attractive on average (the term in the exponent) and/or more common in the economy (θ_ℓ) than other jobs.

Table 1.2.: The Effect of Share of Occupation Female on Log Wages by Gender

	(1) Male	(2) Female
ψ_j	0.032	0.047
	(0.095)	(0.270)
ψ_j^2	-0.188	-0.394
	(0.456)	(0.856)
ψ_j^3	0.421	0.677
	(0.816)	(1.102)
ψ_j^4	-0.306	-0.352
	(0.472)	(0.490)
N	691751	605882
R^2	0.341	0.314

Standard errors in parentheses

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

Note: CPS 2010-2015, all employed adults. ψ is the share of an occupation that is female. See figure 2 for a graphical representation of the implied compensating differential from these results.

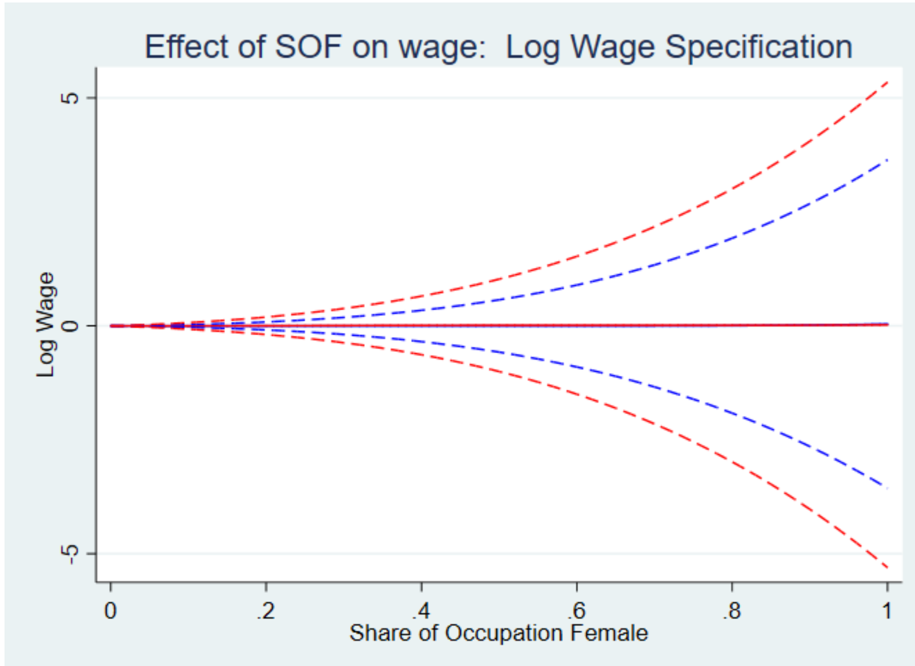

Figure 1.2.: Compensating Differentials for Share Female, by Gender

Notes: The demeaned effect of share of occupation female in a job (ψ_j) on wages for the detailed occupation specification (46 job categories). The curves give the magnitude of the compensating differentials for both men and women as a result of the share of their occupation that is female. Flipping the graph around the x-axis provides the gender composition preference $g_i(\psi_j)$. Standard errors shown in dashed lines.

The results show that men make lower wages in female dominated occupations conditional on the controls included in the specification. This is consistent with men preferring jobs with many female coworkers. Because I include occupation-specific fixed effects, this finding cannot be explained by female-dominated jobs simply earnings lower wages. With the fixed-effects, these results show, for instance, that men in a given job in a state-time with high female job composition make lower wages than men in state-times with slightly lower female job composition. For example, these results suggest than male elementary education teachers make less money in states and times where a higher percentage of elementary education teachers are women than in states and times when a lower percentage are women.

1.5 Conclusion

Our analysis shows that workers may consider the gender composition of occupations when they select an occupation. This causes men and women's labor supplies to differ for jobs based on the proportion of the job that is filled by each gender. My model of occupational selection shows how differences in these preferences can drive both differential selection across occupations and differential wages within an occupation. Compensating differentials within jobs imply that men prefer jobs that are female-dominated while strongly disliking jobs that are roughly 25% female. Women prefer diversity, with their lowest compensating differential at jobs that are approximately 55% female. Women find either extreme less satisfactory, but are least happy with male-dominated jobs.

These results have significant implications for occupational segregation of males and females. Importantly, we can say that the gender composition of jobs are not only important as an outcome, but as an input. We must examine policies which seek to change occupational selection in equilibrium, as they will have direct welfare effects, wage effects, and effects on selection beyond the initial effect of a given policy. Of interest to policymakers, we can say that policies which increase the proportion of women in a job will produce a ripple effect which will increase the representation of the gender with the higher marginal job satisfaction due to increasing the share female. Our results suggest that for male-dominated jobs, increasing the share female will improve satisfaction for women while hurting it for men - thus driving an even higher share female. This effect does eventually reverse for jobs that are less male-dominated, but these jobs are potentially of less interest to policy-makers. Of related importance, the current equilibrium in the economy may not be welfare-maximizing if preferences allow for multiple equilibria with differing job satisfaction levels by gender.

2. INFERENCE OF PERCEIVED RETURNS TO DISCRETE INVESTMENTS: A PRICE NORMALIZATION APPROACH

2.1 Introduction

In this chapter I describe a methodology for estimating the distribution of perceived returns to discrete investments. This approach has four attractive features. First, it provides estimates of perceived returns in terms of compensating variation, which directly inform financial policies that seek to (dis)incentivize the investment. Second, it provides very fine continuously-heterogeneous estimates conditional on a large set of observed characteristics, allowing for differential predictions for how selective, well-publicized policies are likely to affect different types of individuals.[1] Third, because it obtains type-specific perceived returns distributions instead of point elasticities, it provides differential predictions for the effects of type-specific financial interventions depending on the magnitude of the intervention. Finally, the estimates are obtained assuming rational expectations only on prices (one component of returns) rather than on returns as a whole.

The policy problem at hand is that while the socially optimal allocation of individuals into investments requires assignment of individuals based on their actual social returns to the investment, individuals' actual selection decisions are determined

[1] 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 it.

instead by their perceived private returns (and perceived ability to pay).[2] If perceived and actual returns are different in sign, policy interventions that alter individuals' investment decisions can be welfare-improving. Information frictions interfere with optimal allocations of individuals into investments most obviously by driving a wedge between perceived private returns and actual private returns, but also through interactions with other frictions. For instance, 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 the investment. Examples of work on these individual elements in the setting of college attendance include Carneiro, Heckman, and Vytlacil (2011) who find that college attendance is strongly associated with private pecuniary returns to college, Heckman, Humphries, and Veramendi (2018) who estimate returns to college for both financial and health outcomes, Oreopoulos and Salvanes (2011) who find evidence 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. Papers that estimate actual returns to investments, be they private pecuniary returns or otherwise, contribute to identification of the benefits of implementing policies that affect individuals' investment decisions. This paper con-

[2] I will not distinguish between perceived returns and perceived ability to pay in this paper. The method described will identify the magnitude of financial intervention required to induce an individual to change their mind about a binary investment. I leave separate identification of perceived returns and perceived borrowing constraints to future work.

tributes to identification of the costs of implementing such policies. Both of these are needed to determine optimal policy.

A major advantage of the methodology employed in this paper is that because it does not rely on estimates of actual returns to infer perceived returns, there is no 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 practitioners 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 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 marginal effect of prices on agents' perceived returns.

An alternative to the methodology described here is to elicit agents' perceived returns to investments directly via surveys. However, existing data sources may not contain responses regarding beliefs about 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

[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 (for instance, some of the literature on returns to education exclude women because of their historically relatively low labor force participation rate).

[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.

researcher control over question framing and weaker assumptions on the relationship between elicited responses to questions and actual beliefs.[5] In contrast, estimation of beliefs has the benefit that it is based on agents' observed choices rather than potentially less reliable elicited responses, but has the disadvantage that beliefs and preferences cannot be jointly estimated, so assumptions must be made about agent preferences to estimate beliefs (examples of the opposite, making assumptions about beliefs to estimate preferences, are ubiquitous in economics).[6] Elicitation and estimation 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).

Existing methods share some of the advantages of the method described here. Notably, the work surveyed in Cunha and Heckman (2007) describes methods for estimation of distributions of ex ante returns to discrete investments conditional on individual characteristics.[7] They can thus predict heterogeneous effects of investment subsidies on individuals conditional on their characteristics, as well as predicting differential effects of subsidies of varying sizes. These methods rely on the assumption that agents have rational expectations over ex post returns to investments, and identify ex ante returns from the components of ex post returns that are predictive of observed choices. Additionally, because the estimates of ex ante returns obtained are derived from ex post pecuniary returns, they are in pecuniary terms rather than

[5]For instance, Jensen (2010), Zafar (2011), and Wiswall and Zafar (2015) use elicited beliefs as predictors of heterogeneous treatment effects. It is therefore not required that elicited beliefs correspond directly to actual beliefs, but only that they are a valid proxy for actual beliefs.

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

[7]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).

compensating variation.[8] If agents act in accordance with their ex post returns, but subjectively perceive lower returns, these methods will overstate the variance of of ex ante returns. Econometrically speaking, the scale of the latent variable in the decision equation is identified by the rational expectations assumption on ex post returns.

The estimation of perceived returns to college in this paper relies on the same revealed preference intuition, but uses estimates of the effect of price on selection from both maximum likelihood and moment inequalities developed by Dickstein and Morales (2018) (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 price and perceived returns to college which results in an estimated distribution of perceived returns with minimal dependence by construction on real returns.[9] 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.[10] 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. This paper makes a methodological contribution by introducing a maximum likelihood control function approach that makes the same

[8]I describe the agents' beliefs about returns estimated using the method described in this paper as "perceived" rather than "ex ante" in an effort to stress their subjectivity and potential systetmatic bias away from actual returns.

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

[10]In brief, the methods used in the current paper rely on an accurate assumption about the perceived cost to students of one dollar of price, 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.

assumptions on information sets that the moment inequality approach developed by DM makes. The MLE approach is less computationally intensive, which should allow practitioners to estimate models with more explanatory variables, enabling them to explore heterogeneity in perceived returns conditional on observed characteristics.[11]

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 required to perform the estimation and constructs a relevant DGP. Section 5 evaluates the performance of alternative methods on the DGP, including the new maximum likelihood alternative to DM's moment inequalities. Section 6 concludes.

2.2 Model

The generalized Roy (1951) model 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 selecting the discrete investment and Y_{0i} as their perceived present value of lifetime income if they were to abstain. I further define C_i as their perceived cost of selecting the investment, which includes psychic costs as well as their preferences over any other outcomes associated with their investment decision. Given some explanatory variables X, I can express the perceived potential outcomes and costs for individual i with the following linear-in-parameters production functions:

$$\begin{aligned} Y_{1i} =& X_i\beta_1 + \epsilon_{1i} \\ Y_{0i} =& X_i\beta_0 + \epsilon_{0i} \\ C_i =& X_i\beta_C + \widetilde{Price}_i\gamma + \epsilon_{Ci}, \end{aligned} \tag{2.1}$$

[11]DM estimate a model with 2 explanatory variables and a constant.

where agent i's belief about the price, $\widetilde{Price}_i$, contributes only to the perceived pecuniary cost of the investment at known marginal rate γ (the marginal percentage of prices actually borne by the agent)[12] and ϵ_{0i}, ϵ_{1i}, and ϵ_{Ci} are mean zero error terms.[13]

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 β as well as the covariances between error terms in counterfactual states and the cost function. In the current setting, the Roy framework is useful primarily for exposition, but the *perceived* outcomes are not observed and as such the parameters will not be identified. The methods of this paper focus entirely on the agents' discrete choice problem.[14]

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

$$S_i = \begin{cases} 1 \text{ if } u(Y_{1i} - C_i) - u(Y_{0i}) \geq 0 \\ 0 \text{ otherwise,} \end{cases} \tag{2.2}$$

[12] $\gamma = 1$ is a natural choice for many environments, and is helpful for the exposition.

[13] In general, a variable playing the role of price can be included in any of the equations so long as its marginal effect on perceived returns is known to the researcher and to agents. 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.

[14] Applying the methods of this paper to jointly estimate perceived and actual returns in the context of a Roy model is left for future work. It is worth noting that the methods here will identify and price subjective preferences, while estimates of actual returns will identify returns in terms of the outcome variables (income in many contexts). The joint distribution of the two thus provides something of an apples and oranges comparison, in the sense that compensating variation and income are not the same, but they are closely enough related for comparisons between the two to be relevant.

where S_i is an indicator of an agent selecting the investment. Assuming further that utility is monotonically increasing, it follows that

$$S_i = \begin{cases} 1 \text{ if } (Y_{1i} - C_i) - Y_{0i} \geq 0 \\ 0 \text{ otherwise,} \end{cases} \tag{2.3}$$

is necessary and sufficient for the condition in equation 2.2 to hold. This allows me to define the latent variable in the agent's decision equation in as compensating variation.[15] This is useful because perceived returns in terms of compensating variation are linear in price and price subsidies, making these estimates diectly applicable to policy questions. 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 the investment in terms of explanatory variables

$$Y_i = X_i\beta - \widetilde{Price}_i\gamma + \epsilon_i, \tag{2.4}$$

which provides the latent variable as a function of the observed X and perceived prices. The goal of this method is thus to obtain estimates of the unobserved perceived return Y by assuming a relationship between prices and perceived prices, assuming a value for γ, and assuming a distribution for the error term, then estimating values for β and the scale of the error distribution.

[15]Conceiving of $\{\beta_1, \beta_0, \beta_C\}$ as prices on characteristics in the world in which the agent either does or does not select the investment leads to $Y_i = Y_{1i} - C_i - Y_{0i}$ as an expression of the compensating variation required to make a noninvestor indifferent between selecting the investment and not doing so.

2.3 Empirical Strategy

It follows from the model that, given X_i and an assumption on γ, Y_i can be identified with assumptions on the distribution of ϵ_i and on $\widetilde{Price}_i$. I begin by assuming that actual prices are a linear function of agent beliefs about them,

$$Price_i = \frac{\widetilde{Price}_i}{\lambda} + \nu_i, \tag{2.5}$$

in which λ is a known (to the econometrician) constant that captures agents' systematic and proportional mistakes in estimation of price and ν is a mean-zero error term independent of perceived prices that describes unknown (to agents) variation in actual prices at the time of the investment decision.[16]

With the assumption on the relationship between actual and perceived prices, we can add and subtract $\nu_i\lambda\gamma$ to rewrite the latent variable equation as[17]

$$\begin{aligned} Y_i &= X_i\beta - Price_i\lambda\gamma + \nu_i\lambda\gamma + \epsilon_i \\ &= X_i\beta - Price_i\lambda\gamma + \zeta_i. \end{aligned} \tag{2.6}$$

This expression of perceived returns introduces a new error, ζ, and recasts the information frictions in prices as an omitted variable. The empirical challenge will be to deal effectively with correlation between $Price$ and the error term, both through the

[16] This restriction nests that of Dickstein and Morales (2018) that $Price$ must be a mean-preserving spread of $\widetilde{Price}$ under the rational expectations assumptions: $\lambda = 1$ and $\mathbb{E}[\nu] = 0$. It also nests CHN's assumption that either $\widetilde{Price}_i = \mathbb{E}[Price]$ or $\widetilde{Price}_i = Price_i$. Calibration of λ can be performed using elicited responses on perceived prices so long as the calibrated value used reflects the belief of the agent at the time of the decision. Alternatively, λ can be estimated by matching the model's predicted effects of policy shocks on selection to externally obtained estimates, for instance, from studies of natural experiments.

[17] The assumption that $\mathbb{E}[\nu] = 0$ is purely for convenience. If the assumption doesn't hold, the mean of agent misperceptions will be absorbed by the constant in the perceived returns equation if $Price\lambda$ is used in place of $\widetilde{Price}$. In other words, if all agents think an investment is a certain amount more (less) expensive than it really is, the constant in the perceived returns equation will be estimated to be that much less (more) than it would if we could condition on agents' beliefs about prices.

omitted variable bias due to information frictions or due to other sources of endogeneity.

The details of how each method described in this paper handle these concerns can be found in their respective sections. First, note that ν is positively correlated with $Price$ by construction as seen in (2.5). For sensible (positive) values of γ and λ, the failure to account for ν will cause attenuation bias in estimates of the effect of price on selection, which amounts to upward bias in the estimate of the scale of the distribution.[18] Second, if prices are high at times when (or for individuals who) unobserved components of demand for the investment are high, this will introduce positive correlation between prices and ϵ, further biasing the estimate of the effect of price on selection upwards toward (or beyond) zero.

In general, both of these problems will be addressed with the use of instruments, Z, for perceived prices. The following equations describe how instruments can be used to address both sources of endogeneity described above.

$$\begin{aligned} \widetilde{Price}_i &= f(Z_i) + u_i \\ Price_i &= \frac{\widetilde{Price}_i}{\lambda} + \nu_i = \frac{f(Z_i) + u_i}{\lambda} + \nu_i. \end{aligned} \tag{2.7}$$

$f(\cdot)$ provides a mapping between Z and both perceived and realized prices, and u is the potentially endogenous component of perceived prices. In order to obtain unbiased estimates of the causal effect of perceived prices on perceived returns (as is necessary to validate the assumption on γ), the instruments must be independent of both u and ν.

[18] If price variation shifts few people into or out of the investment, it follows either that the perceived returns distribution has low mass near zero (high variance), or that the variation in prices is unknown and therefore not acted upon.

The key to understanding the value of the instruments in addressing information frictions in prices is that, for valid instruments,

$$\widehat{Price_i}\lambda = \widehat{\widetilde{Price}_i} = \hat{f}(Z_i). \tag{2.8}$$

Including the errors in the perceived returns equation in (2.6) leads to causal estimates of the effect of perceived prices on selection:

$$\begin{aligned} Y_i =& X_i\beta - Price_i\lambda\gamma + \zeta_i \\ =& X_i\beta - Price_i\lambda\gamma + u_i\rho_u + \nu_i\lambda\rho_\nu + \eta_i \\ =& X_i\beta - Price_i\lambda\gamma + (u_i + \nu_i\lambda)\rho_{u\nu} + \eta_i. \end{aligned} \tag{2.9}$$

I assume the new error, η_i, is i.i.d. and normally distributed,

$$\eta_i|(X_i, Price_i, u_i + \nu_i\lambda) \sim \mathcal{N}(0, \sigma^2). \tag{2.10}$$

This setup immediately leads to the control function method when estimates of $(u_i + \nu_i\lambda)$ are included in place of the objects themselves, and is useful for motivating the other two methods discussed below.

I will begin by describing a simple benchmark Probit-based method in section 2.3.1 that assumes away the two potential sources of bias, followed by a discussion of the moment inequalities developed by Dickstein and Morales (2018) in section 2.3.2, followed finally with the development of an alternative control function approach in section 2.3.3 that shares many of the advantages of DM's moment inequalities. The control function approach has the advantages of obtaining point estimates of model parameters and requiring fewer computational resources.

2.3.1 Probit Benchmark

I begin by describing a method for inferring perceived returns using a Probit. This procedure will provide consistent estimates of the perceived returns distribution under two assumptions that are likely to be violated in many applications. First, this method assumes that agents have perfect information on prices ($\nu_i = 0 \quad \forall i$, $\lambda = 1$). Second, it assumes independence between prices and unobserved idiosyncratic preferences for the investment such that $u_i = 0 \ \forall i$. Under these assumptions, the empirical specification for perceived returns given in (2.9) reduces to

$$Y_i = X_i\beta - Price_i\gamma + \eta_i.^{19} \tag{2.11}$$

Given the decision rule described in (2.3) and the assumption of normally distributed errors, perceived returns can then be estimated by maximum likelihood. The probability of selecting the investment is given by

$$Pr(S_i = 1|X_i, Price_i) = \Phi\Big(\frac{X_i\beta - Price_i\gamma}{\sigma}\Big), \tag{2.12}$$

where $\Phi(\cdot)$ denotes the standard normal cdf. Defining $\{\beta^*, \gamma^*\} = \{\frac{\beta}{\sigma}, \frac{\gamma}{\sigma}\}$ for notational convenience and taking γ as given, the parameters $\{\beta^*, \gamma^*\}$ are the values that maximize the log-likelihood:[20]

$$\begin{gathered}\mathcal{L}(\beta^*, \gamma^*|X_i, Price_i) = \\ \sum_i S_i \log\left[\Phi\Big(X_i\beta^* - Price_i\gamma^*\Big)\right] + (1 - S_i)\log\left[1 - \Phi\Big(X_i\beta^* - Price_i\gamma^*\Big)\right].\end{gathered} \tag{2.13}$$

The estimates of perceived returns are then given by:

$$Y_i \sim \mathcal{N}(X_i\hat{\beta} - Price_i\gamma, \hat{\sigma}^2). \tag{2.14}$$

[19] Under the assumptions presented in this section, $\eta_i = \epsilon_i \ \forall i$.

[20] Many statistical software packages, such as Stata, impose $\sigma = 1$ in their binary choice estimation commands. It is simple to convert these estimates into scaled estimates using:

$$\hat{\sigma} = \frac{\gamma}{\hat{\gamma}^*} \quad ; \quad \hat{\beta} = \hat{\beta}^*\hat{\sigma},$$

taking to care to apply the delta method to obtain correct standard errors for the scaled estimates.

2.3.2 Moment Inequality Approach

It is likely that agents do not have perfect information on prices. For one, individuals often make investment decisions before prices are fully realized. Evolving cost shocks are often not contracted on prior to the investment decision and can be reflected in prices, for instance when college tuition changes while a student is attending. Individuals may even be uninformed about prices after they have been set. For instance, Bettinger, Long, Oreopoulos, and Sanbonmatsu (2012) find that individuals' elicited beliefs about prices for postsecondary education were over three times higher than actual prices.

It is also unlikely that perceived prices and ϵ, the unobserved component of perceived returns, are independent. Returning to the postsecondary education example, it is possible that high ability students perceive the return to college to be high while also attending more expensive colleges. If this relationship is sufficiently strong, prices will be positively associated with selection, which will be incompatible with the assumed value for γ. In settings without such extreme price discrimination, we may still expect prices to be high for places and times where demand for the product is high, similarly biasing the estimated effect of prices on selection upward, which will imply downward bias on the scale parameter.[21]

This section describes a method developed by Dickstein and Morales (2018) that addresses the bias from imperfect information using moment inequalities, which they use to identify perceived costs in a firm export decision context.[22] I provide

[21] The estimated effect of price on selection is given by $\frac{\gamma}{\sigma}$. Because the effect of price on selection is defined by the inverse of the scale parameter, the scale parameter will be biased in the opposite direction of the effect on selection.

[22] It is worth noting that DM do not use their moment inequalities to address endogeneity. Briefly, this is because their model provides a forecasting equation for profit as a function of revenue and costs. In their framework, revenue forecasts profit at a constant marginal rate defined by the demand elasticity. Naturally, if the relationship were causal, this constant marginal rate would be 1.

a proof in Appendix A of the validity of the moment inequalities in the context of endogeneity, while providing a brief discussion of the intuition here. The method uses two sets of moment inequalities to obtain bounds on the parameters of perceived returns using instruments, Z, that are independent of both the unknown component of prices and the unobserved error in perceived returns.[23]

Revealed Preference Moment Inequalities

The conditional revealed preference moment inequalities are given by

$$\begin{aligned}
&\mathbb{E}\left[-(1-S_i)(X_i\beta^* - Price_i\lambda\gamma^*) + S_i \frac{\phi(X_i\beta^* - Price_i\lambda\gamma^*)}{\Phi(X_i\beta^* - Price_i\lambda\gamma^*)} \middle| Z_i \right] \geq 0, \\
&\mathbb{E}\left[S_i(X_i\beta^* - Price_i\lambda\gamma^*) + (1-S_i) \frac{\phi(X_i\beta^* - Price_i\lambda\gamma^*)}{1-\Phi(X_i\beta^* - Price_i\lambda\gamma^*)} \middle| Z_i \right] \geq 0.
\end{aligned} \tag{2.15}$$

where Z is an instrument for perceived price. These inequalities are consistent with the revealed preference argument that perceived returns are positive for those who select the investment and negative for those who do not. The formal proof of the revealed preference inequalities can be found in Appendix A, but I will provide a brief sketch here.

Consider an agent that selects the investment such that $S_i = 1$. Following the revealed preference argument articulated in (2.3) and the empirical specification given in (2.9), it must be the case that this individual's perceived return for the investment is positive such that

$$S_i(X_i\beta - Price_i\lambda\gamma + (u_i + \nu_i\lambda)\rho_{u\nu} + \eta_i) \geq 0. \tag{2.16}$$

[23] DM describe the first condition on instruments as agents knowing Z. CHN use similar language to designate known and unknown components of returns. At the cost of brevity, I will describe the relevant condition as agents knowing prices insofar as they are predicted by the instruments, rather than knowing the instruments themselves.

We do not ever observe the error, η_i, but this condition will hold on average if it holds for individuals. Taking the conditional expectation across individuals conditional on the observed covariates and the unobserved errors $\{u_i, \nu_i\}$ yields

$$\begin{aligned}\mathbb{E}\Bigg[&S_i(X_i\beta^* - Price_i\lambda\gamma^* + (u_i + \nu_i\lambda)\rho^*_{u\nu})\\ &+(1-S_i)\frac{\phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i + \nu_i\lambda)\rho^*_{u\nu})}{1-\Phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i + \nu_i\lambda)\rho^*_{u\nu})}\Bigg| X_i, Price_i, u_i, \nu_i\Bigg] \geq 0,\end{aligned} \tag{2.17}$$

where the second term is derived from the inverse-mills ratio.

The second moment inequality above is obtained first by applying law of iterated expectations to condition on Z instead of the unobserved objects. Second, the expectation of $(u+\nu\lambda)$ given Z is zero for valid instruments, so this term can be omitted through the application of Jensen's inequality as long as it is weakly positively correlated with η because the function inside of the expectation is globally convex.[24] The necessity of weakly positive correlation between the errors is a restriction that is unique to the moment inequalities, but should be of small consequence in practical applications if unobserved components of perceived returns are generally positively correlated with prices. The first inequality follows from the same intuition applied to individuals who do not select the investment.

[24]The necessary condition is that $Var(u_i + \nu_i\lambda)\rho_{u\nu} + \eta_i) \geq Var(\eta)$. This nests DM's condition in the absence of endogeneity, where $u_i = 0\ \forall i$, and $\nu \perp\!\!\!\perp \eta$. The application of Jensen's inequality is valid for any error distribution with a convex inverse-mills ratio, such as the normal distribution or the logistic distribution.

Odds-Based Moment Inequalities

The conditional odds-based moment inequalities are given by

$$\begin{aligned}
&\mathbb{E}\left[\left(S_i\frac{1-\Phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i+\nu_i\lambda)\rho^*_{u\nu}))}{\Phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i+\nu_i\lambda)\rho^*_{u\nu}))} - (1-S_i)\right)\middle| Z_i\right] \geq 0, \\
&\mathbb{E}\left[\left((1-S_i)\frac{\Phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i+\nu_i\lambda)\rho^*_{u\nu}))}{1-\Phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i+\nu_i\lambda)\rho^*_{u\nu}))} - S_i\right)\middle| Z_i\right] \geq 0.
\end{aligned} \tag{2.18}$$

They are derived from the conditional expectation of the score equation:

$$\begin{aligned}
&\mathbb{E}\left[S_i\frac{\phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i+\nu_i\lambda)\rho^*_{u\nu})}{\Phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i+\nu_i\lambda)\rho^*_{u\nu})}\right. \\
&\left. -(1-S_i)\frac{\phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i+\nu_i\lambda)\rho^*_{u\nu})}{1-\Phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i+\nu_i\lambda)\rho^*_{u\nu})}\middle| X_i, Price_i, (u_i+\nu_i\lambda)\right] = 0.
\end{aligned} \tag{2.19}$$

The derivation proceeds by a similar process by which we obtained the revealed preference inequalities. First, the score equation is rearranged into two equations that are globally convex in their arguments:[25]

$$\begin{aligned}
&\mathbb{E}\left[\left(S_i\frac{1-\Phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i+\nu_i\lambda)\rho^*_{u\nu}))}{\Phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i+\nu_i\lambda)\rho^*_{u\nu}))} - (1-S_i)\right)\middle| X_i, Price_i, u_i, \nu_i\right] = 0, \\
&\mathbb{E}\left[\left((1-S_i)\frac{\Phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i+\nu_i\lambda)\rho^*_{u\nu}))}{1-\Phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i+\nu_i\lambda)\rho^*_{u\nu}))} - S_i\right)\middle| X_i, Price_i, u_i, \nu_i\right] = 0.
\end{aligned} \tag{2.20}$$

As with the revealed preference inequalities, these inequalities still hold conditional on the observed Z by law of iterated expectations. Given the the global convexity of the odds ratios, the equality changes to an inequality when omitting $(u + \nu\lambda)$ by Jensen's inequality, again, as long as this error is weakly positively correlated with η. This leads to the odds-based moment inequalities in (2.18).

It may seem like the two moment inequalities in (2.18) would be redundant as they are both derived from transformations of the same score function. The key

[25] Global convexity of the odds-ratios is a trait of all log-concave distributions.

point, however, is that $(u_i + \nu_i\lambda)$ is omitted 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 $\mathbb{E}[-(1 - S_i)|Z_i] \geq 0$, a violation of 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 (2018).

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 the estimation procedure is available in Appendix B.

2.3.3 Control Function Approach

In this section I describe a control function approach that has three advantages over the moment inequalities. First, it is substantially less computationally costly, allowing for the inclusion of a richer set of explanatory variables. This provides for a broader set of heterogeneous policy predictions conditional on observed covariates. Second, it provides point estimates of model parameters. Third, it places no restrictions on the distribution of the error term.[26]

The control function approach makes use of the following system of equations:

$$\begin{aligned} Y_i &= X_i\beta - \widetilde{Price}_i\gamma + \epsilon_i \\ \widetilde{Price}_i &= Z_i\delta + u_i \\ Price_i &= \frac{\widetilde{Price}_i}{\lambda} + \nu_i = \frac{Z\delta + u_i}{\lambda} + \nu_i, \end{aligned} \tag{2.21}$$

where δ provides the mapping of the instruments to perceived prices. The second line represents what would be the first stage in a two-step instrumental variables procedure if perceived prices were observable. The third line combines the assumption on beliefs given in (2.5) with the unobserved first stage on perceived prices to obtain a first stage equation that consists of only observable objects.[27]

The requirement that $Z \perp\!\!\!\perp \nu$ is made clear here. If the instruments are independent of misperceptions on prices, we can use the predicted value of observed prices as a stand-in for the otherwise unknown predicted value of perceived prices, i.e.,

$$\widehat{Price}_i = \frac{\widehat{\widetilde{Price}}_i}{\lambda} = \frac{Z\hat{\delta}}{\lambda}. \tag{2.22}$$

[26] To use both sets of the moment inequalities, recall that the error term must be both log-concave and have a convex inverse Mills ratio. For most practical purposes, this restricts the applicable distributions to the normal or the logistic. It also does not make assumptions about the sign of the covariance between the first stage error $(u + \nu\lambda)$ and the perceived returns error η.

[27] The presentation here assumes a parametric first stage. It is also possible to construct a nonparametric first stage using the expectation of price conditional on Z.

The error terms $\{\epsilon, u, \nu\}$ can be freely interdependent if Z is a valid instrument for beliefs about prices.[28]

Given the above, we can estimate perceived returns with a control function:[29]

$$\begin{aligned} Y_i =& X_i\beta - \widetilde{Price}_i\gamma + \epsilon_i \\ =& X_i\beta - Price_i\lambda\gamma + (u_i + \nu_i\lambda)\rho_{u\nu} + \eta_i. \\ =& X_i\beta - Price_i\lambda\gamma + (\widehat{u_i + \nu_i}\lambda)\rho_{uv} + \zeta_i. \end{aligned} \tag{2.23}$$

The second line substitutes the linear projection of ϵ_i on $(u_i + \nu_i\lambda)$ in for ϵ_i using the specification of perceived prices in (2.5). The third line substitutes the estimated OLS residuals from the first stage regression of $Price$ on Z in for their unobserved true values, generating a new error, ζ. This new error will converge asymptotically to η, but will differ in small samples based on variation in the estimation of the residual from the first stage, $(\widehat{u_i + \nu_i}\lambda)$. Note that it is unnecessary (and impossible) in this setting to distinguish between u_i and ν_i.

The log-likelihood is then given by:

$$\begin{gathered} \mathcal{L}\Big(\beta^*, \gamma^*, \rho^*_{u\nu} | X, (\widehat{u + \nu\lambda})\Big) = \\ \sum_i S_i \log\left[\Phi\Big(X_i\beta^* - Price_i\lambda\gamma^* + (\widehat{u_i + \nu_i}\lambda)\rho^*_{uv}\Big)\right] \\ +(1 - S_i)\log\left[1 - \Phi\Big(X_i\beta^* - Price_i\lambda\gamma^* + (\widehat{u_i + \nu_i}\lambda)\rho^*_{uv}\Big)\right]. \end{gathered} \tag{2.24}$$

---

[28] 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.

[29] As an alternative, we could perform a two stage procedure with $Y_i = X_i\beta - Z\hat{\delta}\lambda\gamma - \frac{u_i}{\lambda}\gamma + \epsilon_i$, where $\hat{\delta}$ is obtained from the OLS projection of $Price$ on Z. This formulation will obtain valid estimates of β and $\omega^2 = Var(\frac{u_i}{\lambda}\gamma + \epsilon_i)$, leading to $\hat{Y}_i \sim \mathcal{N}(X_i\hat{\beta} - \widehat{Price}_i\gamma, \hat{\omega}^2)$. This approach has the disadvantage of moving individual-specific heterogeneity on perceived returns contained in $(\widehat{\frac{u_i}{\lambda} + \nu_i})$ into the error term, while the control function approach conditions on this observed variation.

Estimates of perceived returns are obtained by plugging the estimated parameters into the latent variable equation:

$$Y_i \Big| \Big(X_i, (\widehat{u_i + \nu_i \lambda}) \Big) \sim \mathcal{N}\Big(X_i \hat{\beta} - Price_i \lambda \gamma + (\widehat{u_i + \nu_i \lambda}) \hat{\rho}_{uv}, \hat{\sigma}^2 \Big). \tag{2.25}$$

2.4 Simulated Data

In this section I apply the methods described above to a variety of simulated datasets in order to demonstrate their performance in various settings. First, I consider a benchmark data generating process (DGP) where each method is asymptotically valid. Second, I introduce imperfect information on prices into the model. Third, I introduce correlation between perceived prices and the unobserved components of perceived returns into the model. Fourth, I successively add explanatory variables to the model in the setting where both imperfect information and endogeneity are present to demonstrate the computational advantages of the control function method. Throughout the following, I make the rational expectations assumptions that $\lambda = 1$ and $\mathbb{E}[\nu] = 0$. For convenience, I repeat the data-generating equations here:

$$\begin{gathered}
Y_i = X_i \beta - \widetilde{Price}_i \gamma + \epsilon_i \\
\widetilde{Price}_i = Z_i \delta + u_i \\
Price_i = \widetilde{Price}_i + \nu_i = Z\delta + u_i + \nu_i \\
\epsilon_i = u_i \rho_u + \nu_i \rho_\nu - \nu_i \gamma + \eta_i
\end{gathered} \tag{2.26}$$

Each DGP will be constructed of $N = 1,000$ observations of individuals who do or do not select the investment.[30] I construct the instrument vector as $Z = [X \quad z]$ where X always includes at least a constant. For the simulations below, I restrict the

[30]The computation time required to run the moment inequalities becomes prohibitive with larger N. Results tables for the Probit and control function methods with N=10,000 are available in Appendix C.

analysis to models with a single instrument. I maintain $\gamma = -1$ and $\sigma = 2$ throughout. The control function method will obtain estimates of $\rho_{u\nu} = Cov(u+\nu, \epsilon)/Var(u+\nu)$.

2.4.1 Simulation 1: Benchmark DGP

I begin with a DGP under which all three methods will provide consistent estimates of perceived returns. In subsequent sections, I will describe how the DGPs differ from this benchmark. I set the following random variables:

$$\begin{bmatrix} z \\ u \\ \nu \\ \eta \end{bmatrix} \sim \mathcal{N}(\mathbf{0}, \Sigma); \quad \Sigma = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 4 \end{bmatrix}. \tag{2.27}$$

where I include ν with a variance of zero for clarity. I set X to include only a constant for simplicity, and I set $\rho_u = \rho_\nu = 0$, $\delta = [0 \quad 1]'$ and $\beta = 1$. Given this DGP, the coefficient on the composite first stage residual in the control function, $\rho_{u\nu}$, should equal 0.

Table C.6 shows the estimates for one simulation of this DGP using all three methods. Figure 2.1 shows the distributions implied by the estimates for each method. The 95% confidence intervals of the Probit and control function methods contain the true values for β and σ, while they are also encompassed by the moment inequality confidence set. The necessary conditions for the Probit to perform well are that $Cov(e, u) = Cov(e, \nu) = Var(\nu) = 0$, three conditions that are unlikely to arise in common empirical applications.

Table 2.1.: Simulation 1, Perceived Returns Estimates

	(1) Probit	(2) Control Function	(3) Moment Inequalities
Constant	1.088	1.040	[0.219, 1.413]
	(.100)	(.112)	N/A
σ	1.849	1.770	[0.203, 2.291]
	(.129)	(.157)	N/A
$\widehat{(u+\nu)}$		.085	
		(.108)	
Observations	1000	1000	1000

Notes: Standard errors in parentheses. Parameters are marginal effects of the variable on perceived returns in dollars. Estimates are from equation (2.9) with the details varying by estimation method. All data is generated in Matlab using random seed 1234.

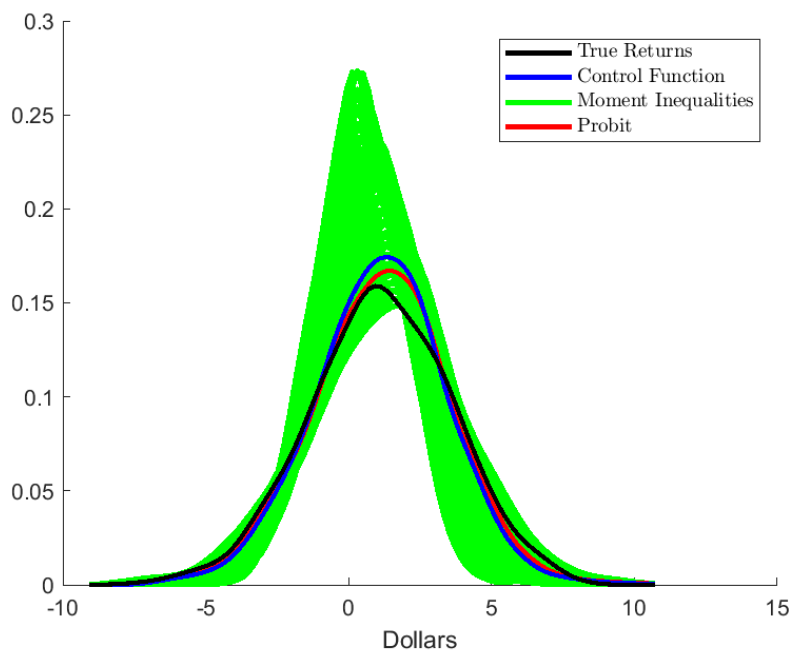

Figure 2.1.: Simulation 1, Implied Perceived Returns Distributions

Notes: Estimated distributions of perceived returns given by each method. The moment inequalities are not point identified, so a distribution is graphed for each parameter vector that I fail to reject satisfy all moment inequalities.

2.4.2 Simulation 2: Information Frictions

In this simulation, I consider a DGP in which agents do not precisely forecast prices such that $Price \neq \widetilde{Price}$. I set the following random variables:

$$\begin{bmatrix} z \\ u \\ \nu \\ \eta \end{bmatrix} \sim \mathcal{N}(\mathbf{0}, \Sigma); \quad \Sigma = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 4 \end{bmatrix}. \tag{2.28}$$

where the imperfect information in prices, ν now has a variance of 1. I set X to include only a constant for simplicity, and I set $\rho_u = 0$, $\rho_\nu = 1$, $\delta = [0 \quad 1]'$ and $\beta = 1$. Given this DGP, the coefficient on the composite first stage residual in the control function, $\rho_{u\nu}$, should equal 0.5.

Table 2.2 shows the estimates for one simulation of this DGP using all three methods. Figure 2.2 shows the distributions implied by the estimates for each method. The 95% confidence intervals of the control function method contains the true values for β and σ, while they are also encompassed by the moment inequality confidence set. The Probit method's estimates are biased upward, as predicted.

Table 2.2.: Simulation 2, Perceived Returns Estimates

	(1) Probit	(2) Control Function	(3) Moment Inequalities
Constant	1.523	1.128	[-0.058, 1.768]
	(.158)	(.137)	N/A
σ	2.779	2.061	[0.291, 2.878]
	(.225)	(.204)	N/A
$\widehat{(u+\nu)}$		.387	
		(.087)	
Observations	1000	1000	1000

Notes: Standard errors in parentheses. Parameters are marginal effects of the variable on perceived returns in dollars. Estimates are from equation (2.9) with the details varying by estimation method. All data is generated in Matlab using random seed 1234.

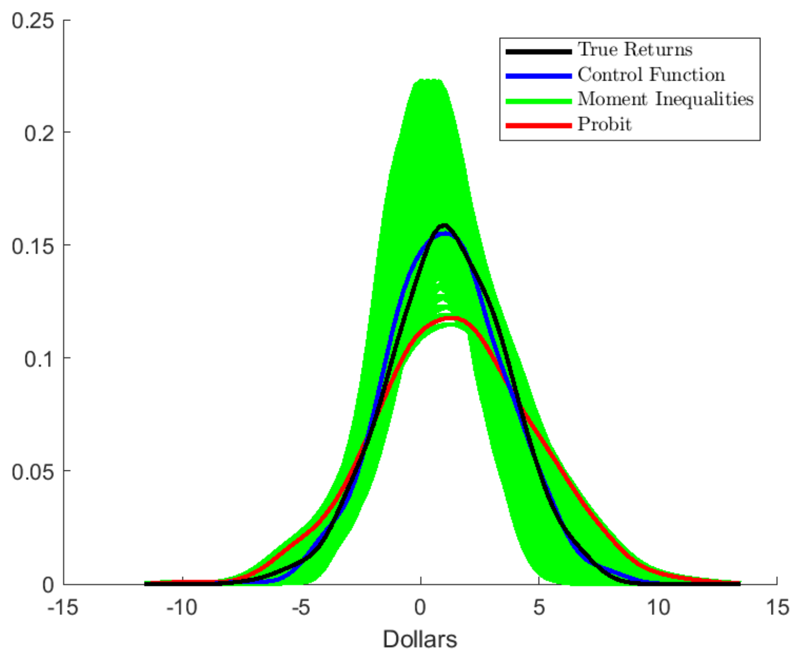

Figure 2.2.: Simulation 2, Implied Perceived Returns Distributions

Notes: Estimated distributions of perceived returns given by each method. The moment inequalities are not point identified, so a distribution is graphed for each parameter vector that I fail to reject satisfy all moment inequalities.

2.4.3 Simulation 3: Endogeneity

In this simulation, I consider a DGP in which $u \not\perp \epsilon$. I set the following random variables:

$$\begin{bmatrix} z \\ u \\ \nu \\ \eta \end{bmatrix} \sim \mathcal{N}(\mathbf{0}, \Sigma); \quad \Sigma = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 4 \end{bmatrix}. \tag{2.29}$$

where I include ν with a variance of zero for clarity. I set X to include only a constant for simplicity, and I set $\rho_u = 1$, $\rho_\nu = 0$, $\delta = [0 \quad 1]'$ and $\beta = 1$. Given this DGP, $\rho_{u\nu} = 1$.

Table 2.3 shows the estimates for one simulation of this DGP using all three methods. Figure 2.3 shows the distributions implied by the estimates for each method. The 95% confidence intervals of the control function method contains the true values for β and σ, while they are also encompassed by the moment inequality confidence set. The Probit method's estimates are biased upward, as predicted.

Table 2.3.: Simulation 3, Perceived Returns Estimates

	(1) Probit	(2) Control Function	(3) Moment Inequalities
Constant	1.615	.839	[-0.008, 1.615]
	(.224)	(.106)	N/A
σ	3.619	1.791	[0.502, 2.973]
	(.397)	(.161)	N/A
$\widehat{(u+\nu)}$		.938	
		(.075)	
Observations	1000	1000	1000

Notes: Standard errors in parentheses. Parameters are marginal effects of the variable on perceived returns in dollars. Estimates are from equation (2.9) with the details varying by estimation method. All data is generated in Matlab using random seed 1234.

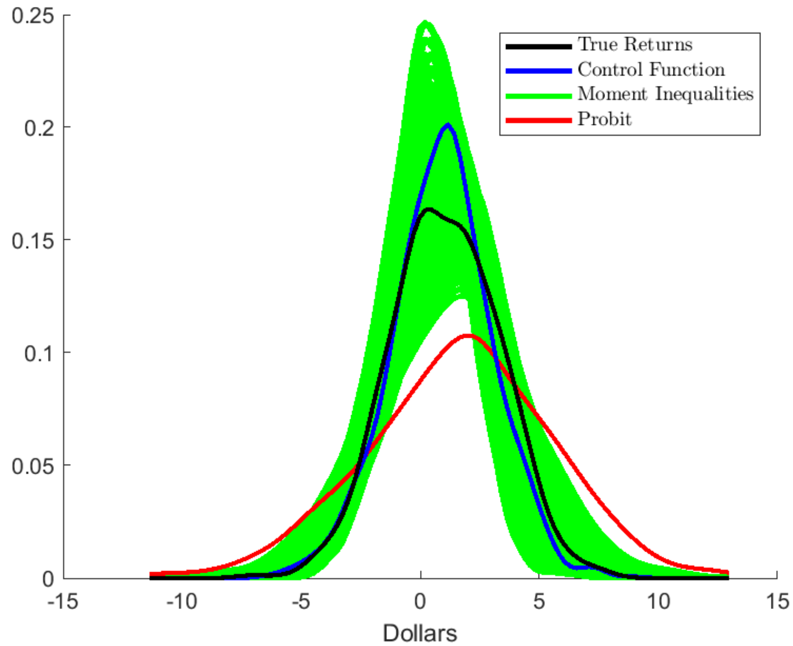

Figure 2.3.: Simulation 3, Implied Perceived Returns Distributions

Notes: Estimated distributions of perceived returns given by each method. The moment inequalities are not point identified, so a distribution is graphed for each parameter vector that I fail to reject satisfy all moment inequalities.

2.4.4 Simulation 4: Endogeneity and Information Frictions

In this simulation, I consider a DGP in which perceived prices are correlated with the error, and there are information frictions in prices. This setting is likely similar to those that occur naturally. Correlation between the information friction ν and the potentially endogenous component of perceived returns, u, could be added but will create no complications for the method as only the composite error $u_i + \nu_i$ affects the estimation. I report the run time of each method in the results table for comparison to subsequent sections with additional explanatory variables. All simulations are run on a machine with an Intel(R) Core(TM) i5-7600 CPU @ 3.50GHz processor with 16 GB RAM. I set the following random variables:

$$\begin{bmatrix} z \\ u \\ \nu \\ \eta \end{bmatrix} \sim \mathcal{N}(\mathbf{0}, \Sigma); \quad \Sigma = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 4 \end{bmatrix}. \tag{2.30}$$

I set X to include only a constant for simplicity, and I set $\rho_u = \rho_\nu = 1$, $\delta = [0 \quad 1]'$ and $\beta = 1$. Given this DGP, the coefficient on the composite first stage residual in the control function, $\rho_{u\nu}$, should equal 1.

Table 2.4 shows the estimates for one simulation of this DGP using all three methods. Figure 2.4 shows the distributions implied by the estimates for each method. The 95% confidence intervals of the control function method contains the true values for β and σ, while they are also encompassed by the moment inequality confidence set. The Probit method's estimates are biased upward, as predicted.

Table 2.4.: Simulation 4, Perceived Returns Estimates

	(1) Probit	(2) Control Function	(3) Moment Inequalities
Constant	3.150	1.062	[-0.222, 2.089]
	(.494)	(.128)	N/A
σ	5.694	1.789	[0.401, 2.830]
	(.817)	(.173)	N/A
$\widehat{(u+\nu)}$		.996	
		(.056)	
Observations	1000	1000	1000
Run Time		1	9

Notes: Standard errors in parentheses. Parameters are marginal effects of the variable on perceived returns in dollars. Estimates are from equation (2.9) with the details varying by estimation method. All data is generated in Matlab using random seed 1234. All run times are rounded to the nearest whole second.

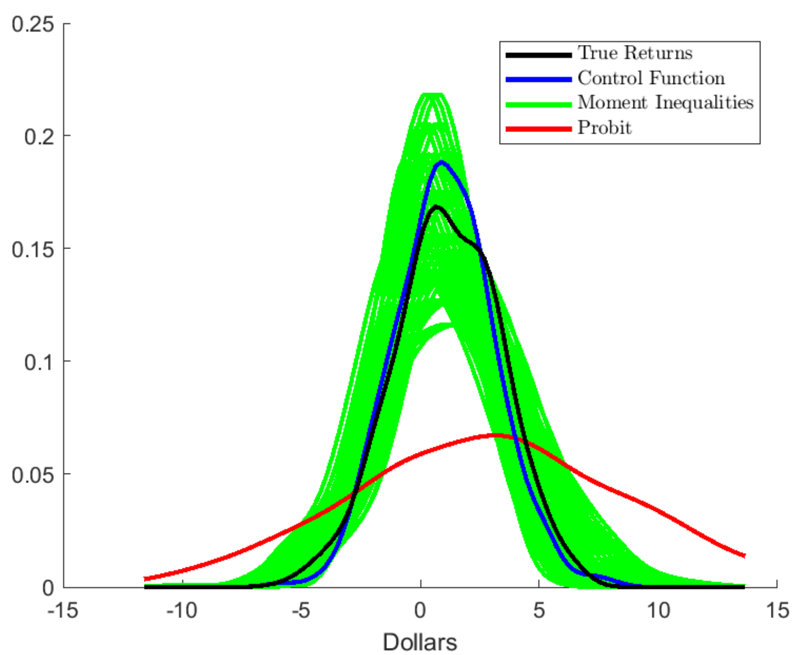

Figure 2.4.: Simulation 4, Implied Perceived Returns Distributions

Notes: Estimated distributions of perceived returns given by each method. The moment inequalities are not point identified, so a distribution is graphed for each parameter vector that I fail to reject satisfy all moment inequalities.

2.4.5 Simulation 5: One Explanatory Variable

In this section, I maintain the DGP from section 4 with the addition of another explanatory variable $x_1 \sim \mathcal{N}(0,1)$ with $\beta_1 = 0.4$. I will report the run time of each method in the results table. The moment inequality run time is much longer than the control function, and increases substantially as explanatory variables are added.

Table 2.5 shows the estimates for one simulation of this DGP using all three methods. Figure 2.5 shows the distributions implied by the estimates for each method. The 95% confidence intervals of the control function method contains the true values for β and σ, while they are also encompassed by the moment inequality confidence set. The Probit method's estimates are biased upward, as predicted.

Table 2.5.: Simulation 5, Perceived Returns Estimates

	(1) Probit	(2) Control Function	(3) Moment Inequalities
Constant	3.55	1.119	[-4.281, 6.519]
	(.626)	(.142)	N/A
x1	1.000	.327	[-1.098, 1.549]
	(.320)	(.102)	N/A
σ	6.566	1.950	[0.359, 3.541]
	(1.072)	(.199)	N/A
$\widehat{(u+\nu)}$		1.03	
		(.061)	
Observations	1000	1000	1000
Run Time		1	641

Notes: Standard errors in parentheses. Parameters are marginal effects of the variable on perceived returns in dollars. Estimates are from equation (2.9) with the details varying by estimation method. All data is generated in Matlab using random seed 1234. All run times are rounded to the nearest whole second.

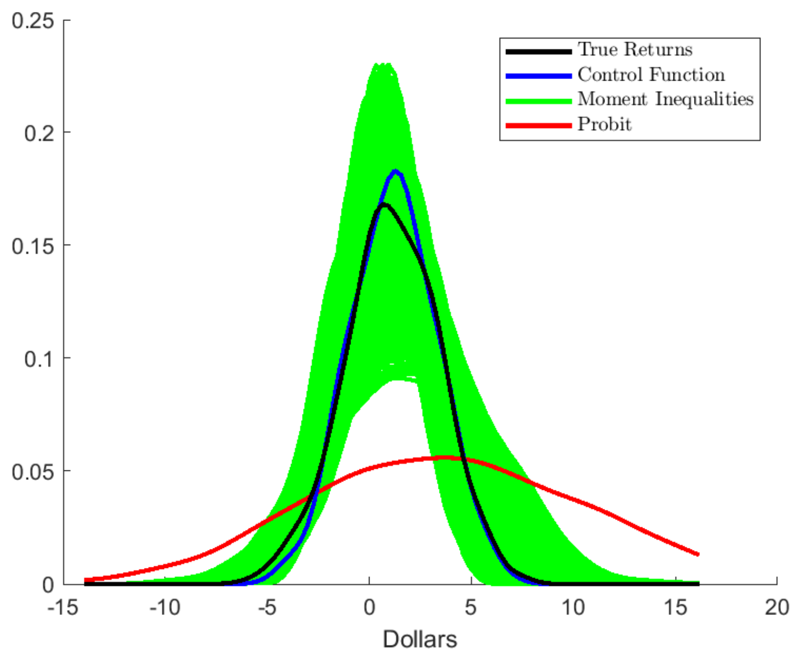

Figure 2.5.: Simulation 5, Implied Perceived Returns Distributions

Notes: Estimated distributions of perceived returns given by each method. The moment inequalities are not point identified, so a distribution is graphed for each parameter vector that I fail to reject satisfy all moment inequalities.

2.4.6 Simulation 6: Two Explanatory Variables

In this section, I maintain the DGP from section 5 with the addition of another explanatory variable $x_2 \sim \mathcal{N}(0,1)$ with $\beta_2 = 0.2$. I report the run time of each method in the results table. The moment inequality run time is much longer than the control function, and increases substantially as explanatory variables are added.

Table 2.6 shows the estimates for one simulation of this DGP using all three methods. Figure 2.6 shows the distributions implied by the estimates for each method. The 95% confidence intervals of the control function method contains the true values for β and σ, while they are also encompassed by the moment inequality confidence set. The Probit method's estimates are biased upward, as predicted.

Table 2.6.: Simulation 6, Perceived Returns Estimates

	(1) Probit	(2) Control Function	(3) Moment Inequalities
Constant	3.455	1.131	[-13.6800, 9.6756]
	(.587)	(.142)	N/A
x1	1.044	.355	[-1.6850, 2.8030]
	(.310)	(.102)	N/A
x2	.595	.230	[-1.7970, 2.6632]
	(.287)	(.101)	N/A
σ	6.280	1.944	[0.3623, 3.5267]
	(.987)	(.198)	N/A
$\widehat{(u+\nu)}$		1.010	
		(.060)	
Observations	1000	1000	1000
Run Time		1	2703

Notes: Standard errors in parentheses. Parameters are marginal effects of the variable on perceived returns in dollars. Estimates are from equation (2.9) with the details varying by estimation method. All data is generated in Matlab using random seed 1234. All run times are rounded to the nearest whole second.

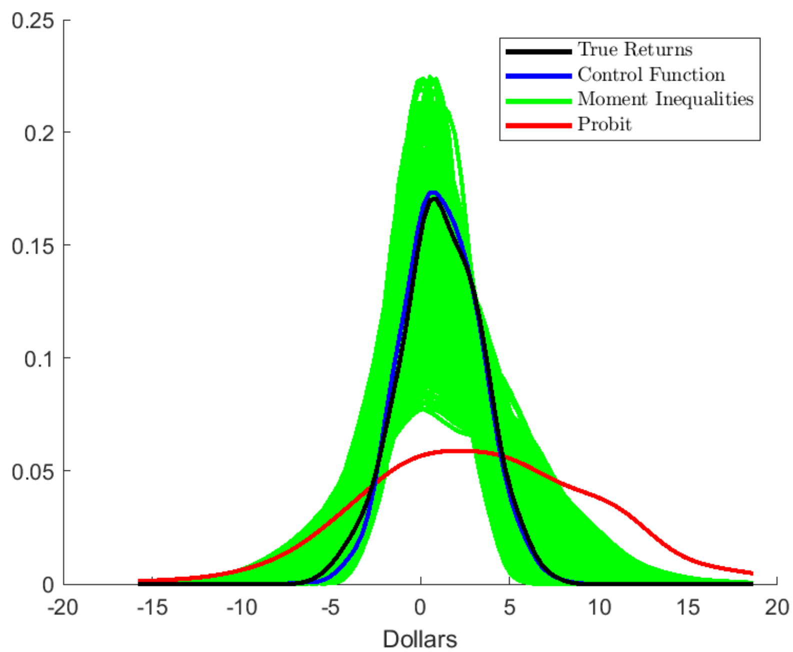

Figure 2.6.: Simulation 6, Implied Perceived Returns Distributions

Notes: Estimated distributions of perceived returns given by each method. The moment inequalities are not point identified, so a distribution is graphed for each parameter vector that I fail to reject satisfy all moment inequalities.

2.5 Conclusions

I describe three methods for obtaining estimates of perceived returns to discrete investments. I show that the control function method developed in this paper performs well with minimal computational demands, allowing for the inclusion of many explanatory variables. Given the common practice of including large numbers of control variables in empirical applications and the relative ease of coding the control function method, it should be directly applicable to wide variety of empirical questions such as college attendance, firm investments such as R&D, and a wide variety of consumer decisions, such as car purchases.

A major advantage of the general empirical framework here is that it provides estimates of the distribution of perceived returns conditional on observed characteristics. This allows for differential predictions on the effects of group-specific subsidies on uptake for the investment. Importantly, the estimates are obtained in terms of compensating variation, which means they are directly applicable to analysis of the effects of subsidies and taxes. Finally, it also allows for differential predictions depending on the magnitude of such subsidies, something that point elasticities do not provide.

The control function method here shows promise for applications to a broader set of empirical settings. The price normalization approach can be applied to multinomial or ordered decision processes. Additionally, it is possible to apply the approach to random coefficient logit or to the BLP method. Finally, because the method uses maximum likelihood, it is possible to apply it in the context of a factor model to address unobserved heterogeneity, as in Carneiro, Hansen, and Heckman (2003). Such applications are left to future work.

3. ESTIMATING PERCEIVED RETURNS TO COLLEGE

3.1 Introduction

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.[1] 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

[1]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.

constrained, policy interventions that alter individuals' 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.[2] 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 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.[3] 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.[4] In contrast, estimation of beliefs has the benefit that it is based on agents' observed choices rather

[2]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).

[3]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.

[4]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.

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.[5] 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.[6] 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.[7] 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 of their real returns (such as the component associated with cognitive ability), they have full information on that component of returns.[8]

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

[6]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.

[7]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).

[8]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.

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 (2018) (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.[9] 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.[10] 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 considers some counterfactual policies. Section 7 concludes.

[9] 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.

[10] 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.

3.2 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 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:

$$\begin{aligned} Y_{1i} =& X_i\beta_1 + \epsilon_{1i} \\ Y_{0i} =& X_i\beta_0 + \epsilon_{0i} \\ C_i =& X_i\beta_C + \widetilde{Tuition}_i\gamma + \epsilon_{Ci}, \end{aligned} \tag{3.1}$$

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.[11] 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.

[11] 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.

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

$$S_i = \begin{cases} 1 \text{ if } u(Y_{1i} - C_i) - u(Y_{0i}) \geq 0 \\ 0 \text{ otherwise,} \end{cases} \tag{3.2}$$

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

$$S_i = \begin{cases} 1 \text{ if } Y_{1i} - Y_{0i} - C_i \geq 0 \\ 0 \text{ otherwise.} \end{cases} \tag{3.3}$$

is necessary and sufficient for the condition in equation (2) to hold.[12] 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

$$Y_i = X_i\beta - \widetilde{Tuition}_i\gamma + \epsilon_i, \tag{3.4}$$

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 distri-

[12]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.

bution of the unobserved perceived return Y by obtaining information about β, γ, $\widetilde{Tuition}$, and the distribution of ϵ.

3.3 Empirical Strategy

It follows from the model that, given X_i and an assumption on γ, Y_i can be identified with assumptions on the distribution of ϵ_i and on $\widetilde{Tuition}_i$. I begin by assuming that actual tuition are a linear function of agent beliefs about them,

$$Tuition_i = \frac{\widetilde{Tuition}_i}{\lambda} + \nu_i, \tag{3.5}$$

in which λ is a known (to the econometrician) constant that captures agents' systematic and proportional mistakes in estimation of Tuition and ν is a mean-zero error term independent of perceived tuition that describes unknown (to agents) variation in actual tuition at the time of the investment decision.[13]

With the assumption on the relationship between actual and perceived tuition, we can add and subtract $\nu_i\lambda\gamma$ to rewrite the latent variable equation as[14]

$$\begin{aligned} Y_i &= X_i\beta - Tuition_i\lambda\gamma + \nu_i\lambda\gamma + \epsilon_i \\ &= X_i\beta - Tuition_i\lambda\gamma + \zeta_i. \end{aligned} \tag{3.6}$$

[13]This restriction nests that of Dickstein and Morales (2018) that $Tuition$ must be a mean-preserving spread of $\widetilde{Tuition}$ under the rational expectations assumptions: $\lambda = 1$ and $\mathbb{E}[\nu] = 0$. It also nests CHN's assumption that either $\widetilde{Tuition}_i = \mathbb{E}[Tuition]$ or $\widetilde{Tuition}_i = Tuition_i$. Calibration of λ can be performed using elicited responses on perceived tuition so long as the calibrated value used reflects the belief of the agent at the time of the decision. Alternatively, λ can be estimated by matching the model's predicted effects of policy shocks on selection to externally obtained estimates, for instance, from studies of natural experiments.

[14]The assumption that $\mathbb{E}[\nu] = 0$ is purely for convenience. If the assumption doesn't hold, the mean of agent misperceptions will be absorbed by the constant in the perceived returns equation if $Tuition\lambda$ is used in place of $\widetilde{Tuition}$. In other words, if all agents think an investment is a certain amount more (less) expensive than it really is, the constant in the perceived returns equation will be estimated to be that much less (more) than it would if we could condition on agents' beliefs about tuition.

This expression of perceived returns introduces a new error, ζ, and recasts the information frictions in tuition as an omitted variable. The empirical challenge will be to deal effectively with correlation between $Tuition$ and the error term, both through the omitted variable bias due to information frictions or due to other sources of endogeneity.

The details of how each method described in this paper handle these concerns can be found in their respective sections. First, note that ν is positively correlated with $Tuition$ by construction as seen in 3.5. For sensible (positive) values of γ and λ, the failure to account for ν will cause attenuation bias in estimates of the effect of Tuition on selection, which amounts to upward bias in the estimate of the scale of the distribution.[15] Second, if tuition are high at times when (or for individuals who) unobserved components of demand for the investment are high, this will introduce positive correlation between tuition and ϵ, further biasing the estimate of the effect of Tuition on selection upwards toward (or beyond) zero.

In general, both of these problems will be addressed with the use of instruments, Z, for perceived tuition. The following equations describe how instruments can be used to address both sources of endogeneity described above.

$$\begin{aligned} \widetilde{Tuition}_i &= f(Z_i) + u_i \\ Tuition_i &= \frac{\widetilde{Tuition}_i}{\lambda} + \nu_i = \frac{f(Z_i) + u_i}{\lambda} + \nu_i. \end{aligned} \tag{3.7}$$

$f(\cdot)$ provides a mapping between Z and both perceived and realized tuition, and u is the potentially endogenous component of perceived tuition. In order to obtain unbiased estimates of the causal effect of perceived tuition on perceived returns (as is necessary to validate the assumption on γ), the instruments must be independent of both u and ν.

[15] If Tuition variation shifts few people into or out of the investment, it follows either that the perceived returns distribution has low mass near zero (high variance), or that the variation in tuition is unknown and therefore not acted upon.

The key to understanding the value of the instruments in addressing information frictions in tuition is that, for valid instruments,

$$\widehat{Tuition_i}\lambda = \widehat{\widetilde{Tuition}_i} = \hat{f}(Z_i). \tag{3.8}$$

Including the errors in the perceived returns equation in (3.6) leads to causal estimates of the effect of perceived tuition on selection:

$$\begin{aligned} Y_i =& X_i\beta - Tuition_i\lambda\gamma + \zeta_i \\ =& X_i\beta - Tuition_i\lambda\gamma + u_i\rho_u + \nu_i\lambda\rho_\nu + \eta_i \\ =& X_i\beta - Tuition_i\lambda\gamma + (u_i + \nu_i\lambda)\rho_{u\nu} + \eta_i. \end{aligned} \tag{3.9}$$

I assume the new error, η_i, is i.i.d. and normally distributed,

$$\eta_i|(X_i, Tuition_i, u_i + \nu_i\lambda) \sim \mathcal{N}(0, \sigma^2). \tag{3.10}$$

This setup immediately leads to the control function method when estimates of $(u_i + \nu_i\lambda)$ are included in place of the objects themselves, and is useful for motivating the other two methods discussed below.

I will begin by describing a simple benchmark Probit-based method in section 3.3.1 that assumes away the two potential sources of bias, followed by a discussion of the moment inequalities developed by Dickstein and Morales (2018) in section 3.3.2, followed finally with the development of an alternative control function approach in section 3.3.3 that shares many of the advantages of DM's moment inequalities. The control function approach has the advantages of obtaining point estimates of model parameters and requiring fewer computational resources.

3.3.1 Probit Benchmark

I begin by describing a method for inferring perceived returns using a Probit. This procedure will provide consistent estimates of the perceived returns distribution under two assumptions that are likely to be violated in many applications. First, this method assumes that agents have perfect information on tuition ($\nu_i = 0 \quad \forall i$, $\lambda = 1$). Second, it assumes independence between tuition and unobserved idiosyncratic preferences for the investment such that $u_i = 0\ \forall i$. Under these assumptions, the empirical specification for perceived returns given in (3.9) reduces to

$$Y_i = X_i\beta - Tuition_i\gamma + \eta_i.^{16} \tag{3.11}$$

Given the decision rule described in (3.3) and the assumption of normally distributed errors, perceived returns can then be estimated by maximum likelihood. The probability of selecting the investment is given by

$$Pr(S_i = 1|X_i, Tuition_i) = \Phi\Big(\frac{X_i\beta - Tuition_i\gamma}{\sigma}\Big), \tag{3.12}$$

where $\Phi(\cdot)$ denotes the standard normal cdf. Defining $\{\beta^*, \gamma^*\} = \{\frac{\beta}{\sigma}, \frac{\gamma}{\sigma}\}$ for notational convenience and taking γ as given, the parameters $\{\beta^*, \gamma^*\}$ are the values that maximize the log-likelihood:[17]

$$\mathcal{L}(\beta^*, \gamma^*|X_i, Tuition_i) =$$
$$\sum_i S_i \log\Big[\Phi\Big(X_i\beta^* - Tuition_i\gamma^*\Big)\Big] + (1 - S_i)\log\Big[1 - \Phi\Big(X_i\beta^* - Tuition_i\gamma^*\Big)\Big]. \tag{3.13}$$

The estimates of perceived returns are then given by:

$$Y_i \sim \mathcal{N}(X_i\hat{\beta} - Tuition_i\gamma, \hat{\sigma}^2). \tag{3.14}$$

[16] Under the assumptions presented in this section, $\eta_i = \epsilon_i\ \forall i$.

[17] Many statistical software packages, such as Stata, impose $\sigma = 1$ in their binary choice estimation commands. It is simple to convert these estimates into scaled estimates using:

$$\hat{\sigma} = \frac{\gamma}{\hat{\gamma}^*} \quad ; \quad \hat{\beta} = \hat{\beta}^*\hat{\sigma},$$

taking to care to apply the delta method to obtain correct standard errors for the scaled estimates.

3.3.2 Moment Inequality Approach

It is likely that agents do not have perfect information on tuition. For one, individuals often make investment decisions before tuition are fully realized. Evolving cost shocks are often not contracted on prior to the investment decision and can be reflected in tuition, for instance when college tuition changes while a student is attending. Individuals may even be uninformed about tuition after they have been set. For instance, Bettinger, Long, Oreopoulos, and Sanbonmatsu (2012) find that individuals' elicited beliefs about tuition for postsecondary education were over three times higher than actual tuition.

It is also unlikely that perceived tuition and ϵ, the unobserved component of perceived returns, are independent. Returning to the postsecondary education example, it is possible that high ability students perceive the return to college to be high while also attending more expensive colleges. If this relationship is sufficiently strong, tuition will be positively associated with selection, which will be incompatible with the assumed value for γ. In settings without such extreme Tuition discrimination, we may still expect tuition to be high for places and times where demand for the product is high, similarly biasing the estimated effect of tuition on selection upward, which will imply downward bias on the scale parameter.[18]

This section describes a method developed by Dickstein and Morales (2018) that addresses the bias from imperfect information using moment inequalities, which they use to identify perceived costs in a firm export decision context.[19] I provide a

[18] The estimated effect of Tuition on selection is given by $\frac{\gamma}{\sigma}$. Because the effect of Tuition on selection is defined by the inverse of the scale parameter, the scale parameter will be biased in the opposite direction of the effect on selection.

[19] It is worth noting that DM do not use their moment inequalities to address endogeneity. Briefly, this is because their model provides a forecasting equation for profit as a function of revenue and costs. In their framework, revenue forecasts profit at a constant marginal rate defined by the demand elasticity. Naturally, if the relationship were causal, this constant marginal rate would be 1.

brief discussion of the intuition here. The method uses two sets of moment inequalities to obtain bounds on the parameters of perceived returns using instruments, Z, that are independent of both the unknown component of tuition and the unobserved error in perceived returns.[20]

Revealed Preference Moment Inequalities

The conditional revealed preference moment inequalities are given by

$$\begin{aligned} &\mathbb{E}\left[-(1-S_i)(X_i\beta^* - Tuition_i\lambda\gamma^*) + S_i\frac{\phi(X_i\beta^* - Tuition_i\lambda\gamma^*)}{\Phi(X_i\beta^* - Tuition_i\lambda\gamma^*)} \middle| Z_i \right] \geq 0, \\ &\mathbb{E}\left[S_i(X_i\beta^* - Tuition_i\lambda\gamma^*) + (1-S_i)\frac{\phi(X_i\beta^* - Tuition_i\lambda\gamma^*)}{1-\Phi(X_i\beta^* - Tuition_i\lambda\gamma^*)} \middle| Z_i \right] \geq 0. \end{aligned} \tag{3.15}$$

where Z is an instrument for perceived Tuition. These inequalities are consistent with the revealed preference argument that perceived returns are positive for those who select the investment and negative for those who do not.

Consider an agent that selects the investment such that $S_i = 1$. Following the revealed preference argument articulated in (3.3) and the empirical specification given in (3.9), it must be the case that this individual's perceived return for the investment is positive such that

$$S_i(X_i\beta - Tuition_i\lambda\gamma + (u_i + \nu_i\lambda)\rho_{u\nu} + \eta_i) \geq 0. \tag{3.16}$$

[20] DM describe the first condition on instruments as agents knowing Z. CHN use similar language to designate known and unknown components of returns. At the cost of brevity, I will describe the relevant condition as agents knowing tuition insofar as they are predicted by the instruments, rather than knowing the instruments themselves.

We do not ever observe the error, η_i, but this condition will hold on average if it holds for individuals. Taking the conditional expectation across individuals conditional on the observed covariates and the unobserved errors $\{u_i, \nu_i\}$ yields

$$\mathbb{E}\Bigg[S_i(X_i\beta^* - Tuition_i\lambda\gamma^* + (u_i + \nu_i\lambda)\rho^*_{u\nu}) \\ +(1-S_i)\frac{\phi(X_i\beta^* - Tuition_i\lambda\gamma^* + (u_i + \nu_i\lambda)\rho^*_{u\nu})}{1-\Phi(X_i\beta^* - Tuition_i\lambda\gamma^* + (u_i + \nu_i\lambda)\rho^*_{u\nu})}\Bigg| X_i, Tuition_i, u_i, \nu_i\Bigg] \geq 0, \tag{3.17}$$

where the second term is derived from the inverse-mills ratio.

The second moment inequality above is obtained first by applying law of iterated expectations to condition on Z instead of the unobserved objects. Second, the expectation of $(u+\nu\lambda)$ given Z is zero for valid instruments, so this term can be omitted through the application of Jensen's inequality as long as it is weakly positively correlated with η because the function inside of the expectation is globally convex.[21] The necessity of weakly positive correlation between the errors is a restriction that is unique to the moment inequalities, but should be of small consequence in practical applications if unobserved components of perceived returns are generally positively correlated with tuition. The first inequality follows from the same intuition applied to individuals who do not select the investment.

[21] The necessary condition is that $Var(u_i + \nu_i\lambda)\rho_{u\nu} + \eta_i) \geq Var(\eta)$. This nests DM's condition in the absence of endogeneity, where $u_i = 0\ \forall i$, and $\nu \perp\!\!\!\perp \eta$. The application of Jensen's inequality is valid for any error distribution with a convex inverse-mills ratio, such as the normal distribution or the logistic distribution.

Odds-Based Moment Inequalities

The conditional odds-based moment inequalities are given by

$$\begin{aligned}
&\mathbb{E}\left[\left(S_i\frac{1-\Phi(X_i\beta^*-Tuition_i\lambda\gamma^*+(u_i+\nu_i\lambda)\rho^*_{u\nu}))}{\Phi(X_i\beta^*-Tuition_i\lambda\gamma^*+(u_i+\nu_i\lambda)\rho^*_{u\nu}))}-(1-S_i)\right)\middle|Z_i\right]\geq 0,\\
&\mathbb{E}\left[\left((1-S_i)\frac{\Phi(X_i\beta^*-Tuition_i\lambda\gamma^*+(u_i+\nu_i\lambda)\rho^*_{u\nu}))}{1-\Phi(X_i\beta^*-Tuition_i\lambda\gamma^*+(u_i+\nu_i\lambda)\rho^*_{u\nu}))}-S_i\right)\middle|Z_i\right]\geq 0.
\end{aligned} \tag{3.18}$$

They are derived from the conditional expectation of the score equation:

$$\begin{aligned}
&\mathbb{E}\Bigg[S_i\frac{\phi(X_i\beta^*-Tuition_i\lambda\gamma^*+(u_i+\nu_i\lambda)\rho^*_{u\nu})}{\Phi(X_i\beta^*-Tuition_i\lambda\gamma^*+(u_i+\nu_i\lambda)\rho^*_{u\nu})}\\
&-(1-S_i)\frac{\phi(X_i\beta^*-Tuition_i\lambda\gamma^*+(u_i+\nu_i\lambda)\rho^*_{u\nu})}{1-\Phi(X_i\beta^*-Tuition_i\lambda\gamma^*+(u_i+\nu_i\lambda)\rho^*_{u\nu})}\Bigg|X_i,Tuition_i,(u_i+\nu_i\lambda)\Bigg]=0.
\end{aligned} \tag{3.19}$$

The derivation proceeds by a similar process by which we obtained the revealed preference inequalities. First, the score equation is rearranged into two equations that are globally convex in their arguments:[22]

$$\begin{aligned}
&\mathbb{E}\left[\left(S_i\frac{1-\Phi(X_i\beta^*-Tuition_i\lambda\gamma^*+(u_i+\nu_i\lambda)\rho^*_{u\nu}))}{\Phi(X_i\beta^*-Tuition_i\lambda\gamma^*+(u_i+\nu_i\lambda)\rho^*_{u\nu}))}-(1-S_i)\right)\middle|X_i,Tuition_i,u_i,\nu_i\right]=0,\\
&\mathbb{E}\left[\left((1-S_i)\frac{\Phi(X_i\beta^*-Tuition_i\lambda\gamma^*+(u_i+\nu_i\lambda)\rho^*_{u\nu}))}{1-\Phi(X_i\beta^*-Tuition_i\lambda\gamma^*+(u_i+\nu_i\lambda)\rho^*_{u\nu}))}-S_i\right)\middle|X_i,Tuition_i,u_i,\nu_i\right]=0.
\end{aligned} \tag{3.20}$$

As with the revealed preference inequalities, these inequalities still hold conditional on the observed Z by law of iterated expectations. Given the the global convexity of the odds ratios, the equality changes to an inequality when omitting $(u+\nu\lambda)$ by Jensen's inequality, again, as long as this error is weakly positively correlated with η. This leads to the odds-based moment inequalities in (3.18).

It may seem like the two moment inequalities in (3.18) would be redundant as they are both derived from transformations of the same score function. The key

[22] Global convexity of the odds-ratios is a trait of all log-concave distributions.

point, however, is that $(u_i + \nu_i\lambda)$ is omitted 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 $\mathbb{E}[-(1 - S_i)|Z_i] \geq 0$, a violation of 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 (2018).

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 the estimation procedure is available in Appendix B.

3.3.3 Control Function Approach

In this section I describe a control function approach that has three advantages over the moment inequalities. First, it is substantially less computationally costly, allowing for the inclusion of a richer set of explanatory variables. This provides for a broader set of heterogeneous policy predictions conditional on observed covariates. Second, it provides point estimates of model parameters. Third, it places no restrictions on the distribution of the error term.[23]

The control function approach makes use of the following system of equations:

$$\begin{aligned} Y_i &= X_i\beta - \widetilde{Price}_i\gamma + \epsilon_i \\ \widetilde{Price}_i &= Z_i\delta + u_i \\ Price_i &= \frac{\widetilde{Price}_i}{\lambda} + \nu_i = \frac{Z\delta + u_i}{\lambda} + \nu_i, \end{aligned} \tag{3.21}$$

where δ provides the mapping of the instruments to perceived prices. The second line represents what would be the first stage in a two-step instrumental variables procedure if perceived prices were observable. The third line combines the assumption on beliefs given in (3.5) with the unobserved first stage on perceived prices to obtain a first stage equation that consists of only observable objects.[24]

The requirement that $Z \perp\!\!\!\perp \nu$ is made clear here. If the instruments are independent of misperceptions on prices, we can use the predicted value of observed prices as a stand-in for the otherwise unknown predicted value of perceived prices, i.e.,

$$\widehat{Price}_i = \frac{\widehat{\widetilde{Price}_i}}{\lambda} = \frac{Z\hat{\delta}}{\lambda}. \tag{3.22}$$

[23] To use both sets of the moment inequalities, recall that the error term must be both log-concave and have a convex inverse Mills ratio. For most practical purposes, this restricts the applicable distributions to the normal or the logistic. It also does not make assumptions about the sign of the covariance between the first stage error $(u + \nu\lambda)$ and the perceived returns error η.

[24] The presentation here assumes a parametric first stage. It is also possible to construct a nonparametric first stage using the expectation of price conditional on Z.

The error terms $\{\epsilon, u, \nu\}$ can be freely interdependent if Z is a valid instrument for beliefs about prices.[25]

Given the above, we can estimate perceived returns with a control function:[26]

$$\begin{aligned} Y_i =& X_i\beta - \widetilde{Price}_i\gamma + \epsilon_i \\ =& X_i\beta - Price_i\lambda\gamma + (u_i + \nu_i\lambda)\rho_{u\nu} + \eta_i \\ =& X_i\beta - Price_i\lambda\gamma + (\widehat{u_i + \nu_i\lambda})\rho_{uv} + \zeta_i. \end{aligned} \tag{3.23}$$

The second line substitutes the linear projection of ϵ_i on $(u_i + \nu_i\lambda)$ in for ϵ_i using the specification of perceived prices in (2.5). The third line substitutes the estimated OLS residuals from the first stage regression of $Price$ on Z in for their unobserved true values, generating a new error, ζ. This new error will converge asymptotically to η, but will differ in small samples based on variation in the estimation of the residual from the first stage, $(\widehat{u_i + \nu_i\lambda})$. Note that it is unnecessary (and impossible) in this setting to distinguish between u_i and ν_i.

The log-likelihood is then given by:

$$\begin{aligned} &\mathcal{L}\Big(\beta^*, \gamma^*, \rho^*_{u\nu}|X, (\widehat{u + \nu\lambda})\Big) = \\ &\sum_i S_i \log\left[\Phi\Big(X_i\beta^* - Price_i\lambda\gamma^* + (\widehat{u_i + \nu_i\lambda})\rho^*_{uv}\Big)\right] \\ &+(1 - S_i)\log\left[1 - \Phi\Big(X_i\beta^* - Price_i\lambda\gamma^* + (\widehat{u_i + \nu_i\lambda})\rho^*_{uv}\Big)\right]. \end{aligned} \tag{3.24}$$

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[25] 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.

[26] As an alternative, we could perform a two stage procedure with $Y_i = X_i\beta - Z\hat{\delta}\lambda\gamma - \frac{u_i}{\lambda}\gamma + \epsilon_i$, where $\hat{\delta}$ is obtained from the OLS projection of $Price$ on Z. This formulation will obtain valid estimates of β and $\omega^2 = Var(\frac{u_i}{\lambda}\gamma + \epsilon_i)$, leading to $\hat{Y}_i \sim \mathcal{N}(X_i\hat{\beta} - \widehat{Price}_i\gamma, \hat{\omega}^2)$. This approach has the disadvantage of moving individual-specific heterogeneity on perceived returns contained in $(\widehat{\frac{u_i}{\lambda} + \nu_i})$ into the error term, while the control function approach conditions on this observed variation.

Estimates of perceived returns are obtained by plugging the estimated parameters into the latent variable equation:

$$Y_i \Big| \Big(X_i, (\widehat{u_i + \nu_i \lambda}) \Big) \sim \mathcal{N}\Big(X_i \hat{\beta} - Price_i \lambda \gamma + (\widehat{u_i + \nu_i \lambda}) \hat{\rho}_{uv}, \hat{\sigma}^2 \Big). \tag{3.25}$$

3.4 Data

The primary dataset used is the Geocode file of the 1979 National Longitudinal Survey of Youth (NLSY79). The NLSY79 is a longitudinal, nationally representative survey of 12,686 youths who were 14-22 years old when they were first surveyed in 1979. Respondents were first interviewed in 1979, were interviewed annually through 1994 and have been interviewed biannually since then. 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.[27] 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.[28]

I choose college attendance as the decision of interest.[29] 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

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

[28] 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.

[29] 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 3.1.: Description of the Primary Variables

	Overall	High School Graduates	College Attendees
Attend College	0.501	0.000	1.000
Female	0.501	0.482	0.520
Black	0.104	0.117	0.092
Hispanic	0.047	0.057	0.038
High School GPA	2.480	2.124	2.835
Mother Education	11.833	11.005	12.658
Father Education	11.997	10.821	13.169
Number of Siblings	3.128	3.485	2.772
ASVAB Score Subtest 3	1.436	0.620	2.250
ASVAB Score Subtest 4	1.903	0.423	3.378
ASVAB Score Subtest 5	2.367	1.119	3.610
Family Income	69675	58858	80456
Broken Home	0.286	0.337	0.234
Age in 1979	16.231	16.081	16.381
Urban Residence at Age 14	0.757	0.723	0.791
Average County Wage at Age 17	11.318	11.418	11.218
State Unem. Rate at Age 17	7.242	7.395	7.090
Net Tuition	11,142	7,151	15,120
Local Tuition at Age 17	12,575	12,559	12,590
Observations	3324	1843	1481

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.

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 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:

$$Tuition_i = \begin{cases} X_{iT}\alpha_T + Local\_Tuition\_17_i\alpha_{LT} + \xi_{iT} & \text{if } S_i = 1 \\ . & \text{otherwise,} \end{cases} \tag{3.26}$$

$$S_i = \begin{cases} 1 \text{ if } Z_{iT}\alpha_S - Local\_Tuition\_17_i\alpha_{LS} + \xi_{iS} > 0 \\ 0 \text{ otherwise,} \end{cases} \tag{3.27}$$

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 (3.27) 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 (3.26) while controlling for selection from (3.27) 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. Fourth, I use the instrumented value of tuition to estimate the causal effect of tuition on selection.[30] 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.2.

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 coeffi-

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

Table 3.2.: 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.

cient on the first principal component of variables associated with individuals' general ability, and a coefficient on the first principal component of variables associated with individuals' local geographic characteristics.[31] The details of the principal component analysis are presented in Appendix D.1.

3.5 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. 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.

The results in Table 3 are scaled using the estimated $\gamma(X)$ described in Appendix D.2 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

[31] 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 3.3.: Perceived Returns Estimates, 2018 Dollars, Principal Components

	Probit	IV Probit	Moment Inequalities
Constant	-0.451	0.120	[-10.310, 3.192]
	(0.321)	(1.300)	N/A
PC1(Ability)	-4.121	26.982	[23.511, 30.326]
	(0.407)	(33.084)	N/A
PC1(Location)	1.631	-0.532	[-4.554, 2.655]
	(0.321)	(2.545)	N/A
σ	-13.154	43.239	[32.246, 60.768]
	(1.338)	(57.458)	N/A
Observations	3324	3324	3324

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 (3.14) with the details varying by estimation method. See text for details.

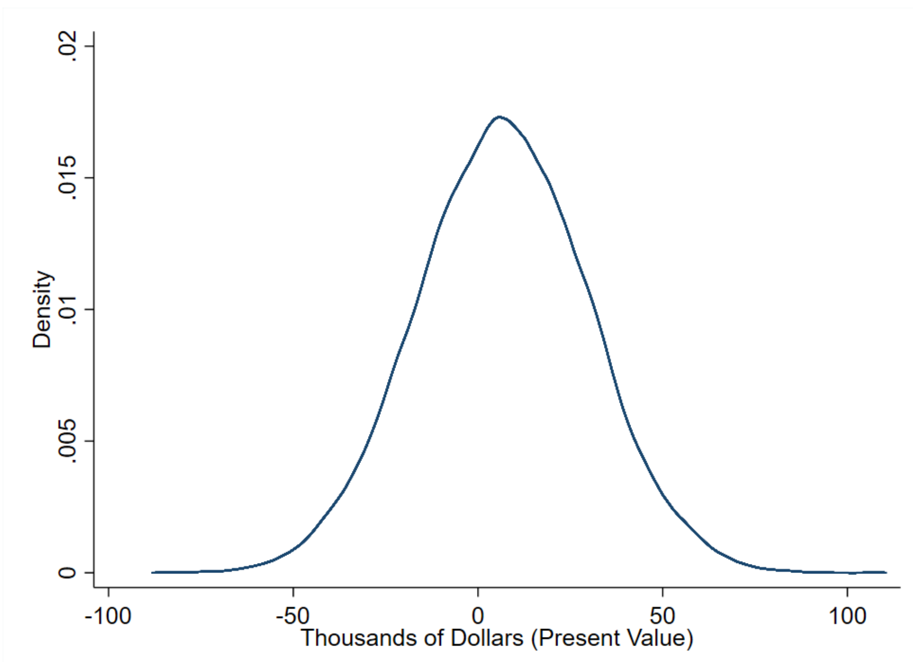

Figure 3.1.: Perceived Returns to College, IV Probit, Principal Components

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

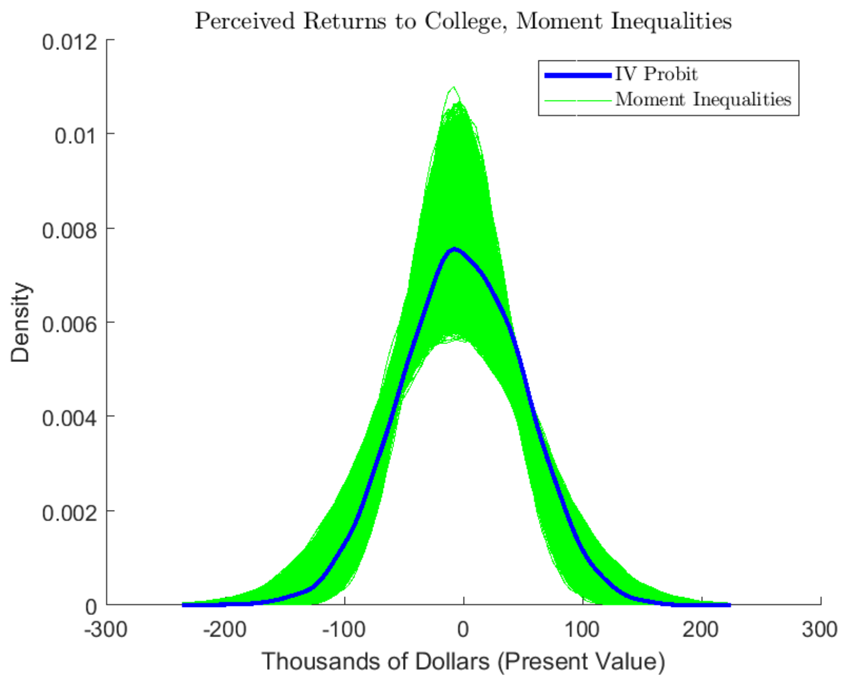

Figure 3.2.: Perceived Returns to College, Moment Inequalities, Principal Components

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 $\hat{\sigma}$.

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 D.4.[32]

Table 3.4.: 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 (3.14) 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.[33] 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.

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

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

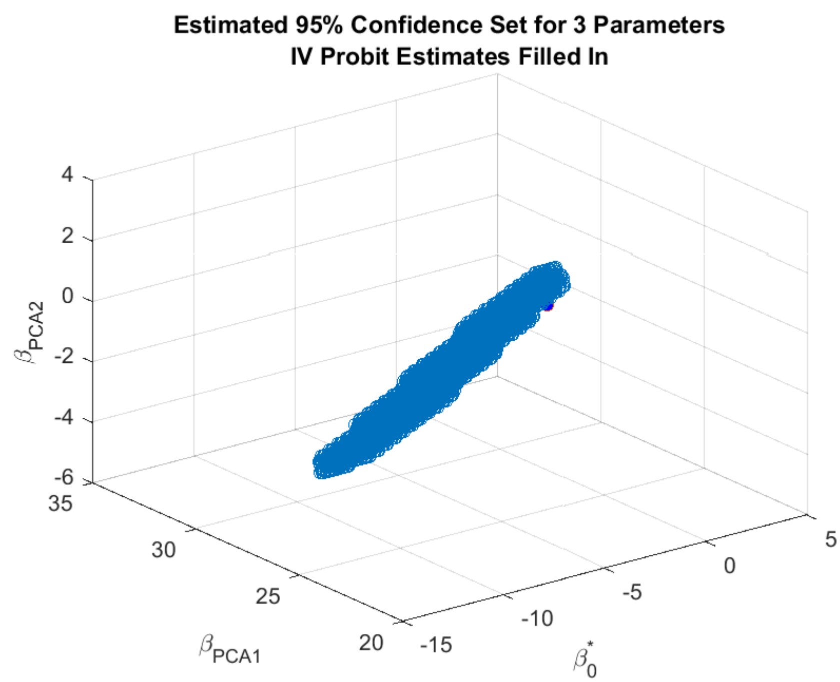

Figure 3.3.: Unscaled Confidence Set for 3 Parameters, Moment Inequalities

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.

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 D.4.

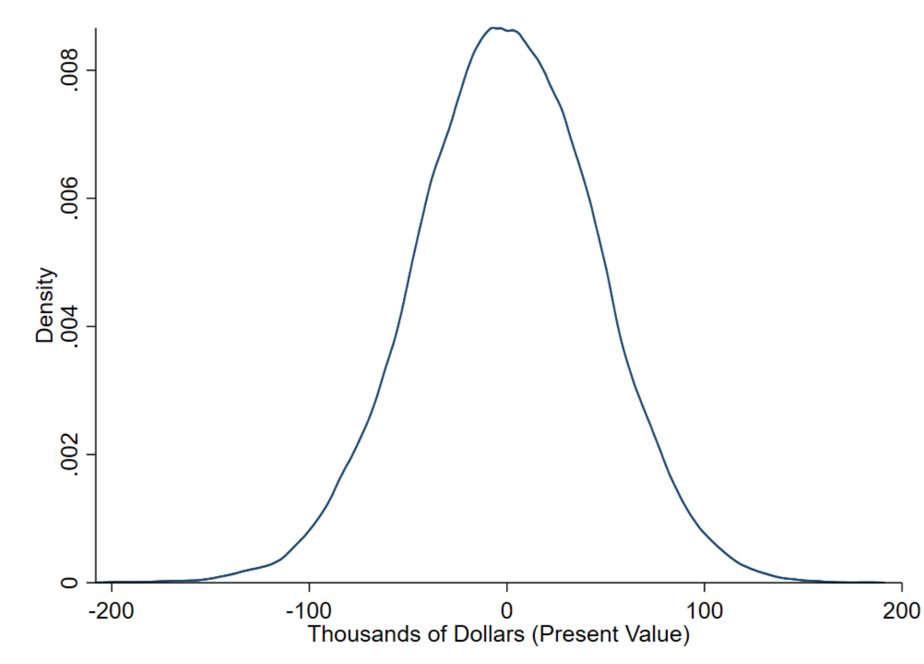

Figure 3.4.: Perceived Returns to College, IV Probit, All Controls

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

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

Table 3.5.: Perceived Returns Estimates, 2018 Dollars, All Controls

	(1) Probit	(2) Std. Error	(3) IV Probit	(4) Std. Error
Constant	-2.107	(3.152)	-0.096	(1.042)
Female	-14.026	(7.384)	-6.681	(5.685)
Black	59.461	(8.540)	17.133	(17.066)
Hispanic	34.472	(9.554)	11.942	(12.620)
Deceased Father	-27.964	(44.749)	-19.777	(22.751)
Deceased Father x Before	82.788	(49.114)	40.634	(37.339)
Before	-5.321	(10.093)	-5.456	(7.166)
Senior Year	-28.145	(3.926)	-10.079	(9.288)
High School GPA	45.219	(18.734)	13.516	(11.192)
High School GPA Squared	2.383	(3.967)	0.794	(1.721)
Mother Education	-15.077	(4.322)	-2.819	(3.730)
Mother Education Squared	0.965	(0.208)	0.238	(0.262)
Father Education	-3.370	(3.677)	-1.208	(1.568)
Father Education Squared	0.413	(0.168)	0.139	(0.125)
Number of Siblings	-16.312	(3.282)	-4.308	(4.151)
Number of Siblings Squared	1.002	(0.296)	0.295	(0.283)
ASVAB Score Subtest 3	2.081	(1.102)	0.882	(0.861)
ASVAB Score Subtest 4	-0.405	(0.791)	0.054	(0.284)
ASVAB Score Subtest 5	-0.813	(0.767)	-0.099	(0.286)
ASVAB Score Subtest 6	1.036	(1.425)	0.401	(0.614)
ASVAB Score Subtest 7	-0.102	(0.404)	-0.192	(0.246)
ASVAB Score Subtest 8	-0.190	(0.271)	-0.032	(0.106)
ASVAB Score Subtest 9	-2.269	(1.020)	-0.817	(0.656)
ASVAB Score Subtest 10	2.751	(0.862)	0.532	(0.548)
ASVAB Score Subtest 11	-0.871	(0.977)	-0.177	(0.359)
ASVAB Score Subtest 12	0.933	(1.206)	0.411	(0.462)
ASVAB Score Subtest 3 Squared	-0.033	(0.141)	-0.034	(0.058)
ASVAB Score Subtest 4 Squared	0.156	(0.081)	0.049	(0.042)
ASVAB Score Subtest 5 Squared	-0.201	(0.063)	-0.054	(0.054)
ASVAB Score Subtest 6 Squared	-0.494	(0.277)	-0.170	(0.164)
ASVAB Score Subtest 7 Squared	-0.079	(0.029)	-0.015	(0.014)
ASVAB Score Subtest 8 Squared	0.002	(0.012)	-0.000	(0.004)
ASVAB Score Subtest 9 Squared	-0.390	(0.114)	-0.165	(0.148)
ASVAB Score Subtest 10 Squared	0.446	(0.101)	0.118	(0.111)
ASVAB Score Subtest 11 Squared	-0.008	(0.126)	-0.014	(0.045)
ASVAB Score Subtest 12 Squared	0.127	(0.184)	0.019	(0.069)
Family Income	0.000	(0.000)	0.000	(0.000)
Family Income Squared	-0.000	(0.000)	-0.000	(0.000)
Broken Home	-6.666	(6.499)	-1.553	(3.357)
Age 1979	-16.936	(4.242)	-5.902	(5.323)
Urban Residence at Age 14	19.175	(6.845)	5.621	(5.535)
Average County Wage at Age 17	-0.824	(1.224)	-0.028	(0.496)
State Unem Rate at Age 17	0.398	(1.695)	0.198	(0.564)
σ	106.208	(149.122)	31.328	(29.084)
Observations	3324	3324	3324	3324

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 (3.14) with the details varying by estimation method. See text for details.

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 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).[34]

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.[35] 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 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

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

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

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. Because the scale is given by the inverse of the effect of tuition on attendance, this 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.

3.6 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.

3.6.1 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.[36] 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.[37]

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

[36] 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.

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

according to the association between paternal death and perceived returns to college.[38] 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 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.[39] 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.

[38]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.

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

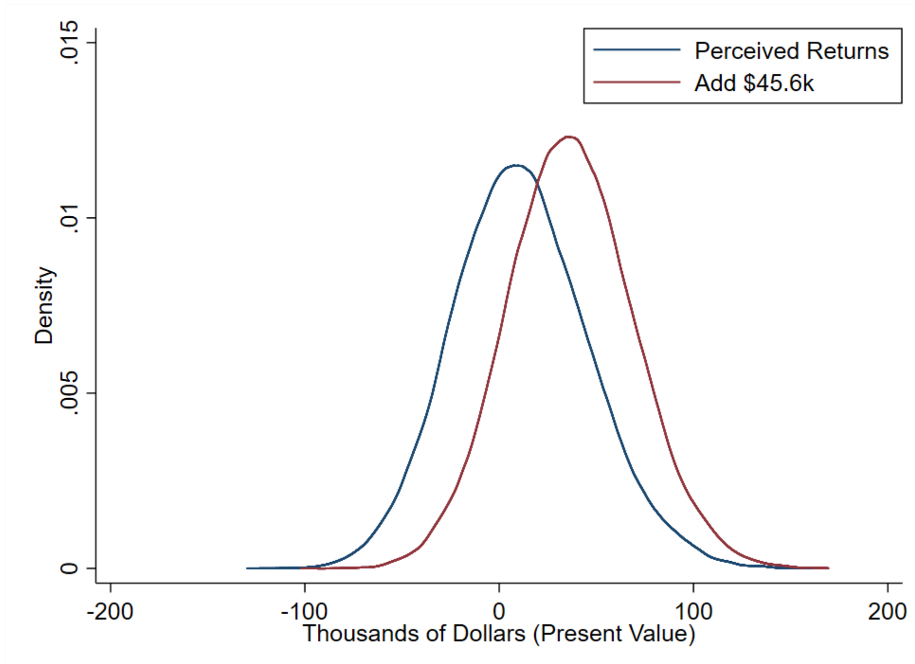

Figure 3.5.: Effect of Universally Applied Aid Equivalent to Social Security Student Benefit

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 $\hat{\gamma}(X) = 0.61$.

3.6.2 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.[40] 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).

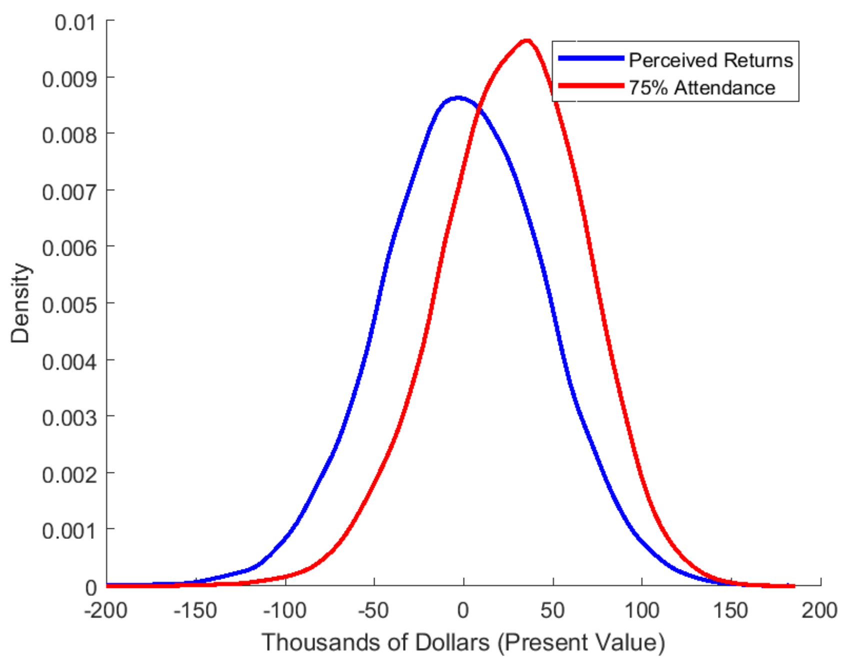

Figure 3.6.: Cost-Minimizing Aid for Attendance Target

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.

[40]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.

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

$$Pr\left(S_i = 1|\hat{Y}_i, a_i\right) = \Phi\left(\frac{\hat{Y}_i + a_i\hat{\gamma}_i}{\hat{\sigma}}\right), \tag{3.28}$$

where $\hat{Y}_i = \mathbb{E}[Y_i|X_i, Tuition_i]$.[41] The expected cost to the government for this financial aid offer is then given by

$$\mathbb{E}[C_i|\hat{Y}_i, a_i] = a_i\Phi\left(\frac{\hat{Y}_i + a_i\hat{\gamma}_i}{\hat{\sigma}}\right), \tag{3.29}$$

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 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.[42] Choosing a_i to set expected marginal benefit equal to expected marginal costs gives

$$b = \frac{\frac{\Phi(\hat{Y}_i^*(a_i))}{\phi_i(\hat{Y}_i^*(a_i))}\hat{\sigma} + a_i\hat{\gamma}_i}{\hat{\gamma}_i}, \tag{3.30}$$

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

[41]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.

[42]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.

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[43]

$$b_{1i} = \begin{cases} b & \text{if } b_{0i} < b, \\ b_{0i} & \text{if } b_{0i} \geq b. \end{cases} \tag{3.31}$$

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:

$$b_{0i} = \frac{\frac{\Phi(\hat{Y}_i^*(0))}{\phi_i(\hat{Y}_i^*(0))}\hat{\sigma}}{\hat{\gamma}_i}. \tag{3.32}$$

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.[44]

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

$$\mathbb{E}\left[\Phi\left(\frac{\hat{Y}_i + a_i(b^*)\hat{\gamma}_i}{\hat{\sigma}}\right)\right] = A. \tag{3.33}$$

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 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

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

[44]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.

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.

3.7 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.[45] Past estimates of the distribution of perceived returns such as those in Cunha, Heckman, and Navarro (2005) that are identified from assumptions on 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

[45]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.

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.[46] 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.

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

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

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 (2018), 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.

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A. Moment Inequalities in the Context of Endogeneity: Proofs

For proofs of the validity of the moment inequalities for providing bounds that contain the true parameter vector, $\theta = \{\beta, \sigma\}$, in the context of information frictions on prices, I refer to Dickstein and Morales (2018). The inequalities can also address correlation between perceived prices and the unobserved error in perceived returns under additional assumptions. The following follows DM closely, while emphasizing the deviations when they appear.

A.1 Proof 1: Odds-Based Moment Inequalities

This section proves the validity of the first odds-based moment inequality. The proof of the second proceeds accordingly. **Lemma A.1** *Let* $\mathcal{L}(S_i|X_i, Price, (\widehat{u+\nu\lambda}); \theta^*)$ *denote the log-likelihood conditional on* $X_i, Price, (u+\nu\lambda)$*. Then*

$$\frac{\partial \mathcal{L}\Big(S_i|X_i, Price, (u+\nu\lambda); \theta^*\Big)}{\partial \theta}$$
$$= \mathbb{E}\left[\left(S_i \frac{1-\Phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i+\nu_i\lambda)\rho^*_{u\nu})}{\Phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i+\nu_i\lambda)\rho^*_{u\nu})} - (1-S_i)\right)\middle| X_i, Price, (u+\nu\lambda)\right] = 0 \tag{A.1}$$

Proof: It follows from the empirical model in section 3 that the log-likelihood conditional on $\{X_i, Price, (u+\nu\lambda)\}$ can be written as

$$\begin{aligned}&\mathcal{L}\Big(S_i|X_i, Price, (u+\nu\lambda);\theta^*\Big) = \\ &\sum_i S_i \log\left[\Phi\Big(X_i\beta^* - Price_i\lambda\gamma^* + (u+\nu\lambda)\rho^*_{uv}\Big)\right] \\ &+(1-S_i)\log\left[1-\Phi\Big(X_i\beta^* - Price_i\lambda\gamma^* + (u+\nu\lambda)\rho^*_{uv}\Big)\right].\end{aligned} \tag{A.2}$$

The score function is given by

$$\begin{aligned}&\frac{\partial\mathcal{L}\Big(S_i|X_i, Price, (u+\nu\lambda);\theta^*\Big)}{\partial\theta} = \\ &\mathbb{E}\Bigg[\Bigg(S_i\frac{\phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i+\nu_i\lambda)\rho^*_{u\nu})}{\Phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i+\nu_i\lambda)\rho^*_{u\nu})} \\ &-(1-S_i)\frac{\phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i+\nu_i\lambda)\rho^*_{u\nu})}{1-\Phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i+\nu_i\lambda)\rho^*_{u\nu})}\Bigg)\Bigg| X_i, Price_i, (u+\nu\lambda)\Bigg] = 0\end{aligned} \tag{A.3}$$

which can be rearranged as

$$\begin{aligned}&\frac{\partial\mathcal{L}\Big(S_i|X_i, Price_i, (u_i+\nu_i\lambda);\theta^*\Big)}{\partial\theta^*} = \\ &\mathbb{E}\Bigg[\frac{1-\Phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i+\nu_i\lambda)\rho^*_{u\nu})}{\phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i+\nu_i\lambda)\rho^*_{u\nu})} \\ &\Bigg(S_i\frac{1-\Phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i+\nu_i\lambda)\rho^*_{u\nu})}{\Phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i+\nu_i\lambda)\rho^*_{u\nu})} - (1-S_i)\Bigg)\Bigg| X_i, Price, (u+\nu\lambda)\Bigg] = 0\end{aligned} \tag{A.4}$$

Given that

$$\frac{1-\Phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i+\nu_i\lambda)\rho^*_{u\nu})}{\phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i+\nu_i\lambda)\rho^*_{u\nu})} \tag{A.5}$$

is a function of $\{X_i, Price, (u_i + \nu_i\lambda)\}$ and is never equal to zero, we can simplify this expression to

$$\frac{\partial\mathcal{L}\Big(S_i|X_i, Price, (u+\nu\lambda);\theta^*\Big)}{\partial\theta}$$
$$= \mathbb{E}\left[\left(S_i\frac{1-\Phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i+\nu_i\lambda)\rho^*_{u\nu})}{\Phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i+\nu_i\lambda)\rho^*_{u\nu})} - (1-S_i)\right)\middle| X_i, Price_i, (u_i+\nu_i\lambda)\right] = 0 \tag{A.6}$$

yielding equation (A.1).

Lemma A.2 *Given the definition of S_i in equation* (3.27)*,* for any $\{\zeta, u, \nu\}$ such that $Cov(u+\nu\lambda, \zeta) \geq 0$,

$$\mathbb{E}\left[\left(S_i\frac{1-\Phi(X_i\beta^* - Price_i\lambda\gamma^*)}{\Phi(X_i\beta^* - Price_i\lambda\gamma^*)} - (1-S_i)\right)\middle| X_i, Price_i, (u_i+\nu_i\lambda)\right]$$
$$\geq$$
$$\mathbb{E}\left[\left(S_i\frac{1-\Phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i+\nu_i\lambda)\rho^*_{u\nu})}{\Phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i+\nu_i\lambda)\rho^*_{u\nu})} - (1-S_i)\right)\middle| X_i, Price_i, (u_i+\nu_i\lambda)\right]. \tag{A.7}$$

This is the point where the proof substantively deviates from that of DM. Allowing for correlation between perceived prices and the error in perceived returns, ϵ, introduces the new error u. The essential condition for the moment inequality to hold is that $Var(u+\nu\lambda+\eta) \geq Var(\eta)$. This condition holds in the case with only information frictions because $u_i = 0\ \forall i$ and $\nu \perp\!\!\!\perp \eta$ by definition. The same condition will hold if we expect upward bias in the effects of prices on selection from positive correlation between unobserved components of perceived returns and prices. This inequality occurs by Jensen's inequality because the odds ratio is globally convex in its arguments.

Corollary 1 *Suppose the distribution of Z_i conditional on $\{X_i, Price_i, (u_i + \nu_i\lambda)\}$ is degenerate. Then*

$$\mathbb{E}\left[\left(S_i \frac{1 - \Phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i + \nu_i\lambda)\rho^*_{u\nu})}{\Phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i + \nu_i\lambda)\rho^*_{u\nu})} - (1 - S_i)\right)\middle| Z_i\right] = 0 \qquad \text{(A.8)}$$

and

$$\begin{gathered}\mathbb{E}\left[\left(S_i \frac{1 - \Phi(X_i\beta^* - Price_i\lambda\gamma^*)}{\Phi(X_i\beta^* - Price_i\lambda\gamma^*)} - (1 - S_i)\right)\middle| Z_i\right] \\ \geq \\ \mathbb{E}\left[\left(S_i \frac{1 - \Phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i + \nu_i\lambda)\rho^*_{u\nu})}{\Phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i + \nu_i\lambda)\rho^*_{u\nu})} - (1 - S_i)\right)\middle| Z_i\right].\end{gathered} \qquad \text{(A.9)}$$

Proof: The result follows from Lemmas A.1 and A.2 and the Law of Iterated Expectations. ■

A.2 Proof 2: Revealed Preference Moment Inequalities

Lemma A.3 Equation (3.27) implies that

$$\mathbb{E}[S_i(X_i\beta - Price_i\lambda\gamma + (u_i + \nu_i\lambda)\rho_{u\nu} + \eta_i)|X_i, Price_i, (u_i + \nu_i\lambda)] \geq 0. \qquad \text{(A.10)}$$

Proof: From (2.2), it follows that

$$S_i = 1(X_i\beta - Price_i\lambda\gamma + (u_i + \nu_i\lambda)\rho_{u\nu} + \eta_i \geq 0), \qquad \text{(A.11)}$$

which implies

$$S_i(X_i\beta - Price_i\lambda\gamma + (u_i + \nu_i\lambda)\rho_{u\nu} + \eta_i) \geq 0. \qquad \text{(A.12)}$$

for all i. Because this condition holds for every individual in the sample, it will hold in expectation conditional on $X_i, Price_i, (u_i + \nu_i\lambda)$. ■

Lemma A.4 *Equations (3.10) and (2.2) imply that*

$$\mathbb{E}\Bigg[S_i(X_i\beta - Price_i\lambda\gamma + (u_i + \nu_i\lambda)\rho_{u\nu}) \\ +(1 - S_i)\sigma\frac{\phi(X_i\beta - Price_i\lambda\gamma + (u_i + \nu_i\lambda)\rho_{u\nu} + \eta_i)}{1 - \Phi(X_i\beta - Price_i\lambda\gamma + (u_i + \nu_i\lambda)\rho_{u\nu} + \eta_i)}\Bigg|X_i, Price_i, (u_i + \nu_i\lambda)\Bigg] \geq 0. \tag{A.13}$$

Proof: Equation (A.11) implies

$$\mathbb{E}[S_i(X_i\beta - Price_i\lambda\gamma + (u_i + \nu_i\lambda)\rho_{u\nu})|X_i, Price_i, (u_i + \nu_i\lambda)] + \mathbb{E}[S_i\eta_i|X_i, Price_i, (u_i + \nu_i\lambda)] \geq 0. \tag{A.14}$$

Given the assumption in (3.10), $\mathbb{E}[\eta_i|X_i, Price_i, (u_i + \nu_i\lambda)] = 0$. This implies

$$\mathbb{E}[S_i\eta_i|X_i, Price_i, (u_i + \nu_i\lambda)] = \mathbb{E}[(1 - S_i)\eta_i|X_i, Price_i, (u_i + \nu_i\lambda)]. \tag{A.15}$$

This implies that

$$\mathbb{E}[S_i(X_i\beta - Price_i\lambda\gamma + (u_i + \nu_i\lambda)\rho_{u\nu})|X_i, Price_i, (u_i + \nu_i\lambda)] \\ +\mathbb{E}[(1 - S_i)\eta_i|X_i, Price_i, (u_i + \nu_i\lambda)] \geq 0. \tag{A.16}$$

Given that $S_i \in \{0, 1\}$ and S_i is a function of $\{X_i, Price_i, (u_i + \nu_i\lambda), \eta_i\}$,

$$\mathbb{E}[(1 - S_i)\eta_i|X_i, Price_i, (u_i + \nu_i\lambda)] = \\ \mathbb{E}[(1 - S_i)\mathbb{E}[\eta_i|X_i, Price_i, (u_i + \nu_i\lambda), S_i = 0]|X_i, Price_i, (u_i + \nu_i\lambda)]. \tag{A.17}$$

Given the normality assumption on η_i, it follows that

$$\mathbb{E}[\eta_i|X_i, Price_i, (u_i + \nu_i\lambda), S_i = 0] = \sigma\frac{\phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i + \nu_i\lambda)\rho^*_{u\nu})}{1 - \Phi(X_i\beta^* - Price_i\lambda\gamma^* + (u_i + \nu_i\lambda)\rho^*_{u\nu})}. \tag{A.18}$$

Applying this condition to equation (A.16) yields equation (A.13). ■

Lemma A.5 *Equations* (2.2) *and* (3.10) *, combined with the assumption that* $Var((u_i + \nu_i\lambda)\rho_{u\nu} + \eta_i) \geq Var(\eta_i)$*, imply*

$$\mathbb{E}\left[S_i(X_i\beta - Price_i\lambda\gamma)\middle|X_i, \widetilde{Price_i}\right] \geq \mathbb{E}\left[S_i(X_i\beta - Price_i\lambda\gamma + (u_i + \nu_i\lambda)\rho_{u\nu})\middle|X_i, \widetilde{Price_i}\right]. \tag{A.19}$$

Proof: This result follows from the definition of $u_i + \nu_i\lambda$ given in (2.7). This term has expectation zero conditional on $\{X_i, \widetilde{Price_i}\}$, leading to $A.19$.

Lemma A.6 Equations (2.2) and (3.10) imply

$$\begin{gathered}\mathbb{E}\left[(1 - S_i)\sigma\frac{\phi(X_i\beta - Price_i\lambda\gamma)}{1 - \Phi(X_i\beta - Price_i\lambda\gamma)}\middle|X_i, \widetilde{Price_i}\right] \\ \geq \\ \mathbb{E}\left[(1 - S_i)\sigma\frac{\phi(X_i\beta - Price_i\lambda\gamma + (u_i + \nu_i\lambda)\rho_{u\nu})}{1 - \Phi(X_i\beta - Price_i\lambda\gamma + (u_i + \nu_i\lambda)\rho_{u\nu})}\middle|X_i, \widetilde{Price_i}\right].\end{gathered} \tag{A.20}$$

Proof This inequality follows from the definition of $(u_i + \nu_i\lambda)\rho_{u\nu})$ and the assumption $Var((u_i + \nu_i\lambda)\rho_{u\nu} + \eta_i) \geq Var(\eta_i)$.

Corollary 2 *Suppose the distribution of* Z_i *conditional on* $\{X_i, Price_i, (u_i + \nu_i\lambda)\}$ *is degenerate. Then*

$$\begin{gathered}\mathbb{E}\Bigg[S_i(X_i\beta - Price_i\lambda\gamma + (u_i + \nu_i\lambda)\rho_{u\nu}) \\ +(1 - S_i)\sigma\frac{\phi(X_i\beta - Price_i\lambda\gamma + (u_i + \nu_i\lambda)\rho_{u\nu})}{1 - \Phi(X_i\beta - Price_i\lambda\gamma + (u_i + \nu_i\lambda)\rho_{u\nu})}\Bigg|Z_i\Bigg] \geq 0,\end{gathered} \tag{A.21}$$

$$\mathbb{E}\left[S_i(X_i\beta - Price_i\lambda\gamma)\middle|Z_i\right] \geq \mathbb{E}\left[S_i(X_i\beta - Price_i\lambda\gamma + (u_i + \nu_i\lambda)\rho_{u\nu})\middle|Z_i\right], \quad \text{(A.22)}$$

and

$$\mathbb{E}\left[(1-S_i)\sigma\frac{\phi(X_i\beta - Price_i\lambda\gamma)}{1-\Phi(X_i\beta - Price_i\lambda\gamma)}\middle|Z_i\right]$$
$$\geq \quad \text{(A.23)}$$
$$\mathbb{E}\left[(1-S_i)\sigma\frac{\phi(X_i\beta - Price_i\lambda\gamma + (u_i + \nu_i\lambda)\rho_{u\nu})}{1-\Phi(X_i\beta - Price_i\lambda\gamma + (u_i + \nu_i\lambda)\rho_{u\nu})}\middle|Z_i\right].$$

Proof: The results follow from Lemmas A.4, A.5, and A.6 and the Law of Iterated Expectations. ■

Proof: Revealed Preference Moment Inequalities Combining equations A.20, A.21, and A.22 yields the first revealed preference moment inequality. The second is obtained through the same process considering individuals who do not select the investment.

B. Moment Inequality Estimation Algorithm

I primarily follow Appendix A.5 and A.7 in Dickstein and Morales (2018) 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 (2018). 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:

$$Q(\psi_p^*) = \sum_{\ell} [min(\sqrt{N}\frac{\bar{m}_\ell(\psi_p^*)}{\hat{\sigma}_\ell}, 0)]^2, \tag{B.1}$$

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. The 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 up to 4 parameters when estimating the moment inequalities, I would need to evaluate $40^4 = 2,560,000$ points, dramatically more than DM. 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 control function 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. In practice, I always fail to reject that the control function estimates satisfy the moment inequalities.

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. Additional Simulations, Probit and Control Function Methods

In this section I provide results for each of the simulations performed in the body of chapter 2 with N=10,000. The estimates exhibit substantial convergence in this context. I present them in the same order as the body of the paper without further comment.

Table C.1.: Simulation 1, Perceived Returns Estimates

	(1) Probit	(2) Control Function
Constant	1.044	1.067
	(0.034)	(0.041)
σ	2.026	2.071
	(0.048)	(0.066)
$\widehat{(u+\nu)}$		-0.044
		(0.042)
Observations	10000	10000

Notes: Standard errors in parentheses. Parameters are marginal effects of the variable on perceived returns in dollars. Estimates are from equation (2.9) with the details varying by estimation method. All data is generated in Matlab using random seed 1234. This simulation considers the case of no endogeneity and no information frictions.

Table C.2.: Simulation 2, Perceived Returns Estimates

	(1) Probit	(2) Control Function
Constant	1.613	1.026
	(0.061)	(0.041)
σ	3.410	2.124
	(0.099)	(0.068)
$\widehat{(u+\nu)}$		0.553
		(0.025)
Observations	10000	10000

Notes: Standard errors in parentheses. Parameters are marginal effects of the variable on perceived returns in dollars. Estimates are from equation (2.9) with the details varying by estimation method. All data is generated in Matlab using random seed 1234. This simulation considers the case of no endogeneity with information frictions.

Table C.3.: Simulation 3, Perceived Returns Estimates

	(1) Probit	(2) Control Function
Constant	2.085	1.002
	(0.102)	(0.040)
σ	4.439	2.010
	(0.191)	(0.063)
$\widehat{(u+\nu)}$		1.023
		(0.027)
Observations	10000	10000

Notes: Standard errors in parentheses. Parameters are marginal effects of the variable on perceived returns in dollars. Estimates are from equation (2.9) with the details varying by estimation method. All data is generated in Matlab using random seed 1234. This simulation considers the case of endogeneity with no information frictions.

Table C.4.: Simulation 4, Perceived Returns Estimates

	(1) Probit	(2) Control Function
Constant	3.140	1.006
	(0.181)	(0.042)
σ	6.771	2.005
	(0.356)	(0.065)
$\widehat{(u+\nu)}$		1.035
		(0.019)
Observations	10000	10000

Notes: Standard errors in parentheses. Parameters are marginal effects of the variable on perceived returns in dollars. Estimates are from equation (2.9) with the details varying by estimation method. All data is generated in Matlab using random seed 1234. This simulation considers the case of both endogeneity and information frictions.

Table C.5.: Simulation 5, Perceived Returns Estimates

	(1) Probit	(2) Control Function
Constant	3.080	0.984
	(0.179)	(0.042)
x1	1.325	0.436
	(0.112)	(0.034)
σ	6.752	1.992
	(0.356)	(0.065)
$\widehat{(u+\nu)}$		1.035
		(0.019)
Observations	10000	10000

Notes: Standard errors in parentheses. Parameters are marginal effects of the variable on perceived returns in dollars. Estimates are from equation (2.9) with the details varying by estimation method. All data is generated in Matlab using random seed 1234. This simulation considers the case of both endogeneity and information frictions.

Table C.6.: Simulation 6, Perceived Returns Estimates

	(1) Probit	(2) Control Function
Constant	3.205	0.998
	(0.191)	(0.043)
x1	1.336	0.429
	(0.116)	(0.034)
x2	0.582	0.195
	(0.098)	(0.032)
σ	6.971	2.003
	(0.379)	(0.066)
$\widehat{(u+\nu)}$		1.047
		(0.020)
Observations	10000	10000

Notes: Standard errors in parentheses. Parameters are marginal effects of the variable on perceived returns in dollars. Estimates are from equation (2.9) with the details varying by estimation method. All data is generated in Matlab using random seed 1234. This simulation considers the case of both endogeneity and information frictions.

D. Auxiliary Results for Perceived Returns to College

D.1 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 D.1.: 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 D.2.: 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.2 Estimation of γ

In order to estimate $\hat{\gamma}(X_i)$ 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:

$$\gamma(X_i) = \frac{Tuition\_Paid_i}{Tuition_i} = X\beta_\gamma + \frac{X}{Tuition_i}\beta_{\gamma T}. \tag{D.1}$$

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).

D.3 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

Table D.3.: 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: T-stats are in parentheses. Estimates are for the part of the NLSY79 sample who attended college in 1979 and provided tuition and tuition paid information.

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.

D.4 Additional Results

The unscaled results with all controls are provided in Table 11. The first stage for the control function approach is provided in Table 12. Recall that the F-stat on local tuition at age 17 should be viewed as a lower bound on the strength of the instrument, as explained in Section 5. This value is 4629.13.

Table D.4.: 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: T-stats in parentheses. Parameters are marginal effects of the variable on college sticker price. See section 4 for details.

Table D.5.: 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: T-stats in parentheses. Parameters are marginal effects of the variable on college sticker price. See section 4 for details.

Table D.6.: 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 (3.14) with the details varying by estimation method. See text for details.

Table D.7.: 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: T-stats in parentheses. Parameters are marginal effects of the variable on thousands of dollars of effective tuition ($Tuition_i\hat{\gamma}(X)\lambda$).

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"Essays in Labor Economics"

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B.A., Marketing, Taylor University, May 2009

Research Fields

Labor Economics, Economics of Education, Applied Econometrics

Working Papers

"Estimating the Perceived Returns to College" - *Job Market Paper*

Abstract: The primary determinant of an individual's college attendance is their perceived lifetime return to college. I infer 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.

"Coworker Gender Preferences: Effects on Gender Gaps in Occupational Selection and Wages"

Abstract: This paper analyzes the effect of occupational gender composition on job-specific labor supply for workers of each gender. I construct a static model of job selection wherein preferences regarding coworker gender composition produce gender-specific compensating differentials. I estimate the model using maximum likelihood to identify the underlying coworker gender preference parameters. Based on estimated compensating differentials, men's preference is highest for occupations that are 60% female and lowest for female-dominated occupations. Women prefer jobs that are female-dominated, and are least satisfied with jobs that are 25% male all else equal.

Work in Progress

"School Attendance and Teen Crime: Evidence From the Chicago Teacher Walkout," with Mary Kate Batistich and Kendall Kennedy

"Separating Perceived Returns to College from Credit Constraints in College Choice," with Kendall Kennedy

Conference and Seminar Presentations

Southern Economics Association, Washington D.C. November 2018

National Tax Association, New Orleans November 2018

Krannert Ph.D. Research Symposium October 2018

Midwest Economics Association SOLE Sessions, Evanston, IL March 2018

Midwest Economics Association, Cincinatti, OH March 2017

Krannert PhD Research Symposium, West Lafayette, IN November 2016

Teaching Experience

Teaching Assistant, Labor Economics Fall 2018

Teaching Assistant, Intermediate Macroeconomics Spring 2016, Spring 2017, Summer 2018

Instructor, Introductory Microeconomics Summer 2016

Recitation Instructor, Principles of Economics Spring 2015

Teaching Assistant, MBA Microeconomics Fall 2014, Fall 2015

Teaching Assistant, MBA Macroeconomics Fall 2014, Fall 2015

Research Experience

Research Assistant to Soojin Kim Spring 2016, Fall 2016, Spring 2017, Fall 2017, Summer 2017, Summer 2018, Fall 2018

Research Assistant to Jillian Carr — Fall 2018

Research Assistant to Trevor Gallen — Fall 2017, Spring 2018

Research Assistant to Anson Soderbery — Summer 2015

Honors and Awards

Krannert Ph.D. Research Symposium Top Presentation Award — 2018

Certificate for Distinguished Recitation Teaching — 2015

Professional Memberships

American Economic Association, Southern Economic Association, National Tax Association, Midwest Economic Association

References

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