Opportunity Unraveled: Private Information and the Missing Markets for Financing Human Capital*

Daniel Herbst† — University of Arizona

Nathaniel Hendren‡ — Harvard University

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Abstract

Investing in college carries high returns but comes with considerable risk. State-contingent or equity-like financial contracts could mitigate this risk, yet college is typically financed through non-dischargeable, government-backed student loans. This paper argues that adverse selection has unraveled private markets for financial contracts that mitigate college-going risks. Using survey data on student's beliefs about the future, we quantify the threat of adverse selection in markets for equity contracts and several state-contingent debt contracts. We find students hold significant private knowledge of their future earnings, academic persistence, employment, and loan repayment likelihood, beyond what is captured by observable characteristics. A typical college-goer would have to pay an estimated \$1.64 in present value for every \$1 of equity financing to sustain profitable contracts for financiers. We find that reasonably risk-averse college-goers are not willing to accept these terms, so markets unravel. We discuss why moral hazard, biased beliefs, and the availability of outside credit options are less likely to explain the absence of these markets. Our framework quantifies significant welfare gains from government subsidies for equity contracts that partially insure college-going risks.

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†dherbst@arizona.edu

‡nhendren@fas.harvard.edu

1 Introduction

Investing in college delivers persistently high returns to both individuals and society, but also incurs significant risk. Nearly half of all college enrollees in the US fail to complete their degrees. Conditional on completion, only 85% find work after graduation. Even by age 40, 15% of college graduates have household incomes below $40,000 a year. The most common method of financing college is student debt, which does little to mitigate these risks. Roughly two-thirds of student borrowers become delinquent or default on their debt within six years of college enrollment.[1]

Economists have long advocated for alternative financial contracts to mitigate the risks of investing in education (Chapman, 2006; Barr et al., 2017; Palacios, 2004; Zingales, 2012). Most famously, Friedman (1955) writes:

> "[Human capital] investment necessarily involves much risk. The device adopted to meet the corresponding problem for other risky investments is equity investment...The counterpart for education would be to 'buy' a share in an individual's earnings prospects; to advance him the funds needed to finance his training on condition that he agree to pay the lender a specified fraction of his future earnings."

A handful of private companies and post-secondary institutions have attempted to put this theory into practice with state-contingent or equity-like contracts for college.[2] Yet despite persistent attempts by private firms, decades of academic advocacy, and increasing college-wage premiums, there is no active private market for equity or state-contingent college financing. Instead, federally-backed debt remains the dominant form of financing higher education in the US.

What explains this absence of risk-abating alternatives to student loans? It's possible that college-goers don't demand these contracts because they place little value on insurance or hold over-optimistic views of the future. An alternative explanation is that adverse selection has unraveled markets for these contracts, preventing otherwise mutually beneficial exchanges between financiers and borrowers from taking place. Distinguishing between these explanations is critical for determining whether and how the government should intervene in financial markets for higher education. In this paper, we use survey measures on college-goers' subjective expectations and other measures of private information to argue these markets have unraveled.

We begin by developing a model of state-contingent financial contracts under private information. We show that market existence depends on two curves: a "willingness-to-accept" (WTA) curve, which corresponds to the minimum amount an individual is willing to accept today to sell a

[1] Employment, completion, default, and delinquency statistics are calculated six years from enrollment using the Beginning Postsecondary Students (BPS) study, a representative sample of first-time college enrollees in 2012. Household income among forty-year-old college graduates are calculated using the 2012 American Community Survey (Ruggles et al., 2022).

[2] Table 5 presents a list of private companies and institutions that have offered income-share agreements (ISAs) to finance higher education over the last fifty years. Most of these providers are no longer in operation. We discuss these efforts in Section 5.5 below.

claim on their future outcome, and an "average value" (AV) curve, which corresponds to the average outcome among those willing to accept less than a given individual for the contract. If the AV curve lies below the WTA curve for all individuals, the market completely unravels—any price that would profitably finance a given pool of borrowers leads those with better expected outcomes to exit the market. We derive this unraveling condition in a dynamic environment with moral hazard, biased beliefs, and credit constraints, allowing us to clarify what role these other forces might play in market existence.

Next, we empirically evaluate our model's market-unraveling condition for several hypothetical contracts: an "earnings equity" contract, in which financiers buy "a share in the individual's earnings prospects" (Friedman, 1955), as well as three state-contingent debt contracts, which respectively require repayment only if the borrower completes their degree, finds a job, or avoids delinquencies on their existing student loans. To estimate college-goers' private information concerning these contracts' payoffs, we use linked administrative and survey data from the 2012 Beginning Postsecondary Students study (BPS). The BPS data include subjective expectations, post-college outcomes, and a variety of background characteristics for 20,000 first-year college students. Our empirical strategy leverages these variables by treating self-reported expected salary, graduation likelihood, and other elicitations as noisy and potentially biased measures of respondents' beliefs about the future.

Our empirical approach proceeds in three steps. First, we provide reduced-form evidence of private information and the potential for adverse selection. Conditional on a comprehensive set of observable characteristics, we find that elicitations are predictive of post-college outcomes, suggesting individuals hold private information about contracts' payoffs beyond what a financier might predict. On average, each individual's earnings are \$2,000 to \$4,000 higher than those of observationally-identical peers with lower elicitation-predicted salaries. We also find evidence that individuals use this information to make financial decisions with income-contingent payoffs, suggesting equity contracts would face a significant threat of adverse selection. But while elicitations contain information about future outcomes and behavior, our estimates suggest they may also reflect measurement error, over-optimistic beliefs, or both.

The second part of our empirical analysis estimates a structural model of beliefs and survey elicitations, which enables us to measure the AV and WTA curves in each setting. Motivated by likely measurement error and the potential for behavioral biases in elicitations, we estimate distributions for two types of beliefs: (1) the rational beliefs that individuals would hold if they knew the mapping between their private information and future outcomes (or learned of that mapping once contracts were offered, as in Lucas (1972)), and (2) the potentially biased beliefs that individuals would hold if their survey responses were unbiased measures of their true expectations of the future.[3] We estimate both belief distributions using joint variation in what is known to

[3]This second approach requires elicitations that directly correspond to individuals' beliefs about the outcome of interest. Our data can plausibly satisfy this requirement for post-graduate earnings, but not for all outcomes we

individuals (their elicitations) and realized outcomes. Our approach explicitly allows individuals to (i) hold biased beliefs and (ii) imperfectly express those beliefs in the survey.

Our results suggest that adverse selection has unraveled the earnings-equity market. Under rational beliefs, the median individual expects to earn $MV(0.5)$ =\$20,397, but the average earnings of those willing to accept lower valuations are just $AV(0.5)$ =\$12,471. Using calibrated values of relative risk-aversion and marginal propensity to consume out of earnings, we estimate this individual would be willing to accept a valuation no lower than $WTA(0.5)$ =\$16,827. At this price, the financier would lose \$0.26 for every dollar they finance, so the market unravels. When we allow elicitations to reflect potentially biased beliefs, we find that respondents' over-optimism amplifies our unraveling result by increasing individuals' willingness-to-accept even higher. In theory, if everyone's willingness-to-accept exceeded their actuarially fair value to the financier, this over-optimism could explain missing markets independently of adverse selection. Our findings, however, reject this theory: our estimates suggest at least 23% of borrowers would accept actuarially fair equity contracts, even if they maintained irrationally optimistic beliefs.

We also discuss how the presence of outside financing or credit constraints affects our results. Our baseline results speak to the non-existence of financial markets conditional on existing forms of credit, like federally subsidized student loans. If such loans were not available, credit-constrained college-goers would be more likely to accept other methods of financing. We find our unraveling results are robust to such increases in demand. Moreover, our analysis suggests private markets would sooner satiate this demand with debt contracts less prone to adverse selection than offer less profitable state-contingent contracts like equity. Consistent with this intuition, private student lending is common in populations without access to government-subsidized loans, but equity markets are still virtually non-existent.

Beyond the earnings-equity market, we find markets for debt contracts that provide forgiveness if (i) students don't graduate, (ii) don't find a job after college, or (iii) fall delinquent on their federal student loans would all unravel due to adverse selection. In each of these state-contingent debt markets, the WTA curve lies everywhere above the AV curve. These patterns explain why non-dischargeable student debt is the dominant method of financing available for college-goers. They also suggest that private student loans might no longer be profitable if they could be discharged in bankruptcy, as they would attract borrowers with private knowledge of higher delinquency risk.[4]

If market unraveling is leaving Pareto-improving exchanges on the table, should the government facilitate these exchanges by subsidizing risk-mitigating financial contracts for college? In the third and final step of our empirical analysis, we translate our estimates into the implied marginal values of public funds (MVPFs) for subsidizing equity contracts, state-contingent loans, and untargeted

study.

[4]The 2005 Bankruptcy Abuse Prevention and Consumer Protection Act prevents private student loans from being automatically discharged in bankruptcy (Siegel, 2007). We observe delinquency but not bankruptcy, so we treat delinquency on existing student loans as a proxy for hypothetical discharge circumstances.

grants.[5] Our results suggest that subsidizing an equity market option for college-goers has the highest MVPF of any of the financing schemes we study. Equity subsidies provide an estimated consumption-smoothing benefit four times larger than the fiscal externality induced by the higher implicit tax rate, generating an MVPF of 1.58. By comparison, the MVPF of untargeted grants is 1.17. This means that subsidizing the availability of equity contracts yields a higher welfare gain per dollar of government spending than untargeted grants.

This paper relates to several strands of literature. Beginning with Friedman (1955), researchers have documented both theoretical benefits and potential information asymmetries of equity-like financing for education (Gary-Bobo and Trannoy, 2015; Chapman, 2006; Barr et al., 2017; Nerlove, 1975; Del Rey and Verheyden, 2011; Findeisen and Sachs, 2016).[6] Closely related to our focus, Mumford (2022) finds that participants in an income-share agreement at Purdue are more likely to major in lower-income fields and take lower-paying jobs after graduation.[7] More generally, a number of studies investigate adverse selection in other financial markets, including mortgages (Stroebel, 2016; Gupta and Hansman, 2019), auto loans (Adams et al., 2009; Einav et al., 2012), credit cards (Ausubel, 1999; Agarwal et al., 2010), and personal loans (Dobbie and Skiba, 2013; Karlan and Zinman, 2009).

Methodologically, our paper complements a large literature using subjective information to measure expectations and uncertainty (Manski, 2004; Jappelli and Pistaferri, 2010; d'Haultfoeuille et al., 2021; Mueller et al., 2021), especially those concerning earnings risk (Dominitz, 1998; Manski and Straub, 2000; Van der Klaauw, 2012; Spinnewijn, 2015; Conlon et al., 2018; Mueller et al., 2021) or college-goers' beliefs about the future (Attanasio and Kaufmann, 2009; Hoxby and Turner, 2015; Gong et al., 2019; Crossley et al., 2021; Wiswall and Zafar, 2021).[8] We also relate to a large behavioral literature on the impact of information nudges in higher education (Bettinger et al., 2012; Wiswall and Zafar, 2015; Baker et al., 2018; Marx and Turner, 2019; Dynarski et al., 2021) and insurance markets (Handel, 2013). Our empirical approach builds upon strategies from Hendren (2013, 2017), which use data on subjective beliefs to study missing markets for health-related insurance and private unemployment insurance. We extend this approach to settings with continuous contracts, indirect elicitations, and potentially biased beliefs.

Relative to existing literature, our paper provides new evidence on how private information

[5]The MVPF measures the benefits to individuals divided by the net cost to the government. Importantly, these costs include not only the subsidization of negative profits but also any fiscal externalities from behavioral responses that affect tax revenue.

[6]These studies form part of a larger literature on optimal human-capital financing (Jacobs and van Wijnbergen, 2007; Lochner and Monge-Naranjo, 2011; Stantcheva, 2017; Abbott et al., 2019). See Lochner and Monge-Naranjo (2016) for a review.

[7]In Appendix F, we offer a more detailed discussion of Mumford (2022)'s results. We generally find his results to be consistent with our paper's conclusions.

[8]The *Handbook of Economic Expectations* (Bachmann et al., 2022) provides an extensive review on the role of subjective expectations in the economics literature. Chapters on educational expectations (Giustinelli, 2023), labor market beliefs (Mueller and Spinnewijn, 2023), and survey methods (Fuster and Zafar, 2023) are especially pertinent to our study.

unravels state-contingent financing for higher education. We place this evidence in a theoretical framework that quantifies how adverse selection can more easily explain the absence of these markets than alternative mechanisms like moral hazard, biased beliefs, or outside credit options. Our paper also documents large welfare gains from government subsidies to programs that provide the option of equity-like financing to college-goers.

The rest of this paper proceeds as follows: Section 2 develops a theoretical model of human-capital financing markets under private information, moral hazard, biased beliefs, and credit constraints. Section 3 describes the data we use to test the model's no-trade condition. Section 4 provides reduced-form evidence of college-goers' private information and investigates how that information maps to subjective beliefs and real-world financial decisions. Section 5 provides point estimates for the average value and willingness-to-accept curves, which we use to formally test the unraveling condition. Section 6 discusses the welfare impact of government subsidies for risk-mitigating college financing products. Section 7 concludes.

2 Model of Market Unraveling

In this section, we develop a model of human-capital financing markets for risk-mitigating contracts under asymmetric information. Our model builds on insights in the insurance-market framework in Einav et al. (2010) to provide conditions for market unraveling for college financing under adverse selection, moral hazard, and biased beliefs. We also discuss a simple extension that captures credit constraints.[9] We use the model to clarify the role of these forces in determining market existence and to provide guidance on the welfare impact of government subsidies that would help open up these markets.

Consider a population of college-goers facing the status-quo set of college financing options, most notably government-backed student loans. Now imagine a financier offers a contract that provides a payment $\lambda\eta$ today (period 1) in exchange for a repayment of ηY after college (period 2), where Y is some stochastic outcome realized in period 2. The size $\eta \geq 0$ measures the fraction of the future outcome that the individual agrees to repay. The valuation $\lambda \geq 0$ represents the amount the individual can receive today per unit of Y that is pledged for repayment.

We assume the outcome, Y, is generated from both luck and effort, $Y = f(a,\zeta)$, where ζ is the realization of a random variable and a is a vector of actions taken by the individual. Y can be either continuous or discrete. For example, $Y = Salary$ corresponds to an equity contract pledging η-share of post-college earnings, whereas $Y = \mathbb{1}\{Complete\}$ corresponds to a completion-contingent

[9] In Appendix B, we extend our theoretical analysis to a dynamic stochastic model with biased beliefs and endogenous college enrollment, nesting several models from previous literature (Abbott et al., 2019; Lochner and Monge-Naranjo, 2011). We show how our core results and definitions of the WTA and AV curves below map into this more general setting.

loan requiring repayment of η only if the borrower graduates.[10]

Individuals are observationally identical to the financier, representing a population that has already been screened on observable characteristics.[11]

Individuals may hold private information about their own future Y, captured by the "type" parameter θ, which cannot be observed by the financier. We assume the preferences of a given type, θ, are governed by the following utility function:

$$u\left(c_1,c_2,a\right) \equiv u\left(c_1;\theta\right) + \beta u\left(c_2;\theta\right) + \psi\left(a;\theta\right), \tag{1}$$

where c_1 and c_2 denote consumption in periods 1 and 2, respectively, and a represents all actions the individual takes in either period that affect the realization of Y, like choosing a field of study or career.

Let $E_S\left[Y|\theta\right]$ denote type θ's subjective beliefs about their future Y, and let $E\left[Y|\theta\right]$ denote the mean realization of Y conditional on information in θ. We assume there is no aggregate uncertainty in Y, so if individuals formed beliefs correctly using all of their private information, their subjective beliefs would correspond to the mean realization of Y conditional on θ, $E_S\left[Y|\theta\right] = E\left[Y|\theta\right]$.

In this environment, when can financiers profitably exchange risk-mitigating contracts with college-goers? To answer this question, imagine a financier offers a small contract of infinitesimal size $d\eta$ at valuation λ. A type θ will accept this small contract if and only if

$$\lambda u_1\left(\theta\right) - \beta E_S\left(Y u_2|\theta\right) \geq 0, \tag{2}$$

where $u_1 \equiv \frac{\partial u}{\partial c_1}$ and $u_2 \equiv \frac{\partial u}{\partial c_2}$. The first term in (2) is the marginal utility from \$$\lambda$ in period 1, and the second term is the expected disutility from future repayment. This latter term is a subjective expectation, reflecting the college-goer's potential misconceptions about post-college outcomes and consumption.[12] Because we consider a small contract, $d\eta$, these marginal utilities are evaluated using status-quo allocations, (c_1,c_2,a), and any behavioral changes in a are not included in equation (2).[13]

[10] We assume realizations of Y are verifiable by the financier. Existing providers of income-contingent contracts commonly verify incomes with the IRS (form 4506-C); colleges can also easily verify enrollment and graduation status.

[11] We allow financiers to observe public information about each individual, X, which they can use to price contracts. While we omit these "X" terms to ease exposition, the model applies to a subpopulation of individuals with observables matching a particular value, $X = x$. We also assume financiers know the data generating process, so that they can form unbiased beliefs about the distribution of Y conditional on X. Under rational expectations, individuals would also know this mapping from X to outcomes, $E[Y|X]$. A potential lack of awareness about $E[Y|X]$ could be one source of bias in beliefs.

[12] Note that while we allow beliefs to be biased, we assume borrowers' behavior is rational given their (potentially biased) beliefs. One could easily incorporate other behavioral biases like present bias into the model by modifying equation (2).

[13] Under a wide class of primitive assumptions, the envelope theorem implies that behavioral responses are irrelevant to decisions over small contracts (Milgrom and Segal, 2002). See Appendix B.

We define the *willingness to accept*, $WTA(\theta)$, as the minimum valuation (valued in period 2) that type θ would accept in a contract pledging a small portion of their future Y,

$$WTA(\theta) = \frac{\beta E_S\left[Y u_2|\theta\right]}{u_1\left(\theta\right)}R, \tag{3}$$

where $R-1$ is the risk-free rate of return in financial markets. Equation (2) shows that all types θ for whom $WTA(\theta) \leq \lambda R$ will accept the contract.

We let $R_\theta = u_1(\theta)/(\beta E_S[u_2(\theta)])$ denote type θ's implicit cost of borrowing for a non-contingent loan. In our baseline model, we assume $R_\theta = R$, which would be true if financiers could offer borrowers non-contingent loans at their own cost of capital. Allowing $R_\theta \neq R$ would imply students and financiers hold different risk-free costs of borrowing, which could reflect credit constraints ($R_\theta > R$) or access to student loans that are subsidized below market rates ($R_\theta < R$). We discuss outside credit options and robustness to credit constraints in Section 5.4.

We can then rewrite willingness to accept in equation (3) as the sum of three terms:

$$WTA(\theta) = \underbrace{E\left[Y|\theta\right]}_{MV(\theta)} + \underbrace{\left(E_S\left[Y|\theta\right] - E\left[Y|\theta\right]\right)}_{\text{Bias}(\theta)} - \underbrace{\left[-cov_s\left(Y, \frac{u_2}{E_S\left[u_2|\theta\right]}|\theta\right)\right]}_{\text{Risk Discount}(\theta)}. \tag{4}$$

The first term, $E[Y|\theta]$, denotes the mean realized value of Y among those of type θ. We refer to this term as the *marginal value* of type θ, $MV(\theta) \equiv E[Y|\theta]$, because it reflects the "actuarially fair" contract valuation under which the financier and a borrower of that type would break even. The second term, $E_S[Y|\theta] - E[Y|\theta]$, denotes the borrower's potential bias. A more positive bias term (over-optimism) increases borrowers' $WTA(\theta)$. The third term, $-cov_s\left(y, \frac{u_2}{E_S[u_2|\theta]}|\theta\right)$, is the (subjective) risk discount the individual is willing to accept below their perceived actuarially fair valuation, $E_S[Y|\theta]$. It reflects the insurance value that risk-averse individuals place on the contract's consumption-smoothing benefits.

Facing this population of borrowers whose contract choices are governed by equation (4), the financier sets the valuation to maximize profits. For any valuation λ, let θ_λ denote the borrower type that is indifferent to accepting the contract at that valuation, $WTA(\theta_\lambda) = \lambda R$. If the financier could exchange this λ-valuation contract with only type θ_λ, they would expect to recoup the marginal value for that type, $MV(\theta_\lambda) \equiv E[Y|\theta = \theta_\lambda]$. So long as $WTA(\theta_\lambda) < MV(\theta_\lambda)$, this θ_λ-specific contract would earn positive profits.

However, because the financier cannot observe types, they cannot prevent borrowers with $\theta \neq \theta_\lambda$ from opting into the contract. The λ-valuation contract would therefore be accepted by all types θ such that $WTA(\theta) \leq WTA(\theta_\lambda)$. So instead of recouping the marginal value, $MV(\theta_\lambda)$, the financier recoups the *average value*, defined as

$$AV(\theta_\lambda) \equiv E[Y|WTA(\theta) \leq WTA(\theta_\lambda)]. \tag{5}$$

The average value, $AV(\theta_\lambda)$, of contract λ is given by the average outcome, Y, among all types θ with $WTA(\theta) \leq WTA(\theta_\lambda)$. Assuming the financier can borrow at the risk-free rate, R, their profits are given by

$$\Pi(\lambda) = \Pr\{WTA(\theta) \leq \lambda R\}(AV(\theta_\lambda) - \lambda R), \tag{6}$$

where $\Pr\{WTA(\theta) \leq \lambda R\}$ is the fraction of the market that purchases the contract. Recalling the identity $WTA(\theta_\lambda) = \lambda R$, we obtain a classic Akerlof (1970) unraveling condition: the market will not be profitable at any valuation λ if and only if

$$AV(\theta) < WTA(\theta) \;\; \forall\theta. \tag{7}$$

Unless someone is willing to accept a valuation corresponding to the pooled outcomes of those who would also select the contract, the market will unravel.[14]

Notably absent from our unraveling condition (7) is any impact of contracts on borrowers' behavior, a. While state-contingent contracts can certainly elicit a behavioral response, like improved academics or reduced labor supply, these responses do not have first-order effects on the financier's profits for a small contract, $d\eta$. This insight, first noted by Shavell (1979) and extended to this setting in Hendren (2017), implies that behavioral responses like moral hazard can attenuate the gains to trade, but cannot explain the absence of a market. By contrast, even a small "$d\eta$-amount" of state-contingent financing can be adversely selected by strictly worse risks, so that private information imposes a first-order cost on a financier's profits.[15]

Also absent from condition (7) are borrowing costs or interest rates. Each contract we consider consists of both intertemporal and state-contingent components. But under our benchmark assumption that $R_\theta = R$, only the latter can influence market existence, reducing our unraveling condition (7) to one for an insurance contract offered to college-goers. In theory, credit constraints ($R_\theta > R$) or the availability of government-subsidized loans ($R_\theta < R$) could influence borrowers' desire to move money across time, affecting their demand for both state-contingent and non-contingent financial contracts. We explore credit constraints and outside lending options in Section 5.4.

[14] Inequality (7) characterizes when the financier can profitably sell a small contract, $\eta \approx 0$. Because the marginal profits to the financier are declining in the size of the contract, η, the unraveling of small-contract markets implies unraveling of markets for larger contracts as well (Hendren, 2017). See Hendren (2013) for a discussion of why equation (7) also characterizes market existence when financiers can use menus of contracts instead of a single contract, (η,λ).

[15] Appendix B shows that this logic extends to ex-ante decisions, such as the decision to enroll in college, allowing us to focus on the existing population of college-goers. Note that while behavioral responses have only second-order effects on a private financier's profits, they may have first-order effects on government tax revenue. These externalities will play an important role in the welfare analysis in Section 6.

Benchmark Case We can further refine the unraveling condition (7) under a set of benchmark assumptions. First, we assume that individuals form unbiased beliefs about Y when making financial decisions, so that $E_S[Y|\theta] = E[Y|\theta] = MV(\theta)$. Second, we assume a single dimension of heterogeneity in $WTA(\theta)$, such that $WTA(\theta) > WTA(\theta')$ if and only if $E[Y|\theta] > E[Y|\theta']$. Under these two assumptions, the average outcome of those who purchase at valuation λ is equal to the average outcome of those who expect to have lower outcomes than the person who is indifferent to the contract. Formally, for any type θ', the average value curve can be rewritten as the average Y among those with marginal values (expected realizations) no higher than θ''s:

$$AV(\theta') = E[Y|MV(\theta) \leq MV(\theta')]. \tag{8}$$

Because $MV(\theta) \equiv E[Y|\theta]$, equation (8) allows us to derive the average value curve using only the distribution of expected outcomes, $E[Y|\theta]$, conditional on observables.

Figure 1 provides an illustrative example of this benchmark model for the earnings-equity market, where Y is post-college salary. In each panel, the vertical axis presents the $AV(\theta)$, $WTA(\theta)$, and $MV(\theta)$ curves as functions of type θ, which is enumerated on the horizontal axis. Without loss of generality, we order types by ascending $WTA(\theta)$ on the unit interval, so that θ captures the fraction of the market accepting the contract. The blue line plots the $MV(\theta)$ curve, which is equal to quantiles of $E[Y|\theta]$. The red line plots the $WTA(\theta)$ curve, which falls below $MV(\theta)$ due to risk discounting. The green line plots the $AV(\theta)$ curve, which is simply the cumulative average of the blue $MV(\theta)$ curve. Condition (7) states that market existence requires $AV(\theta) \geq WTA(\theta)$ for some value of θ.

Figure 1A depicts a scenario in which individuals' privately expected post-college salaries, $E[Y|\theta]$, are uniformly distributed between \$20,000 and \$80,000. In this scenario the median individual ($\theta = 0.5$) expects to earn $MV(0.5)$ = \$50,000, but is willing to accept a valuation of $WTA(0.5)$ = \$30,000. Because this reservation price is \$5,000 lower than the average value of worse risks ($AV(0.5)$ = \$35,000), the firm can set λ = \$30,000 and earn positive profits, depicted by the yellow rectangle. Figure 1B depicts a scenario in which the outcome distribution of Y has not changed but the distribution of ex-ante beliefs about those outcomes, $E[Y|\theta]$, is more dispersed – i.e. college-goers have more private information about those outcomes. In particular, we assume $E[Y|\theta]$ is uniformly distributed between \$0 and \$100,000. We assume for simplicity that the financier must set the same valuation (λ = \$30,000) to attract the median borrower who expects to earn $50K$.[16]

In this scenario, the pool of worse risks ($WTA(0.5) <$ \$30,000) is particularly adversely selected—the average value of contracts valued at \$30,000 is only \$25,000, so the financier would lose \$5,000 per person who accepts. If the financier tries to break even by lowering their offer to \$25,000, those

[16] In a more realistic simulation of scenario B, the median borrower would have a slightly higher WTA because their increased private information would decrease residual uncertainty about Y, resulting in a smaller risk discount.

with $WTA(0.5) > \$25{,}000$ would now decline the contract, rendering that contract unprofitable as well. Because no one is willing to accept the average value of risks worse than their own, the market unravels.

Beyond the Benchmark Case The benchmark case is helpful empirically because it enables the AV curve to be estimated solely from knowledge on the distribution of $E[Y|\theta]$. But there are several important economic forces to consider that go beyond the benchmark case. First, existing literature suggests many college-goers may hold upwardly biased beliefs about their future outcomes. Equation (4) implies such over-optimistic college-goers would require a higher valuation to accept the contract, making markets more likely to unravel.[17] Second, heterogeneity in individuals' risk aversion or belief biases would create variation in a given type's willingness-to-accept, $WTA(\theta)$, conditional on their marginal value, $MV(\theta)$. Such variation could potentially prevent unraveling among subpopulations of very risk-averse or pessimistic borrowers with sufficiently low $WTA(\theta)$. Finally, and as noted above, credit constraints ($R_\theta > R$) increase the demand for college financing, whereas the availability of subsidized outside credit ($R_\theta < R$) lowers this demand. We consider each of these extensions—biased beliefs, heterogeneous preferences, and credit constraints—in Section 5.

Summary and Empirical Goals To summarize, the core result of our model is the unraveling condition given by inequality (7): state-contingent contracts will fail to make profits whenever the WTA curve (equation (4)) lies everywhere above the AV curve (equation (5)). These curves depend on individuals' private beliefs of future outcomes, but do not depend on behavioral responses to the provision of contracts. In the following sections, we use elicitations data to test this condition for four hypothetical contract markets, culminating in our estimation of the WTA and AV curves for both the benchmark model and the extensions discussed above.

3 Data and Summary Statistics

Because we cannot observe individuals' contract decisions, our empirical strategy uses imperfect measures of their beliefs to estimate hypothetical contract decisions. We use data from the 2012/2017 Beginning Postsecondary Students (BPS) longitudinal study, a dataset from the National Center for Education Statistics. The BPS data consist of administrative student loan and financial aid records linked to survey responses for a nationally representative sample of entering first-time college students in 2012, with follow-ups in 2014 and 2017. They include three categories of variables that are critical to our strategy. First, the 2017 wave of the survey includes ex-post realized outcomes corresponding to our hypothetical contracts—earnings, degree completion, employment

[17] In principle, overly optimistic beliefs alone could shut down a market even in the absence of private information. If no borrower were willing to accept the actuarially fair value for their contract ($WTA(\theta) > MV(\theta)$ for all θ), even a fully informed financier would be unable to write profitable contracts. See Section 5 for a more detailed discussion.

status, and loan-repayment status. Second, the dataset includes a wide array of observable information that hypothetical financiers could potentially use to set contract terms. Finally, the 2012 survey includes private survey responses related to individuals' future outcomes, including subjective expectations of post-college earnings and the likelihood of completing college, along with other information unlikely to be observable by financiers, like their parents' level of financial support.

Outcomes, Y, for the Four Hypothetical Markets Our unraveling analysis considers four state-contingent contracts, each with payoffs that depend on an outcome, Y, observed in the 2017 BPS data. First, we consider an earnings-equity contract requiring individuals to repay a fraction of their annual post-college earnings in 2017, $Y = Salary$. Figure 2A reports the distribution of post-college salary in 2017.[18] The average salary six years after enrollment is \$24,032, with a standard deviation of \$25,376.[19] Over 40 percent of those with positive earnings report annual salaries less than \$25,000.

We also consider three state-contingent debt contracts with payoffs that depend on binary outcomes: a completion-contingent loan that only requires repayment if borrowers finish their degree ($Y = \mathbb{1}\{Complete\}$), an employment-contingent loan that only requires repayment if borrowers find employment ($Y = \mathbb{1}\{Employed\}$), and a dischargeable loan that only requires repayment if one avoids delinquencies on their existing student loans, ($Y = \mathbb{1}\{No\ Delinquency\}$). This last contract can be thought of as debt that is dischargeable in times of financial distress, where financial distress is proxied by delinquency on existing student debt.Figure 2 illustrates the variability in each of the binary outcomes corresponding to these state-contingent loan contracts. In 2017, 51% of 2012 enrollees had completed their degree and only 73% were employed. Of those who borrowed, over two-thirds had experienced at least one delinquency since leaving college. A full 17% of borrowers have already defaulted on their debt.[20]

Observable Information, X Testing for private information requires controlling for publicly observable information, X, which financiers might use to price financial contracts. To this aim, the BPS data includes linked FAFSA records, administrative high school and college records, administrative loan data, and a battery of survey data on family backgrounds. Appendix Table A1 lists the observable variables used in our analysis, and Table 2 reports their summary statistics. We

[18] Respondents could report earnings in annual, monthly, weekly, or hourly amounts. To construct annual salary, the BPS included annual amounts as reported, multiplied monthly amounts by 12, multiplied weekly amounts by 52, and multiplied hourly amounts by 52 times the number of hours the respondent reported working at that job per week.

[19] Employment and salary outcomes are excluded for the 22 percent of the sample still seeking a degree.

[20] We exclude borrowers who are still enrolled in a degree program and therefore do not require repayment. A student loan is considered delinquent as soon as the borrower misses a payment, though loan servicers will often only record delinquencies if payments are not received within a week or two. Defaulted borrowers have made no payments on their student loans for at least 270 days. Defaulted student debt cannot be discharged in bankruptcy and often carries severe penalties like reduced credit and wage garnishment.

classify these observables into five groups: (1) academic characteristics, which include the college-goer's degree type, field of study, and age at enrollment; (2) institution characteristics such as the enrollment size of the institution, admission rate, tuition, degree offerings, urban versus rural location, demographic compositions, and test scores of the entering class;[21] (3) high school performance measures, which include high school GPA and SAT/ACT scores;[22] (4) demographic information, which includes citizenship status, marital status, number of children, state of residence prior to enrollment; and (5) parental characteristics, including annual income, expected family contribution (EFC) from the FAFSA, number of children, and marital status.[23] Controlling for these different sets of observable characteristics allows us to simulate how private information might change with the financier's underwriting capabilities. We note that our observables include all information that companies and schools have used in pricing past attempts at income-share agreements.

Elicitations, Z Our approach to identifying private information relies on variables that are not verifiable to a financier, which we denote by Z. We use a battery of elicitations that were elicited in the 2012 BPS survey concerning uncertain outcomes, including their likelihood of degree completion on a scale of 0 to 10, expected post-college occupation, expected salary after college, and their expected salary if they did not go to college. We also use several difficult-to-publicly-verify variables such as the level of financial support they expect to receive from their parents.[24] Table 1, panel B reports the summary statistics for these elicitations. Importantly, the responses to these questions are not verifiable, so a hypothetical financier could not use them to price contracts. They could, however, reflect private information used by individuals when making contract decisions.

4 Exploring the Relationship Between Elicitations versus Outcomes

In this section we explore several patterns of the relationship between elicitations and outcomes. In particular, we (i) test for asymmetric information by assessing the predictive content of elicitations, (ii) assess the magnitude of this private information, (iii) discuss the extent to which this information would be used to adversely select state-contingent contracts, and (iv) discuss the evidence for the potential of biased beliefs.

[21]We also observe institution identifiers (OPEID), which we use in institution–fixed-effect specifications.

[22]For simplicity, Table 2 reports a single "SAT Score" variable, which includes ACT scores transformed to an SAT scale (Dorans, 1999).

[23]Categorical variables are simplified to binary indicators in Table 1 (e.g., STEM indicator in lieu of field of study). Race and gender are separated from demographic controls because they are protected classes and cannot be used in pricing or screening for financial products. In Section 4 we show their inclusion does not significantly affect our results.

[24]Full elicitation wording and descriptions are provided in Appendix C.

4.1 Evidence of Private Information: Do Elicitations Predict Outcomes?

To assess the potential threat of adverse selection, we ask whether elicitations (Z) can predict outcomes (Y), conditional on observable information (X). If we assume elicitations are no more informative than true beliefs, $E[Y|X,\theta,Z] = E[Y|X,\theta]$,[25] then any predictive information found in Z must reflect predictive information in θ.[26] We can therefore establish the presence of private information by rejecting the null hypothesis $H_0 : \beta = 0$ in the following model:

$$Y_i = \alpha + \beta Z_i + \gamma X_i + \epsilon_i. \tag{9}$$

To investigate the relationship in equation (9), Figure 3 presents binned scatter plots of each outcome against a single elicitation without any controls. In Table 3, we report the corresponding OLS estimates of β conditional on a variety of observable characteristics financiers might use to price contracts. For all four outcomes, we find significant predictive power in the elicitations, Z.

In Figure 3A, we plot employed individuals' log salary in 2017 against the log of the "expected future salary" they reported in 2012. Those who report higher expected salaries in 2012 earn higher average salaries in 2017. Table 3A shows that without controls, we find a slope of $\hat{\beta}$=0.113 (SE=0.016). Some of this relationship is explained by observable characteristics—adding academic and institutional controls reduces this point estimate to 0.045 (SE=0.016). Conditional on these academic and institutional characteristics, however, additional controls do little to change estimates of β. We find a slope of 0.043 (SE=0.016) after adding controls for student performance and demographics; a slope of 0.045 (SE=0.015) when further adding parental characteristics controls and institutional fixed effects. Even including institution-by-major fixed effects—a particularly demanding specification given the small samples within schools—retains a slope of $\hat{\beta}$=0.037 (SE=0.020, p=0.060). The robustness of this relationship suggests earnings-equity markets would face a threat of adverse selection, even if financiers could price contracts based on individuals' institution of attendance, field of study, SAT scores, and other observable characteristics.

Note that if college-goers (i) hold unbiased beliefs about their future earnings ($E_S[Y|\theta] = E[Y|\theta]$) and (ii) report exactly those beliefs in their elicitations ($Z = E_S[Y|\theta]$), then we would expect to find a slope of $\beta = 1$ in Figure 3A.[27] We clearly reject a slope of $\beta = 1$, so elicitations cannot be precise measures of unbiased beliefs—either individuals form biased beliefs, their elicitations contain measurement error, or both. We discuss this further in Section 4.4.

Turning to our next market setting, Figure 3B displays the relationship between six-year grad-

[25] Note that this assumption does not require true beliefs to be unbiased ($E_S[Y|X,\theta] = E[Y|\theta]$), nor does it require individuals know how observables relate to outcomes ($E[Y|X,\theta] = E[Y|\theta]$).

[26] If Z holds predictive power, then $E[Y|X,Z] \neq E[Y|X]$. So assuming θ contains all the information in Z implies $E[E[Y|X,\theta]|X,Z] \neq E[Y|X]$, which can only be true if $E[Y|X,\theta] \neq E[Y|X]$.

[27] Because Figure 3A plots earnings and elicitations in logs, unbiased beliefs would yield a slope of $\beta = 1$ as long as uncertainty realization is multiplicative (i.e., $Y = E[Y|\theta]\,e^{\epsilon}$) A levels-levels regression yields estimates of $\hat{\alpha}$=28,968 and $\hat{\beta}$=0.

uation status and respondents' reported 0 to 10 likelihood of completing their degree "on-time." Those reporting higher completion likelihoods in 2012 are more likely to have graduated by 2017 ($\hat{\beta}$=0.049, SE=0.002). Table 3B shows how this slope changes with the inclusion of controls. Similar to the salary outcome, the slope attenuates when adding controls for academic and institutional characteristics ($\hat{\beta}$=0.036, SE=0.002), but it remains relatively stable when adding further controls.

Next, we consider college-goers' private information about their future employment. Unlike salary and degree completion, the BPS does not directly ask respondents about their subjective employment likelihood. Fortunately, however, our test for private information in equation (9) does not require the elicitation, Z, to directly correspond to outcome, Y. Any choice of Z that correlates with individuals' private information about Y will yield non-zero estimates of β, albeit with less statistical power. For employment, we let Z be the log salary respondents say they would expect to earn if they were not attending college. In Figure 3C, we show that the likelihood that students are employed in 2017 is increasing in this measure of subjective earnings potential ($\hat{\beta}$=0.031, SE=0.0107). In Table 3C, we show that this predictive content remains after including controls for academic and institutional characteristics ($\hat{\beta}$=0.021, SE=0.0108). Introducing additional controls yields less precise coefficients that are statistically indistinguishable from both the academic controls specification and from zero.

Finally, we test for private information concerning federal student loan repayment. As with the employment outcome, individuals are not directly asked about their likelihood of delinquency, but they are asked about their expected financial support from parents, which potentially relates to their ability to repay student debts. Figure 3D shows that student borrowers who report greater parental encouragement for college on a 1 to 5 scale are more likely to make timely payments on their federal student loans (no delinquencies, defaults, or forbearances) through 2017. Table 3D shows that this pattern remains even after including our full set of control variables. As with the other outcomes, this slope generally stabilizes after including academic and institution controls ($\hat{\beta}$=0.034, SE=0.0050).

4.2 Magnitude of Private Information

Table 3 establishes the existence of private information in a single elicitation but says nothing about its magnitude. To measure the magnitude of information contained in elicitations more generally, we consider the threat to market existence if contract choice were determined by the predicted outcomes given elicitations and observables, $E[Y|Z,X]$. Borrowing from Hendren (2013), we define the *magnitude of information in Z* as

$$m_i^Z \equiv r_i - E\left[r|r < r_i\right], \tag{10}$$

where $r_i \equiv E[Y|X = X_i, Z = Z_i] - E[Y|X = X_i]$. The magnitude, m_i^Z, measures the average difference between an individual's outcome and those of observationally-identical peers with lower elicitation-predicted outcomes. Under our model's benchmark assumptions, Hendren (2013) shows that averaging these magnitudes forms a lower bound on the average difference between the true marginal and average value curves:[28]

$$E_\theta [MV(\theta) - AV(\theta)] \geq E_i \left[m_i^Z\right]. \tag{11}$$

In Table 4 we report estimates of $E\left[m_i^Z\right]$ using out-of-sample predictions of $E[Y|X]$ and $E[Y|X,Z]$ in equation (29).[29] To reflect the entire body of private information contained in surveys, we let Z_i include all elicitations. In each specification, public information, X, includes the set of observable variables designated by the column label. Panel A considers the equity market case when Y is salary.[30] Without conditioning on observable characteristics, the average college-goer's elicitations predict \$5,256 higher earnings than their peers with lower predicted salaries. Conditioning on institutional and academic characteristics, this difference is reduced to \$4,319; it remains \$2,691 even conditional on parents' income and education, which would likely be difficult to use in contract pricing. In our benchmark model with rational beliefs, these results would imply that the average individual would have to be willing to accept a valuation that is at least 10–22% lower than their expected future income.

Panel B of Table 4 reports the estimates for the state-contingent contract in which individuals repay only if they complete college. Across increasing controls for public information, we find that the average college-goer has a completion probability that is 11–22pp higher than those who are observationally identical but whose private elicitations imply they are less likely to complete college. If contract choices were determined rational beliefs, college-goers would have to be willing to accept a level of financing that is at least 22–43% below their actuarially fair value for this market to exist.

In state-contingent debt markets we find similarly large markdowns in valuation, depending on the categorization of public information. Panels B–D of Table 4 show that the average college-goer is 11–22pp more likely to complete college than observationally-identical peers whose elicitations predict higher dropout risk. Similarly, they are 5–12pp more likely to find employment and 4–12pp more likely to repay their federal student loans than observationally-identical peers with private knowledge of worse risks. In our benchmark model with rational beliefs, these values imply that, on average, individuals would have to accept financing that is 22–43%, 6–16%, and 6–17% below

[28] Formally, we require that the average belief, $E_S[Y|\theta]$ conditional on X and Z is equal to the empirical average: $E[E_S[Y|\theta]|X,Z] = E[Y|X,Z]$.

[29] Appendix D provides a detailed derivation of m^Z and describes our estimation procedure.

[30] Note that for the equity contract, equation (30) is written in terms of predicted salary level, including the likelihood of being unemployed and earning zero. We transform predicted employment and predicted log earnings conditional on employment into predicted unconditional level earnings before we calculate m_i^Z. Details are provided in Appendix D.

actuarially fair values in order to these sustain each respective state-contingent debt market.

These results suggest that if college-goers selected contracts using the information contained in their elicitations, it would impose considerable costs on would-be financiers. In the next subsection, we provide suggestive evidence that individuals would indeed act upon this information in hypothetical financial markets.

4.3 Do Elicitations Reflect Information Used for Financial Decisions?

If elicitations reflect private information, would individuals use that information to select contracts? Because we cannot observe take-up of our hypothetical financial contracts, our model assumes individuals would make contract choices according to equation (2), so that those expecting higher realizations of Y would require a higher valuation to accept the contract.

While we cannot observe hypothetical decisions over non-existent contracts, we can test whether elicitations can predict actions in a similar context: income-driven repayment (IDR). IDR is an opt-in public program that pegs monthly minimum payments on federal student loans to a fraction of borrowers' post-graduate incomes. While IDR differs from the earnings-equity contract in our paper, both contracts benefit borrowers with lower expected income—equity contracts decrease their financial obligations, while IDR allows them to push those obligations further into the future. If those who report lower expected future income are more likely to opt into IDR, we would expect to see a similar pattern of selection for hypothetical earnings-equity contracts.

To test how private information predicts IDR enrollment, we use data from the 2016 Baccalaureate and Beyond (B&B16) study, which asks college seniors both their self-reported likelihood of IDR enrollment and their expected salary after graduation.[31] In Appendix Figure A1 Panel A, we show that student borrowers who expect higher salaries report significantly lower likelihoods of enrolling in IDR, even conditioning on age, college type, and college major. In Panel B, we show they are also less likely to actually enroll in IDR when they begin loan repayment.[32] These patterns suggest the salary elicitation contains information individuals would use in deciding whether to sign our hypothetical contracts.

[31] The B&B16 data include survey responses for a representative sample of four-year college graduates in the spring of 2016, with a follow-up in 2017 (https://nces.ed.gov/surveys/b&b/). We focus on this dataset of seniors because it includes elicitations on both expected future salary and expected IDR enrollment, measured shortly before borrowers' actual IDR enrollment decisions. We also find a significant negative relationship between salary elicitations and eventual IDR enrollment in our baseline BPS sample of first-year students.

[32] These patterns are broadly consistent with findings in previous literature. Mumford (2022) finds that participants in an income-share agreement reported higher self-reported salary expectations than those who applied but did not participate.Abraham et al. (2020) finds that selection into hypothetical income-driven repayment plans positively correlates with students' self-reported likelihood of earning below $35,000. Herbst (2023) and Karamcheva et al. (2020) show that high-balance, low-income borrowers are more likely to opt into IDR.

4.4 Biased Beliefs versus Elicitation Error

The previous subsection suggests borrowers use their beliefs about the future to make strategic financial decisions. But even if college-goers acted rationally on their beliefs, those beliefs themselves could reflect biased expectations of the future. In their elicitations, college-goers report expected salaries of \$64,064 on average, but employed graduates earn only \$32,701 on average in 2017. They also report an average on-time completion likelihood of 8.40 out of 10, but only 41% of respondents complete on-time and only 51% complete by 2017. If salary and degree-completion elicitations were exactly equal to respondents' subjective expectations about their corresponding outcomes in 2017, these patterns would imply considerable over-optimism ($E_S[Y|\theta] > E[Y|\theta]$) on average. Unless this over-optimism is subdued when making contract decisions (Lucas, 1972), these upwardly biased beliefs could make market existence more difficult by increasing individuals' willingness-to-accept above the marginal value they would offer the financier.

It is important to note, however, that a bias in beliefs that is common across the population will not cause attenuation in the slopes in Figure 3A. Rather, biased beliefs can only cause attenuation if the bias is heterogeneous in the population. From a theoretical standpoint, this heterogeneity can actually make a market more likely to exist because it generates variation in the WTA curve that is orthogonal to the outcome. In other words, there could be enough pessimists who undervalue their earnings prospects, generating a lower WTA. For these reasons, our approach to identify the distribution of biased beliefs in Section 5 will allow for this heterogeneity in the potential bias in beliefs.

An alternative explanation for the observed relationship between elicitations and outcomes is measurement error in the elicitations. In other words, respondents might form unbiased beliefs about 2017 outcomes ($E_S[Y|\theta] = E[Y|\theta]$) but report something different in survey questionnaires ($Z \neq E_S[Y|\theta]$).[33] Indeed, subjective survey responses like those in Figure 3 are notoriously prone to reporting errors. Responses often heap on round numbers, violate the law of iterated expectations, and vary with question framing.[34] This kind of elicitation error generates variation in Z that can affect OLS estimates of β in Figure 3, even if it is orthogonal to outcomes.

Elicitation error might also arise from systematic misinterpretations of survey questions, influencing the mean level of responses. For example, rather than reporting beliefs about earnings immediately after college, some respondents may answer questions like "What is...your expected

[33] Assuming unbiased beliefs allows us to interpret our magnitude estimates in Table 4 as lower bounds on $E[MV(\theta) - AV(\theta)]$.

[34] In Fischhoff et al. (2000), more than 12% of survey respondents report a higher likelihood of dying in the next year than dying in the next three years. Hurd and McGarry (2002) show that bunched responses to mortality questions are best interpreted as coarse measures subjective probabilities, where responses like "50%" correspond to anything in the 30% to 70% range. Armantier et al. (2013) report survey predictions about "prices in general" are higher and more variable than predictions concerning "inflation." Charness et al. (2021) discuss a range of more advanced methods for eliciting beliefs and discuss the tradeoffs.

yearly salary?" with their beliefs about earnings later in the life cycle.[35] Consistent with this conjecture, the average earnings among 35- to 40-year-old college-goers in the 2012 American Community Survey is \$60,759, which is close to the \$64,064 average expected salary reported in the BPS.[36]

In the end, both biased beliefs and elicitation error likely contribute to the patterns we observe. In the next section, we allow for both phenomena in our approach to estimating the unraveling condition.

5 Estimation of Unraveling Condition

In this section, we estimate belief distributions for each outcome, Y, conditional on observables, X, and use those estimates to construct WTA and AV curves for each of the contracts we consider. Motivated by our results from Section 4, we estimate distributions for two types of beliefs: (1) the rational beliefs implied by the empirical mapping of private information onto future earnings, and (2) the potentially biased beliefs implied by expected-salary elicitations under mean-zero measurement error.

It is important to note that our unraveling condition ultimately depends on the beliefs individuals would hold when making hypothetical contract decisions, not the beliefs they hold when answering survey questions. These beliefs might be different for a given individual, especially if they subdue their biases or acquire public information in face of high-stakes financial decisions, as in Lucas (1972). Indeed, previous studies have shown that providing students with public information can cause them to rationally update their self-reported beliefs (Wiswall and Zafar, 2015). Estimating both rational and biased belief distributions allows us test for unraveling under two scenarios—one in which individuals "rationalize" their beliefs before deciding whether to accept a contract, and another in which their contract choices reflect the beliefs implied by mean-zero elicitation error.

5.1 Identification of Beliefs

To ease exposition, our description focuses on a single outcome—log salary—and assumes data have been residualized on academic and institutional characteristics.[37] In Appendix E, we provide

[35] See Appendix C for complete text of survey questions. The prompt for earnings expectations mentions salary "once you begin working" in your expected occupation. In Section 5.3, we isolate a 10% subsample of BPS respondents who received an "abbreviated interview," which asked directly about earnings without discussing occupation. We find nearly identical patterns to those in Figure 3A.

[36] This relationship persists if we condition on respondents' expected occupation. In Appendix Figure A2, we find a strong correlation between a respondent's log expected salary elicitation and the log average earnings of ACS 35- to 45-year-olds employed in their expected occupation.

[37] This set of observables is more extensive than those typically used by existing private student lenders (Hahn, 2022). Moreover, Table 3 shows that adding additional observables beyond these variables does not significantly reduce the information contained in the elicitations.

details on the residualization process and how we adapt our method for degree completion, loan repayment, and employment outcomes.

For each individual i, let $y_i = log\,(Y_i)$ denote the log of their realized salary and θ_i denote their type, which corresponds to the information they have about their future earnings.[38] We let μ_i equal the rational beliefs implied by the empirical mapping of private information onto future earnings, $\mu_i \equiv E[y_i|\theta_i]$. The realization y_i can be written as the sum of those rational beliefs and a mean-zero homoskedastic error term, $\epsilon_i \sim f_\epsilon\,(\epsilon_i)$, which captures i's uncertainty around y:

$$y_i = \mu_i + \epsilon_i. \tag{12}$$

We let $z_i = log\,(Z_i)$ denote the log of the individuals' elicited expected salary. We assume z_i is a noisy and potentially biased measure of true beliefs, $\mu_{S\,i} \equiv E_S[y_i|\theta_i]$:

$$z_i = \alpha + \gamma\mu_{S\,i} + \nu_i, \tag{13}$$

where $\nu_i \sim f_\nu\,(\nu_i)$ denotes mean-zero measurement error in the elicitations, and α and γ allow for systematic deviation of elicitations from individuals' beliefs.

5.1.1 Rational Expectations, μ

To estimate the distribution of rational beliefs, $f_\mu\,(\mu_i)$, we seek to decompose the observed distribution of y_i into μ_i and ϵ_i in equation (12). To perform this decomposition, we substitute $\mu_i = \mu_{S\,i} + (\mu_i - \mu_{S\,i})$ into equation (13) to yield

$$z_i = \alpha' + \gamma\mu_i + \nu_i', \tag{14}$$

where $\alpha' \equiv \alpha + \gamma E\,[\mu_{S\,i} - \mu_i]$ and $\nu_i' = \gamma\,(\mu_{S\,i} - \mu_i) - \gamma E\,[\mu_{S\,i} - \mu_i] + \nu_i$. Equations (12) and (14) form a system of two linear equations with three latent variables—ϵ_i, μ_i, and ν_i'. To identify the distributions of these latent variables, we must first identify γ in equation (14).

To identify γ, we use a canonical instrumental-variables technique for measurement-error correction (Fuller, 1987). Equation (12) lets us treat y_i as an unbiased measurement of μ_i in equation (14). We can therefore estimate γ with an IV regression of z_i on y_i, where we instrument for y_i using a second elicitation, w_i. Identification of γ requires $cov\,(w_i,\nu_i') = 0$.[39] This exclusion restriction would be violated if any idiosyncratic variation in biased beliefs or elicitation error captured in z_i

[38] A log specification allows us to model uncertainty in the earnings process as a proportional shock, as is common in previous literature (Guvenen, 2007). Later, we transform beliefs about log salary, $F(Y|Y > 0,\theta)$, and beliefs about employment, $\Pr(Y > 0|\theta)$, into beliefs about level earnings, $E[Y|\theta]$. See Appendix E.

[39] We also require w_i be uncorrelated with ϵ_i, but this assumption is mechanically satisfied as long as w_i reflects no more information than what is contained in θ_i. By definition, any variation in y_i that is not explained by μ_i must be independent of elicitations, so $cov\,(w_i,\epsilon_i) = 0$.

is also contained in w_i. We therefore seek an instrument, w, that is unlikely to induce the same kind of reporting error or bias as the primary elicitation, z.

To plausibly meet this criteria, we make use of BPS survey questions concerning respondents' expected occupations. Using realized occupation and earnings from a separate dataset of college graduates, we construct w_i as the average 2012 salary in individual i's expected occupation.[40] This constructed instrument is devoid of many classic forms of survey-induced measurement error like heaping or left-digit bias, making correlation in elicitation errors ($cov\,(w_i,\nu_i) \neq 0$) unlikely. We also require w_i to be uncorrelated with any idiosyncratic bias in beliefs, $\mu_{S_i} - \mu_i$, so that those who report higher paying occupations do not hold higher-than-average earnings optimism—they are more confident than their counterparts because they expect especially high pay within a given occupation, not because they expect to enter an occupation with especially high pay. While this assumption could plausibly be violated, we find our unraveling results are robust to alternative estimation or calibration methods for γ.[41]

Using w_i to instrument for beliefs about log salary, we estimate γ=0.69 (SE=0.16) in equation (14).[42] With this estimate of γ in hand, we can use equations (12) and (14) to perform a linear deconvolution of y_i and z_i.[43] The deconvolution yields non-parametric estimates of distributions for the latent variables in our model—$f_\mu(\mu_i)$, $f_\epsilon(\epsilon_i)$, and $f_{\nu'}(\nu'_i)$. We summarize this identification result in Remark 1.

Remark 1 (Rational Beliefs) *Suppose that ϵ_i in equation (12) is distributed with pdf $f_\epsilon\,(\epsilon_i)$ that is independent of μ_i. Suppose that elicitations, z_i, can be expressed as in equation (14) with ν'_i distributed according to pdf $f_{\nu'}\,(\nu'_i)$ that is independent of μ_i. Suppose that γ is either known or there exists a second elicitation, w_i, which is correlated with y_i only through its correlation with the unbiased component of beliefs, μ_i: $cov\,(w_i,\nu'_i) = 0$. Then, the distributions of μ_i, ϵ_i, and ν_i are identified with linear deconvolution (Bonhomme and Robin, 2010).*

In brief, our rational-beliefs estimation uses joint variation in elicitations and outcomes to estimate the distribution of beliefs individuals would hold if they used their private information to form unbiased predictions. The strategy exploits the fact that realizations of y_i are unbiased measures of rational beliefs, $\mu \equiv E\,[y|\theta]$, while allowing elicitations, z_i, to be noisy and potentially biased measures of true beliefs, $\mu_S \equiv E_S\,[y|\theta]$.

[40] Post-graduate salaries are taken from the 2008 Baccalaureate and Beyond (B&B08) study, which we match to BPS occupation elicitations (occ_i) using three-digit occupation codes. Details in Appendix C.

[41] In Section 5.3, we estimate γ using alternative elicitations as instruments. We also add a specification where we assume $\gamma = 1$, so that a one-unit higher belief corresponds to a one-unit higher elicitation on average as in Hendren (2013, 2017). Both approaches yield similar results to our baseline specification.

[42] Appendix Table A2 reports estimates of γ for all four outcomes, as well as the associated elicitation and instrument used in each estimation.

[43] We provide details on the deconvolution method in Appendix E.

5.1.2 Potentially Biased Beliefs, μ_S

To identify the distribution of potentially biased beliefs, $f_{\mu_S}(\mu_{Si})$, we can no longer use realized y_i as an unbiased measure of beliefs ($E[y|\mu_{Si}=\mu_S]\neq\mu_S$). We instead assume elicitations are unbiased measures of true beliefs, $E[Z_i|\mu_{Si}=\mu_S]=E_S[Y|\mu_S]$. This assumption implies $z_i=log(Z_i)$ in equation (13) can be written as

$$z_i=\bar{\alpha}+\mu_{Si}+\nu_i, \tag{15}$$

where $\bar{\alpha}=log\left(E\left[\exp\left(\epsilon_i\right)|\theta_i\right]\right)-log\left(E\left[\exp\left(\nu_i\right)\right]\right)$.[44] Importantly, equation (15) still allows elicitations to be noisy measures of true beliefs, $\nu_i\neq 0$.

To specify how beliefs relate to the distribution of realized outcomes, we write log income, y_i, as the sum of its belief-conditional mean and an orthogonal error term:

$$\begin{aligned} y_i &= E\left[y_i|\mu_{Si}\right]+\xi_i \\ &= E\left[\mu_i|\mu_{Si}\right]+\xi_i \end{aligned} \tag{16}$$

where the second line follows from taking expectations in equation (12). We assume a linear approximation to this conditional expectation function, $E\left[\mu_i|\mu_{Si}\right]=a+b\mu_{Si}$, so that beliefs may be biased in both level and slope—i.e., a one-unit increase in beliefs corresponds to a b-unit increase in outcomes.[45] We then write (16) as

$$y_i=a+b\mu_{Si}+\xi_i, \tag{17}$$

where ξ_i is orthogonal to $a+b\mu_{Si}$. Equations (15) and (17) form a system of two linear equations with three latent variables. As in the rational-beliefs case, we can use an IV strategy to estimate b and a linear deconvolution to estimate the distributions of μ_{Si}, ξ_i and ν_i.

Our approach to identify b is similar to the approach to identifying γ above, except we now assume z_i is the unbiased measure of beliefs instead of y_i. We therefore estimate b by regressing y_i on z_i and instrumenting with a second elicitation, w_i. We require that w_i is uncorrelated with both the idiosyncratic bias contained in ξ_i, and with the elicitation error, ν_i. For our baseline implementation, we use the same instrument, w_i, as we did to instrument for rational beliefs—average salary in expected occupation. This instrument is valid as long as people's biases in beliefs concern their earnings conditional on occupation, as opposed to systematic bias in people's expected occupations. This IV strategy yields an estimate of b =0.70 (SE=0.17) (see Appendix Table A3). We again stress that our results are not very sensitive to estimates of b. In Section 5.3, we show

[44] The $\bar{\alpha}$ term ensures Z_i is unbiased in levels, $E[Z_i|\theta]=E_S[Y_i|\theta]$.

[45] We assume for simplicity that individuals have correct views about the variation in y_i conditional on their beliefs about mean y_i. In other words, we assume $\Pr_S\left(y_i-\mu_{Si}\leq x\right)=F_{\xi_i}(x)$. One could relax this assumption with additional elicitations about higher order moments of the subjective belief distribution, such as the elicitation procedures studied in d'Haultfoeuille et al. (2021) and Crossley et al. (2021).

results are qualitatively similar for a variety of alternative estimations or calibrations of b (e.g. $b = 0.5$ or $b = 1$).

With estimates of b in hand, we can once again use a deconvolution framework to identify the distribution of beliefs, $f_{\mu_S}(\mu_{S_i})$. We state this identification result in Remark 2.

Remark 2 (Potentially Biased Beliefs with Unbiased Elicitations) *Suppose that ξ_i in equation* (17) *is distributed with pdf $f_{\xi_i}(\xi_i)$ that is independent of μ_{S_i}. Suppose that elicitations, z_i, can be expressed as in equation* (15) *with ν_i distributed according to pdf $f_\nu(\nu_i)$ that is independent of μ_{S_i}. Suppose that b is either known or there exists a second elicitation, w_i, that is correlated with z_i only through its correlation with beliefs, μ_{S_i}: cov $(w_i,\nu_i) = 0$. Then, the distribution of μ_{S_i}, ξ_i, and ν_i are identified with linear deconvolution (Bonhomme and Robin, 2010). Moreover, the mean outcome conditional on true beliefs is identified for each true belief, $E[\mu_i|\mu_{S_i}] = a + b\mu_{S_i}$.*

Unlike identification of rational beliefs, identifying the distribution of potentially biased beliefs requires knowledge of how beliefs map to elicitations. If we assume elicitations are noisy but unbiased measures of respondents' subjective expectations, μ_S, we can estimate this biased-belief distribution, f_{μ_S}, without assuming rationality.

Beliefs about Binary Outcomes Appendix E provides details on belief estimation for binary outcomes (degree completion, employment, and student-loan repayment), which is similar to the method described above. For each binary outcome, we identify the distribution of rational beliefs using the joint distribution of outcomes and elicitations. For degree completion, we also estimate a biased-belief distribution by assuming elicited completion likelihood is an unbiased measure of true beliefs about completion. Binary-beliefs estimates are primarily used to test for unraveling in state-contingent debt markets, though we also use beliefs about employment to adjust our log-salary belief estimates (conditional on employment) into beliefs about earnings in levels.[46]

Estimation Results Estimated belief densities for each outcome are plotted in Appendix Figure A3. We find a wide dispersion in beliefs about future earnings. The standard deviation of the distribution of rational beliefs is \$17,304 conditional on X. Compared to the standard deviation of realized salary (SD(Y)=\$25,376), these estimates suggest there is significant private information but also considerable uncertainty: 32 percent of the variation in earnings is unknown at the time of enrollment. Risk-averse college-goers should be willing to accept a discounted valuation in order to insure against this uncertainty.

[46] See Appendix E. Because we do not have direct measures of subjective employment likelihood, we assume rational beliefs about employment likelihood when allowing salary conditional on employment to be biased. If biases between employment and earnings are positively correlated, over-optimism about employment prospects would amplify our market unraveling results below.

5.2 Estimating AV and WTA Curves

Having estimated distributions of subjective beliefs, we can now construct the two components of the unraveling condition (7)—average value $AV(\theta)$ and $WTA(\theta)$.

Average Value We index types by their estimated beliefs, so that $\theta \equiv F_{\mu}$ under rational expectations and $\theta \equiv F_{\mu_S}$ under potentially biased beliefs. The marginal value curve, $MV(\theta)$, is therefore given by the inverse CDF of $E[Y|\theta]$. Assuming unidimensional heterogeneity in preferences, we can construct the average value curve, $AV(\theta)$, as the cumulative average of marginal values among all those with worse beliefs:

$$AV(\theta) = E\left[MV(\theta)|\theta \leq \theta'\right]. \tag{18}$$

Willingness-to-Accept We measure the willingness to accept (WTA) curves by adapting an approach from the literature on optimal social insurance. Assuming a constant relative risk aversion (CRRA) utility function, we can rewrite equation (4) to define type θ's willingness to accept, $WTA(\theta)$, as

$$WTA(\theta) = E_S\left[Y|\theta\right] + cov_S\left(Y, \frac{c(Y)^{-\sigma}}{E\left[c(Y)^{-\sigma}|\theta\right]}|\theta\right), \tag{19}$$

where σ is the coefficient of relative risk aversion, and $c(Y)$ is consumption as a function of outcome Y.

To estimate equation (19) for the earnings-equity market, we assume a consumption function of the form $c(Y) = \bar{c}Y^{\rho}$ for employed states of the world ($Y > 0$), where ρ is the impact of variation in income on consumption. For the unemployed state ($Y = 0$), we assume individuals consume $1 - \delta_C$ times the amount they expect to consume in employment, $c(0) = (1 - \delta_C)\, E_S\left[c(Y)|Y > 0,\theta\right]$, where the consumption response to unemployment is calibrated to $\delta_C = .09$.[47]

Drawing from a range of possible values found in the literature, we calibrate our baseline value of relative risk aversion to be $\sigma = 2$ but assess robustness to $\sigma = 1$ and $\sigma = 3$ in Section 5.3.[48] We draw our baseline estimate of ρ from Ganong et al. (2020), who find that a 1% earnings shock corresponds to a 0.23% change in consumption. We then use the perceived distribution of Y given θ to construct the covariance term and measure $WTA(\theta)$ in equation (19).

Willingness-to-accept curves for state-contingent debt markets are also derived from equation 19, but estimation requires calibrating individuals' consumption response to completion, employment, and loan-repayment outcomes. Details of these calibrations are provided in Appendix E.

[47] Hendren (2017) estimates a causal effect of unemployment on consumption ranging from 7% to 9%, while Ganong and Noel (2019) estimate values between 6% and 12%.

[48] Empirical estimates of relative risk aversion often fall in the range of 0.5 to 4 (Chetty, 2006; Gandelman et al., 2015; Gourinchas and Parker, 2002; Pålsson, 1996), and calibrating σ to 2 is standard practice in many consumption-savings models (Jeanne and Rancière, 2006). Note that because our population of interest is relatively young, individuals may be less risk averse than the general population (Pålsson, 1996).

5.2.1 Unraveling Results for Earnings-Equity Market

Unraveling results for the earnings-equity market are reported in Figure 4. Panel A corresponds to the rational beliefs specification. The solid blue line displays the marginal value curves, $MV(\theta)$, and the solid green line reflects the average value curve, $AV(\theta)$. The results suggest that college-goers would have to be willing to accept significantly lower than actuarially fair valuations in order for a market to exist. The median individual has an average earnings of $20,397 in 2017. On average, the people whose beliefs are at or below $20,397 have an average salary of $12,471.[49] So, the median individual would have to accept a 39% discount on the value of their future earnings for the financier to break even on their contract. In expectation, accepting this contract would mean repaying $1.64 plus interest for every dollar of upfront financing. Our willingness-to-accept estimates imply the median individual would reject any such contract—the median individual is willing to accept a valuation of $16,827, which falls below the $12,471 average salary of those who would also select the contract. More generally, we find that the WTA curve lies above the AV curve across the distribution of types—no borrower is willing to cover the financier's cost of adverse selection, so the market unravels. The p-value for the test that there exists a value of θ such that $AV(\theta) \geq WTA(\theta)$ is less than 0.001.

Figure 4, Panel B reports the results for the case of potentially biased beliefs. As noted in Section 4.4, college-goers appear to be overly optimistic. If these elicitations reflect unbiased measures of true beliefs, market existence is even more difficult than in the case of rational expectations. We estimate the median college-goer expects to earn $30,313, but the true value of a stake in their earnings is $21,165. The average salary among those with lower earnings potential is just $13,197, so this individual would have to accept a perceived discount of 56% for the financier to profit from their contract. The individual is unwilling to accept any valuation below $24,925, so there exists no profitable contract for the median college-goer. As in the case of rational expectations, we find that the WTA curve among potentially biased college-goers lies everywhere above their AV curve. The p-value for the test that there exists a θ such that $AV(\theta) \geq WTA(\theta)$ is again less than 0.001.

The results in Figure 4B also suggest that biased beliefs alone is unlikely to explain the absence of equity markets. To set the stage, note that if there were no asymmetric information, financiers could use information in θ to price type-specific contracts at $\lambda(\theta) = MV(\theta)$. But if borrowers' over-optimism inflated their willingness-to-accept above this actuarially fair valuation (i.e., $WTA(\theta) > MV(\theta)$), even a fully informed financier would be unable to write them profitable contracts. Figure 4B suggests that, while borrowers' overvaluation might attenuate a market without information asymmetries, the magnitude of this over-optimism is not enough to explain

[49] We can also use our point estimates of AV and MV curves to construct the mean magnitude of information, $E[m(\theta)] = E[MV(\theta) - AV(\theta)]$, and compare it with the estimated lower bounds, $E\left[m^Z\right]$, from Section 4. For the earnings-equity market, we estimate a mean magnitude equal to $E[m(\theta)]$ =14,049. As expected, this point estimate exceeds the lower bound of $4,319 reported in Table 4. Appendix Table A4 reports point estimates of the mean magnitude alongside lower bound estimates for each of the four outcomes.

complete market absence. Even if respondents' irrationally high salary elicitations reflected true over-optimism about their immediate post-college earnings, we would still expect 23% of college-goers to accept equity contracts below their marginal values. If, on the other hand, just some responses reflected respondents' beliefs about their later-career earnings, we would expect an equity market without adverse selection to be even larger.

In the presence of biased beliefs, financiers could offer contracts exclusively to pre-screened subgroups they find particularly promising, like those with high predicted earnings based on observables, $E[Y|X]$. If these high achievers were unaware of their own income potential, this strategy could create a profitable market segment for the financier. To test this theory, Appendix Figure A4B plots estimated curves for those in the top quartile of predicted income, $E[Y|X]$, allowing for biased beliefs. It shows that, even though high-potential students show less optimism than their low-potential counterparts, their willingness-to-accept still lies above the AV curve, so the market unravels. Moreover, 67% of these high-achievers would be willing to accept actuarially fair contracts ($WTA(\theta) < MV(\theta)$) in the absence of private information. This finding reinforces our conclusion that biased beliefs alone are unlikely to explain the absence of the market. By contrast, our results suggest that adverse selection would unravel equity markets regardless of whether individuals made contract choices using rational or potentially biased beliefs.

5.2.2 Unraveling Results for State-contingent Loan Markets

Figure 5 turns to the other three markets we consider, focusing on the estimates of the WTA and AV curves under rational expectations. We find that all three of these markets unravel. Figure 5A shows that for the completion-contingent loan market, the median individual has an 62% chance of completing college. But the average probability of those who believe they have less than an 62% chance of completing college is 35%; a profitable contract would require the median individual to repay an expected \$1.79 plus interest for every dollar of financing. But our estimates imply their maximum premium is just \$0.13 on the dollar—the median individual is willing to accept no less than $WTA(0.5)$ =\$0.55 in financing for each dollar owed in the event they graduate. This level of financing exceeds the the financier's expected revenue, $AV(0.5)$ =\$0, so there exists no profitable contract for the median borrower. More broadly, the WTA curve lies everywhere above the AV curve; the p-value for the test that there exists a value of θ such that $AV(\theta) \geq WTA(\theta)$ is less than 0.001.[50]

Figure 5B presents the results for the employment-contingent loan market that requires repayment only in the event of employment after graduation. The median individual has an 72%

[50]Appendix Figure A5 presents completion-contingent loan results allowing for potentially biased beliefs. This approach assumes self-reported completion likelihoods on a 0 to 10 scale provides an unbiased measurement of subjective beliefs, $E[Z_i/10|\theta] = \Pr_S(Complete)$. Under these assumptions, we find considerable over-optimism, with median beliefs exceeding true completion likelihood by 37pp. This over-optimism amplifies market non-existence, so that the AV curve once again lies everywhere below the WTA curve (p-value <0.001).

chance of being employed, but the average probability of employment among those with worse employment prospects is just 60%. We estimate that the median individual is willing to accept $WTA(0.5)$ =\$0.69 in financing for each dollar owed in employment, which is more than the \$0.60 they would need to accept for the financier to make a profit. We again find the WTA curve lies everywhere above the AV curve, so that the market unravels. The p-value for the test that there exists a value of θ such that $AV(\theta) \geq WTA(\theta)$ is less than 0.001.

Finally, Figure 5C presents the results for the dischargeable debt contract that only requires repayment in the event of non-delinquency on traditional student loans. The median individual has a 27% chance of not being delinquent; but the average repayment rate of those who expect higher delinquency likelihood is 16%. The median individual is willing to accept no less than $WTA(0.5)$ =\$0.25 in financing for each dollar owed in non-delinquency, which is higher than \$0.16. We again find that the WTA curve lies everywhere above the AV curve, so the market unravels. The p-value for the test that there exists a value of θ such that $AV(\theta) \geq WTA(\theta)$ is less than .001. These results suggest that the market for private student debt might depend on lenders' ability to enforce their repayment more stringently than other types of consumer debt.[51] In sum, in all four market settings, we find that the $WTA(\theta)$ curve lies everywhere above the $AV(\theta)$ curve, suggesting that these markets have unraveled due to adverse selection.

5.3 Robustness

Our baseline estimates made a series of assumptions. Here, we discuss how variations on these assumptions affect our core conclusions.[52]

Risk Aversion Our baseline case assumes a coefficient of relative risk aversion of $\sigma = 2$. Appendix Figure A6 shows the WTA curves for coefficients of relative risk aversion equal to $\sigma = 1$ and $\sigma = 3$. Higher risk aversion leads to a lower WTA curve, but the WTA curve continues to lie everywhere below the AV curve.

Preference Heterogeneity The benchmark case assumes those with a higher expected income, $E_S[y|\theta]$, always have a a higher $WTA(\theta)$. In reality, individuals may also differ in their risk preferences. Preference heterogeneity can increase the expected incomes of those who select a given contract because they select based on risk aversion rather than income. To assess the potential implications of modifying this assumption, we consider a specification with heterogeneous risk preferences by drawing σ from a distribution conditional on each type θ.[53] Appendix Figure A7, shows

[51] Prior to the 2005 law making private student loans non-dischargeable in bankruptcy, lenders frequently denied credit to borrowers they deemed too risky (Siegel, 2007).

[52] For brevity, we report robustness results for the case of rational beliefs for most robustness analyses below; the robustness patterns presented also hold for the case of potentially biased beliefs.

[53] Our simulation assumes that preference heterogeneity is not correlated with the level of the expected outcome. We view this as a natural benchmark. There is no robust reduced form evidence of correlated preference heterogeneity in

the results for two cases: $\sigma \sim Unif\,[1,3]$ and $\sigma \sim Unif\,[0,4]$. Allowing for preference heterogeneity in this way does lead to slightly flatter AV curves, as expected, but the broad pattern is virtually unchanged; the market would continue to unravel even under heterogeneous risk preferences.[54]

Exclusion Restriction Our approach relies on instruments to identify γ in the case of rational beliefs and b in the case of potentially biased beliefs. Appendix Tables A5 and A6 shows we find similar values of γ and b using alternative instruments. Appendix Figure A8 also replicates our baseline figure 4 but calibrates the values of γ and b to a range of plausible values between 0.5 and 1. Broadly, we find very similar patterns, suggesting that the market unraveling results are not that sensitive to reasonable values of γ and b.

Survey Question Interpretation The BPS survey asks about salary expectations after respondents report their expected occupation. This question structure could elicit beliefs about expected salary conditional on particular career rather than beliefs about salary more broadly. We address this concern in two ways. First, we isolate a 10% subsample of BPS respondents who received an "abbreviated interview," with more general question wording.[55] In Appendix Figure A9, we find a similar elicitation-outcome relationship when we separate this subsample from the remaining 90% of respondents who saw the full-text question referencing their expected occupation. Second, we re-estimate the belief distribution replacing the salary elicitation Z_{sal} with a composite elicitation constructed as follows:

$$Z_{composite} = Z_{\Pr(occ)} Z_{sal} + (1 - Z_{\Pr(occ)}) Z_{salnocoll}, \tag{20}$$

where $Z_{\Pr(occ)}$ is the subjective likelihood of finding a job in one's expected occupation and $Z_{salnocoll}$ is the expected salary respondents say they would have earned had they not attended college. Estimates of the AV and WTA curves using this composite elicitation are almost identical to our baseline earnings-equity specification (see Appendix Figure A10).

Subgroups Finally, our baseline results focus on the residual distribution of beliefs about the outcome Y after conditioning on observables, X. While we condition on X, we pool across Xs when conducting our analyses using the methods described in Appendix E. One concern with this

other settings. In health contexts, several earlier studies have argued that there is "advantageous selection" generated by the "worried well", however Section 8.4 in Hendren (2013) argues that these correlations in earlier literature are likely driven by insurance companies choosing not to insure observably sick applicants as opposed to sick applicants having less preference for insurance.

[54]Note that we evaluate average value (equation (5)) at the same values of θ_λ as in the baseline case with homogenous risk preferences. As a result, the horizontal axis in Appendix Figure A7 corresponds to quantiles of WTA among individuals with $\sigma = 2$, rather than quantiles of the entire WTA distribution under preference heterogeneity.

[55]The abbreviated interview simply asked "What do you expect your salary to be once you finish your education?," as opposed to asking about "[the] salary you expect to make once you begin working a [EXPECTED OCCUPATION] job." See Appendix C.

approach is that the WTA and AV curves might look different within subgroups of observable characteristics. With infinite data, we would verify that $AV(\theta) > WTA(\theta)$ for all θ within each market segment, $X = x$. We of course do not have the power to test for this, but we can explore the heterogeneity in our estimates across various subgroups. In Appendix Figures A11–A16, we report the WTA and AV curves separately for subgroups based on gender, school type, and STEM versus non-STEM major field of study.[56] In each split of the data and across our four market settings, we generally continue to find that the AV curve lies everywhere below the WTA curve.

5.4 Credit Constraints and Outside Lending Options

In Section 2, our baseline model assumes individuals can borrow at the same rate as private financiers. In theory, however, credit constraints could lower the WTA curve and make some financial markets more likely to exist. To assess how credit constraints could affect our results, we consider an alternative specification where individuals face a cost of borrowing, R_θ, that is 10pp higher than the risk-free rate, R. Appendix Figure A6 shows that all four markets would still unravel. In the earnings-equity market with rational beliefs, the median individual is willing to accept \$15,298, which is \$1,530 lower than what they would accept without credit constraints, but still higher than the \$12,471 they would need to accept for the market to exist. To be sure, one could imagine credit constraints ($R_\theta > R$) large enough to push the WTA curve below the AV curve.[57] However, instead of offering equity contracts, financiers would sooner offer debt contracts at a liquidity premium of $\Delta R = R_\theta - R$ without incurring the added cost of adverse selection.[58] Our results continue to explain why markets for state-contingent financing unravel.

While credit constraints could make unraveling less likely, an abundance of available credit could have the opposite effect. For example, government-subsidized lending could lower individuals' cost of borrowing, R_θ, below the risk-free rate faced by financiers, R. This decreased demand for private credit would raise the WTA curve, making market unraveling more likely. With sufficiently large subsidies, no private financial contract would be able to profitably compete with government loans, even in the absence of private information. However, even in the presence of subsidized credit, risk-averse students would pay a premium to insure their post-college outcomes. So in the absence of asymmetric information, we would expect credit-rich borrowers to form a market for state-contingent insurance contracts with no intertemporal component.[59] So while generous public subsidies could perhaps explain why government-backed loans dominate most private lending, they cannot explain the general absence of state-contingent contracts. They also cannot explain why

[56] Appendix Table A7 reports our lower-bound and reduced-form significance by the same subgroups.

[57] Our estimates suggest R_θ would have to exceed R by at least 24% to prevent equity markets from unraveling.

[58] Our results suggest such contracts would rely on the status of student debt as non-dischargeable in bankruptcy. If such priveliges were removed, our results show that borrowers' private information about their likelihood of future financial distress would lead to adverse selection in debt markets as well.

[59] For example, financiers could offer income insurance by modifying an earnings-equity contract to provide fixed, post-college payments that are timed to coincide with individuals' income-share obligations.

those without access to government-subsidized loans face so few private financing options. As we discuss in Section 5.5, private attempts at targeting equity-like contracts towards these credit-constrained populations have generally failed, leaving a market dominated by non-dischargeable private student loans.

In short, our paper considers financial contracts that move money both across time and across states of the world. Credit constraints and outside lending options can influence demand for the intertemporal component of these contracts, but our results suggest the state-contingent portion of those contracts would unravel regardless of those factors.

5.5 Mapping to Existing Income-Contingent Contracts

Our findings suggest that adverse selection would unravel equity markets for financing college. Yet we can observe a number of colleges, trade schools, and private companies have attempted to offer equity-like contracts called "Income-Share Agreements" (ISAs). Can our results explain the experiences of these financiers?

Table 5 provides a comprehensive list of past and present ISA programs.[60] The entry strategy of these ISA providers is broadly consistent with many features of our model in a world where some investors underestimate the threat of adverse selection. In particular, ISAs have tended to target groups of students with more observable characteristics and fewer credit options than those in our study sample. For example, several ISAs finance coding bootcamps, technical certificates, or professional degrees. Unlike our sample of first-time enrollees, students at these schools often have established credit histories (less private information) and limited access to subsidized student loans (lower willingness-to-accept). The few ISAs that are marketed to traditional undergraduates are generally not available to entering freshman and are always sold as "top-up financing" for the small population of students who have exhausted their federal student loan eligibility. To our knowledge, there is no ISA marketed to undergraduates as a replacement for traditional student loans.

Despite targeting market segments potentially less prone to unraveling, ISAs have struggled to make profits. Of the thirty-five ISA providers listed in Table 5, only ten are still in operation. The "Tuition Postponement Option" at Yale University folded after providing just 3,300 contracts over seven years (Ladine, 2001). A more recent example is *Placement.com*'s ISA program, which folded in 2022. At the time its founder tweeted, "I think the ISA experiment has failed" and "ISAs tend to have significant adverse selection problems" (Linehan, 2022). Even the few ISA providers currently in operation face questionable profitability. None has been in operation longer than six years, which is shorter than most ISA contract periods.[61] These providers may fold once they observe the full outcomes of their initial cohorts.

[60]For details on the structure of many of these ISAs, see (Zaber and Steiner, 2021). We are grateful to Melanie Zaber for her help in completing this list.

[61]Most ISAs require payments for five to ten years following graduation (Berman, 2017).

The most prominent ISA in recent years has been the "Back-a-Boiler" program at Purdue University. Mumford (2022) studies the Purdue ISA program in detail and finds that both expected and realized post-college incomes of ISA participants are roughly $5,000 lower than those of students who applied for the ISA but did not enroll. In Appendix F, we show that Mumford's findings are consistent with our estimates of AV and WTA curves, suggesting the Purdue ISA is unlikely to yield profits. This result might help explain why the program has indefinitely suspended new contracts as of June 2022 (Moody, 2021).

Note that the existence of these ISAs, however short-lived and unprofitable, suggests that fixed costs, legal constraints, or income verification are unlikely to blame for their rareness. Existing consumer finance law does not prohibit ISA contracts,[62] and ISA providers can easily verify individual incomes with the IRS.[63] More generally, the presence of several small but brief ISA ventures suggests equity-like contracts are entirely feasible, just not profitable.

Finally, note that many of the remaining ISAs in existence are not designed to be profitable; some are explicitly philanthropic ventures (Student Freedom Initiative), while others receive federal subsidies (Mentorworks). Our results do not rule out the existence of such not-for-profit ISAs. In fact, they suggest that scaling up subsidies for ISAs or similar contracts could potentially improve welfare by opening up unraveled markets. In the next section, we discuss these welfare impacts and estimate their magnitudes.

6 Welfare Impacts of Government Subsidies

If private firms cannot profitably finance college with equity or state-contingent debt, should the government subsidize these contracts as alternatives to federal student loans?[64] In this section, we measure the welfare impact of such subsidies by constructing their marginal values of public funds (MVPFs). The MVPF measures the dollar value of the policy provided to its beneficiaries per dollar of net cost to the government, so that spending on subsidies for each method of college financing can be compared to other potential government expenditures.[65] Appendix G provides a detailed derivation of the MVPF in each market setting.

[62] A recent consent order from the Consumer Financial Protection Bureau (CFPB) classifies ISAs as "private education loans" (CFPB, 2022).

[63] Both ISA providers and a variety of other companies reguarly verify incomes by requiring participants to sign form 4506-T that provides transcripts of tax returns to third parties. Income verification details for the Purdue ISA can be found in a sample ISA contract(Purdue University, 2022).

[64] These questions have obtained considerable theoretical interest in the economics literature (e.g. Jacobs and van Wijnbergen (2007); Stantcheva (2017)), and in recent consideration in political debates about student debt burdens and debt forgiveness(Warren, 2020; Harrison, 2021).

[65] Comparisons of MVPFs across policies correspond to statements about the welfare impact of hypothetical budget neutral policies (Hendren and Sprung-Keyser, 2020). As a result, the MVPFs we construct here can be compared not only to each other, but to the broader library of MVPFs for government expenditure policies constructed in Hendren and Sprung-Keyser (2020), Finkelstein and Hendren (2020), and others.

Earnings-Equity Contracts To calculate the MVPF of earnings-equity subsidies, we imagine the government offers $1 of college financing in exchange for a share of future income valued at average earnings, $\lambda = E[Y] = \$24{,}032$.[66] The MVPF for this subsidy is given by its welfare benefit to those who accept, divided by its net cost to the government. Figure 6A decomposes the welfare impact into transfer and consumption-smoothing benefits, derived from the marginal-value and risk-discount components of our WTA estimates.[67] Figure 6B decomposes the subsidy's net cost to the government, incorporating the revenue impacts of behavioral responses induced by the contract. Table 6 reports point estimates for these components and the resulting MVPF.

The WTA curves in Figure 4 imply that 72% of the population would accept an earnings-equity contract if they held rational beliefs and 52% if they held the upwardly-biased beliefs implied by their elicitations. For those who take it up, the contract delivers a net welfare benefit given by $\lambda - WTA(\theta)$, which is the difference between the contract's valuation and their willingness to accept. If beliefs are rational, this benefit averages to $0.47 per person who takes up the contract—the sum of $0.34 in average net transfers from the government and a $0.12 risk premium for the contract's insurance value. For our biased beliefs specification, the individuals taking up the contract perceive a benefit of $0.45 on average, but in reality they experience an ex-post welfare gain of $0.58.

The net government costs of earnings-equity subsidies come from three sources: the net transfer to individuals ($0.34 under rational beliefs), plus two additional costs that might arise from individuals' behavioral responses to equity financing. First, an earnings-equity contract imposes a higher implicit tax rate on future earnings, which may distort labor supply and reduce tax revenue. While the behavioral response to this implicit tax is second order to a financier, it is first order to the government, which already has a stake in college-goers' incomes. Assuming a taxable income elasticity of 0.3, we estimate this labor supply response costs the government an additional $0.03 per dollar of mechanical government spending.[68] Second, the availability of equity financing can cause more individuals to enroll in and complete college, resulting in higher future earnings and greater tax revenue. Drawing upon on estimates from Gervais and Ziebarth (2019), who find that $1,000 in student-loan financing increases earnings by 2.8 percent ten years after graduation, we find that the contract's impact on later-life earnings would increase long-term government revenue by $0.08 per dollar of mechanical government spending.

Putting these estimates together suggests an MVPF of $1.58 under rational beliefs and $1.41 if take-up is determined by biased beliefs (but welfare is measured by the true realizations). Com-

[66]Our hypothetical subsidiy is offered to all individuals at the same price, regardless of their observable characteristics. We therefore use estimates of WTA and AV curves that do not condition on observables. Appendix G provides the precise derivation of how the MVPF depends on the WTA and AV curves.

[67]See equation (4). While we consider take-up decisions based on both rational and potentially biased beliefs, we assume that the true realizations of Y determine the welfare gains from subsidizing these contracts.

[68]0.3 is roughly equal to the median estimate of taxable income elasticity found in the literature (Saez et al., 2012). Appendix G shows how we derive the fiscal cost of implicit tax increases from taxable income elasticity.

paring to the library of estimates in Hendren and Sprung-Keyser (2020), these MVPFs are higher than most other social programs in the US, aside from targeted direct investments in low-income children.

Other State-Contingent Debt Markets and Free College In addition to the earnings-equity contract, Table 6 reports the MVPFs for government subsidies to our three other state-contingent loan markets.[69] Broadly, we find that subsidizing completion-based repayment contracts, employment-based repayment contracts, and dischargeable loans yield lower MVPFs than equity contracts. For the completion-contingent loan valued at λ =51% completion likelihood, we estimate that 52% of the population would take up the contract. Willingness-to-accept estimates for these contractees imply an MVPF of 1.17. For the employment-based repayment contract, we estimate an MVPF of 1.44; for the dischargeable loan contract we estimate an MVPF of 0.77. Compared to our earnings-equity subsidies, these subsidies for state-contingent debt carry more modest returns to society.

Finally, we estimate an MVPF for untargeted government grants that would subsidize college-going without requiring repayment. In the model, we can express a grant as an equity contract with $\lambda \to \infty$—an infinite valuation of future earnings would provide up-front financing in exchange for zero percent of future income. Assuming all college-goers would take up a free grant, we estimate an MVPF of 1.17.[70] This MVPF is lower than the earnings-equity MVPF (1.58) because requiring zero repayment results in lower consumption-smoothing benefit per dollar of spending. Moreover, those expecting high earnings would take up the grant but not the equity contract. This means that the grant's welfare benefits are less targeted towards low earners. In this sense, subsidizing equity is not only more efficient than offering untargeted grants, it also provides redistributive benefits by attracting those with lower earnings prospects.

7 Conclusion

This paper quantifies the frictions imposed by private information in markets for financing human capital investment. Our results suggest that the threat of adverse selection prevents private markets from offering risk-mitigating financial contracts like the equity contracts envisioned by Friedman (1955). As a result, government-backed student debt is effectively the only method of financing available for college. While private markets have unraveled, our results suggest there are significant welfare gains to be gained from moving beyond traditional student loans to state-contingent

[69]Throughout, we consider government subsidies for contracts with valuations equal to the population means in each setting, $\lambda = E[Y]$.

[70]The MVPF of an unconditional grant is greather than one because it increases tax revenue by an estimated 0.14 (Gervais and Ziebarth, 2019), so that the net cost per dollar of mechanical spending is 0.86.

contracts like equity financing, which reduces the debt burden for those with poor post-college outcomes.

Our results add to a growing body of evidence suggesting that information asymmetries prevent private markets from providing products that mitigate risk, such as health-related insurance Hendren (2013) or unemployment insurance Hendren (2017). Our results move beyond the role of private information in insurance settings to think about their potential impact on the shape of investment markets. To that aim, insights from this study might extend beyond the education financing literature to other settings. For example, the Small Business Administration spends significant resources intervening in capital markets for firms. Our framework could be applied to this settings to understand the frictions preventing efficient capital markets and the welfare impacts of this type of government intervention. Our methods could also be used to investigate the role of private information elsewhere in the labor market. For example, adverse selection might help explain why some industries do not form unions, or why some occupations pay piece rates rather than flat wages. The economy is rife with examples where unraveled markets might reduce societal well-being. In the case of human-capital financing, our results show this unraveling may create considerable barriers to economic opportunity for millions of potential college-goers.

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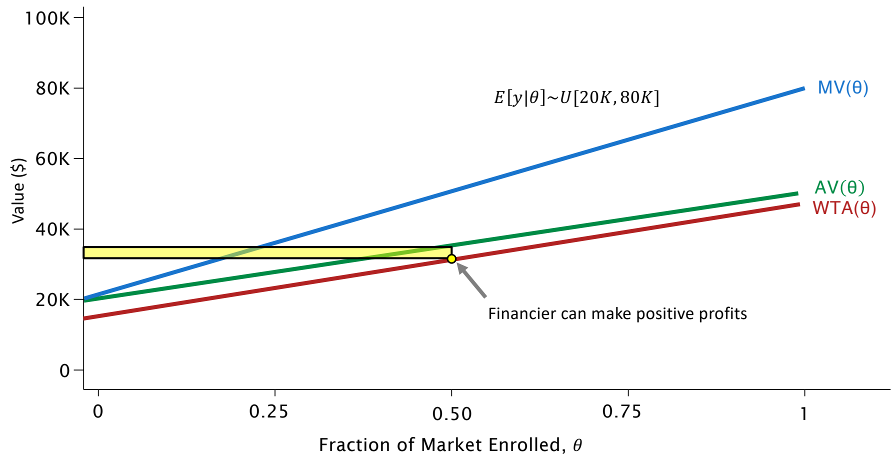
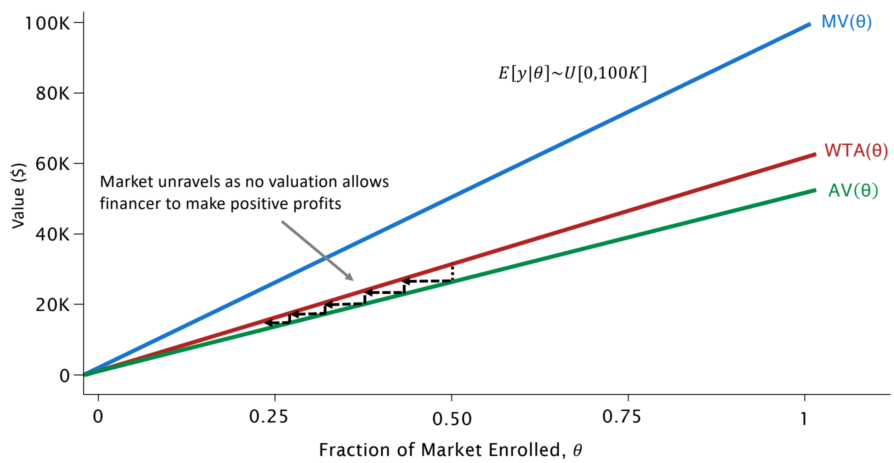
Figures and Tables

Figure 1: Model of Market Unraveling: $AV(\theta)$ and $WTA(\theta)$ Curves



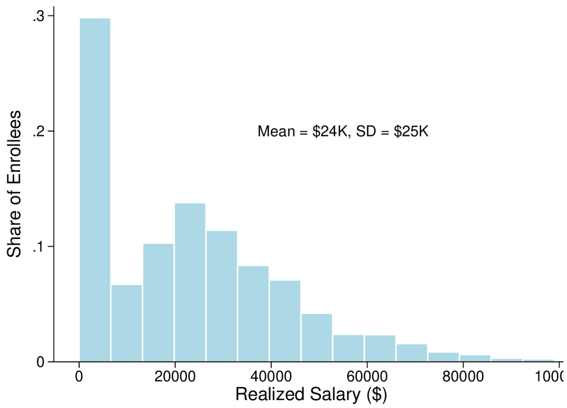
(A) Firms Can Make Profits, $WTA(\theta) < AV(\theta)$ For Some θ



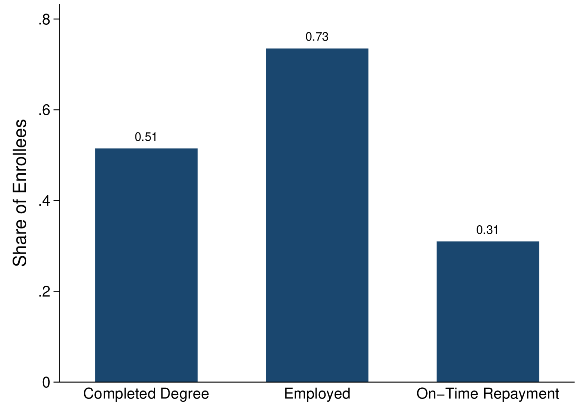
(B) Market Fully Unravels, $AV(\theta) < WTA(\theta)$ For All θ

Note: This figure provides a graphical representation of market unraveling for an earnings-equity contract. The blue line plots the $MV(\theta)$ curve, which is equal to the inverse CDF of expected salary conditional on private information, $E[y|\theta]$. The red line plots the willingness-to-accept curve, $WTA(\theta)$. The green line plots the average value curve, $AV(\theta)$, which corresponds to the average expected salary among those with who expect incomes below the corresponding point on the $MV(\theta)$ line. On the horizontal axis, types θ are enumerated in ascending order based on their willingness to accept, $WTA(\theta)$. Panel A depicts a scenario in which private information is uniformly distributed between \$20,000 and \$80,000. In Scenario A, the financier can make a profit because individuals are willing to accept less than the \$35,000 necessary for a market to be profitable when $\theta = 0.5$. Panel B depicts a scenario in which $E[y|\theta]$ is uniformly distributed \$0 and \$100,000. In Scenario B no one is willing to accept the average value of expected incomes lower than their own, so the market unravels.

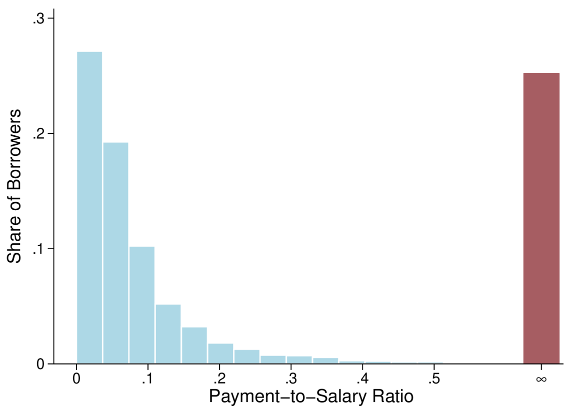
Figure 2: Summary Statistics for Contract Outcomes



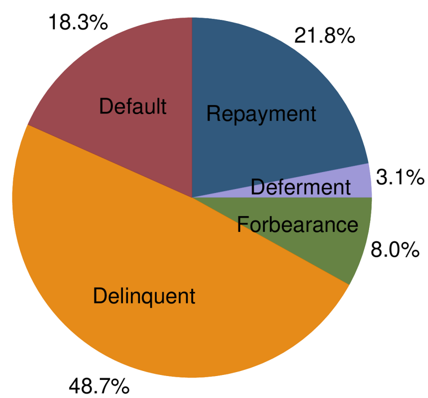
(A) Histogram of Realized Salary



(B) Mean Binary Outcomes



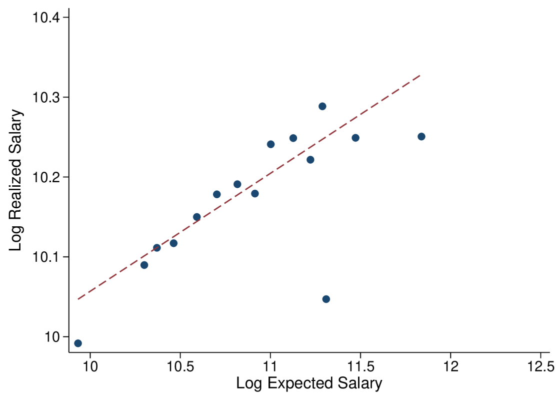
(C) Debt-Payment-to-Salary Ratio



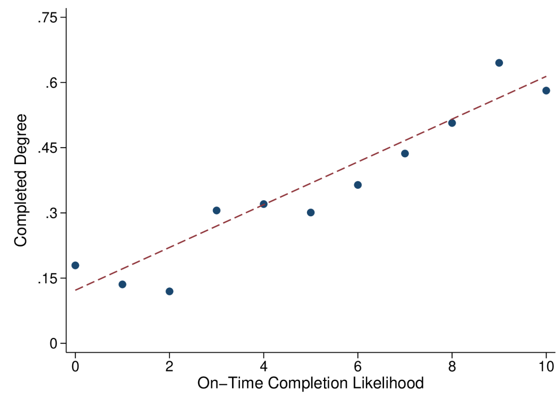
(D) Loan Repayment Status

Note: This figure reports employment and financial outcomes among student borrowers in the 2012 cohort as of 2017. Panel A reports realized salaries, including zeros for those who are unemployed or not in the labor force. Panel B reports mean degree completion and employment for all students in our sample, as well as the share of borrowers in our sample with no delinquencies. Panel C reports a histogram of monthly loan-payment-to-salary ratios among student borrowers who have begun the repayment period on their federal student loans. The "∞" bar represents the portion of borrowers who report not having employment in 2017. Panel D reports a pie chart of loan status among borrowers in repayment. Each portion of the pie represents the share of borrowers whose most severe non-repayment event since leaving college corresponds to the labeled status. For example, those who are in default are delinquent but are counted as "Default" in the chart above. Sample and variable definitions are provided in Table 1. Statistics are adjusted using cross-sectional BPS survey weights to reflect the national population of first-time college enrollees in 2012. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

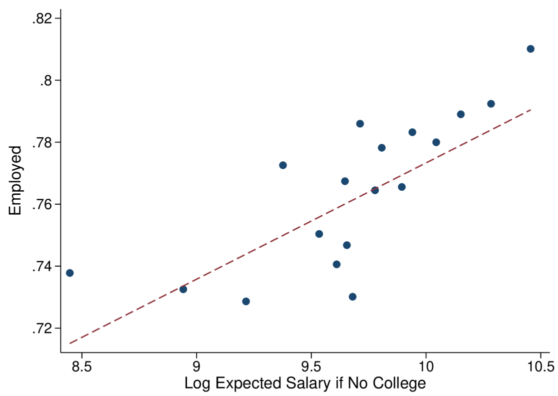
Figure 3: Realizations Versus Elicitations



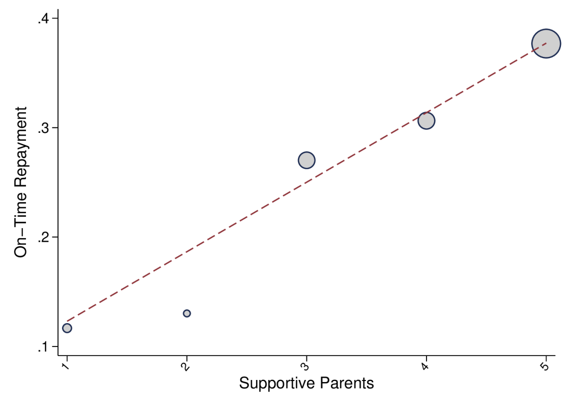
(A) Salary



(B) Completion



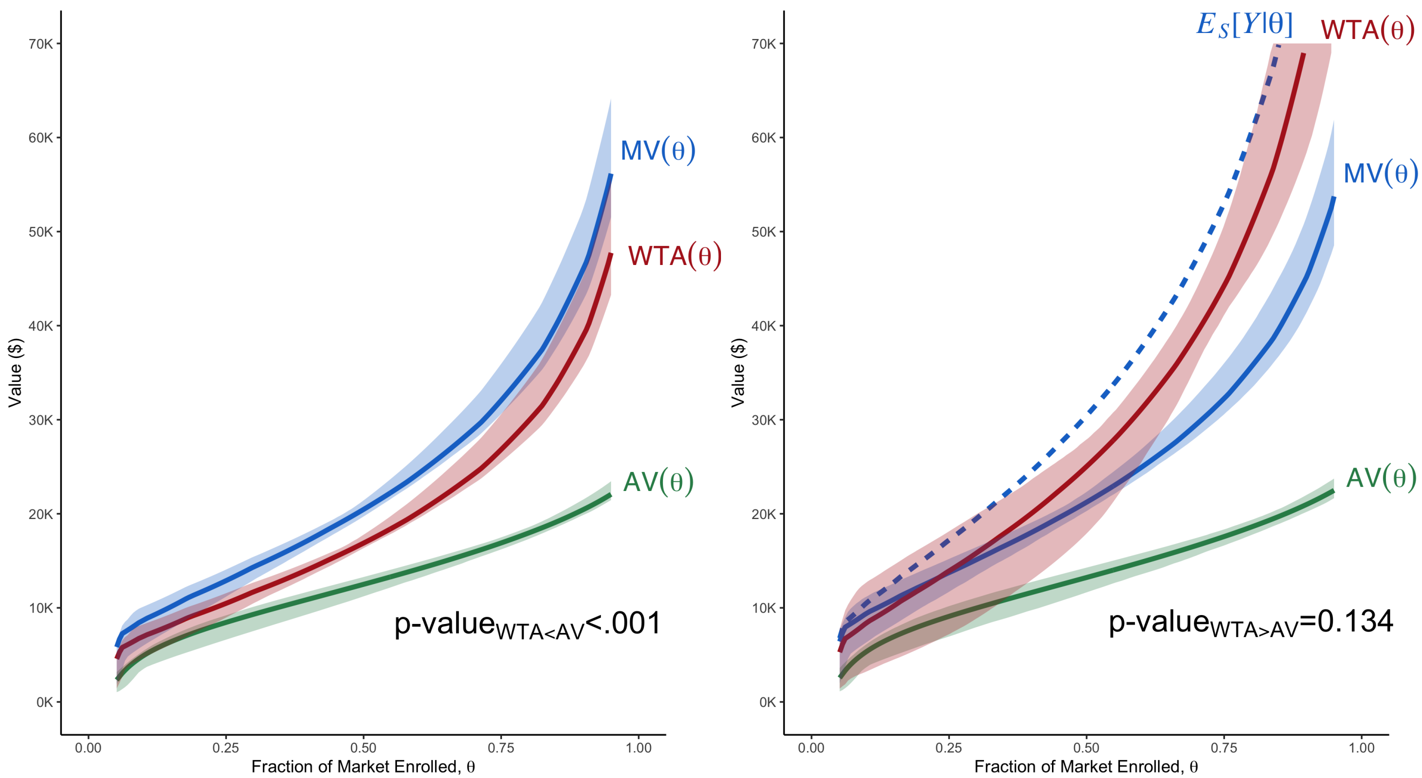
(C) Employment



(D) On-Time Repayment

Note: This figure plots realized outcomes against subjective elicitations asked in the 2012 survey. Panels A through C report binned scatter plots. Panel A reports the relationship between log salary in 2017 against an individual's log of expected salary. Panel B reports reports the likelihood of completing college against the elicited likelihood of on-time completion. Panel C reports the likelihood of being employed against the log salary the respondent would expect if they were not enrolled in college. Panel D reports average loan repayment by respondents' responses when asked whether they agree with the statement, "My parents encourage me to stay in college." Responses are coded as (1) "Strongly disagree," (2) "Somewhat disagree," (3) "Neither disagree nor agree," (4) "Somewhat agree," and (5)"Strongly agree." Grey bubbles reflect relative number of individuals reporting each response. In all four panels, dotted lines denote linear OLS predictions. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

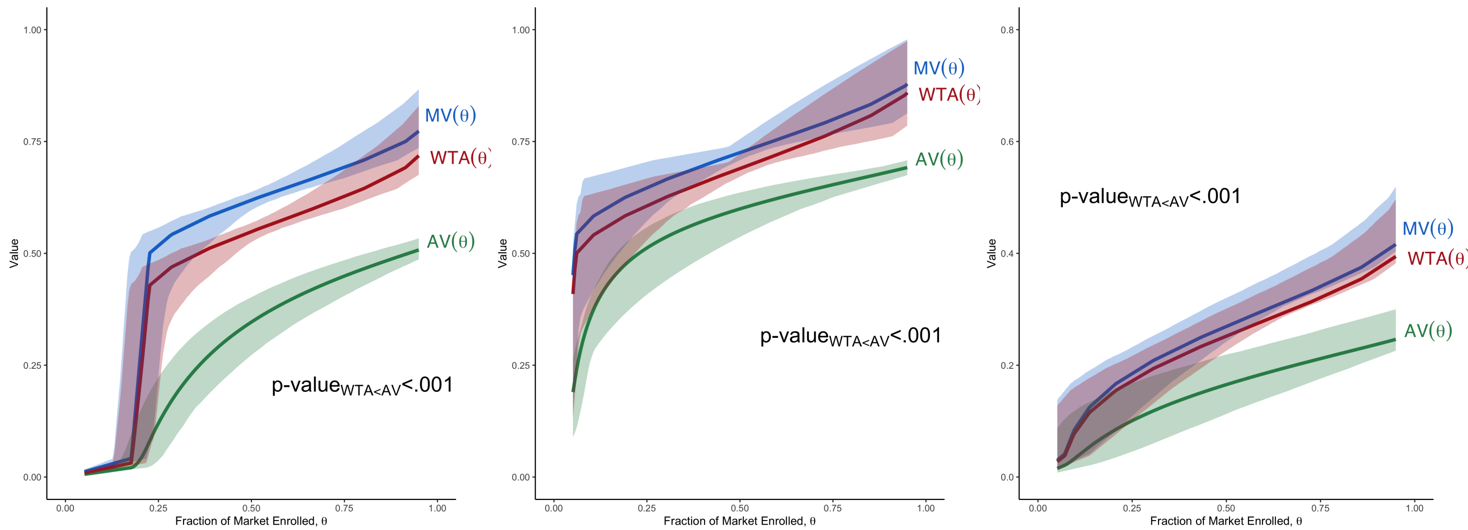
Figure 4: Estimates of Average Value and Willingness-to-Accept Curves for Earnings Equity Market



(A) Rational Beliefs **(B) Biased Beliefs**

Note: This figure plots willingness-to-accept and value curves for the earnings-equity market. We plot each curve against the fraction of the market insured, θ, on the horizontal axis. The solid blue line plots the marginal value curve, $MV(\theta)$. The green line presents the average value curve, $AV(\theta)$. The red line presents the willingness-to-accept curve, $WTA(\theta)$. Panel A plots the rational belief specification, in which $MV(\theta)$ corresponds to unbiased beliefs of future salary. Panel B plots the biased beliefs specification, in which the CDF of subjective salary expectations, $E_S[y|\theta]$, is given by the dashed blue line. Results are conditional on academic and insitution categories of public information, as defined in Appendix Table A1. The shaded region presents 95% confidence intervals constructed via bootstrap resampling. We also present the p-value for a test of the market unraveling condition in equation (7), which is given by the fraction of bootstrap draws for which there exists a value of θ such that $WTA(\theta) < AV(\theta)$. Note that this p-value accounts for correlated sampling error between the $WTA(\theta)$ and $AV(\theta)$ curves. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

Figure 5: Estimates of Average Value and Willingness-to-Accept Curves for State-Contingent Loan Markets

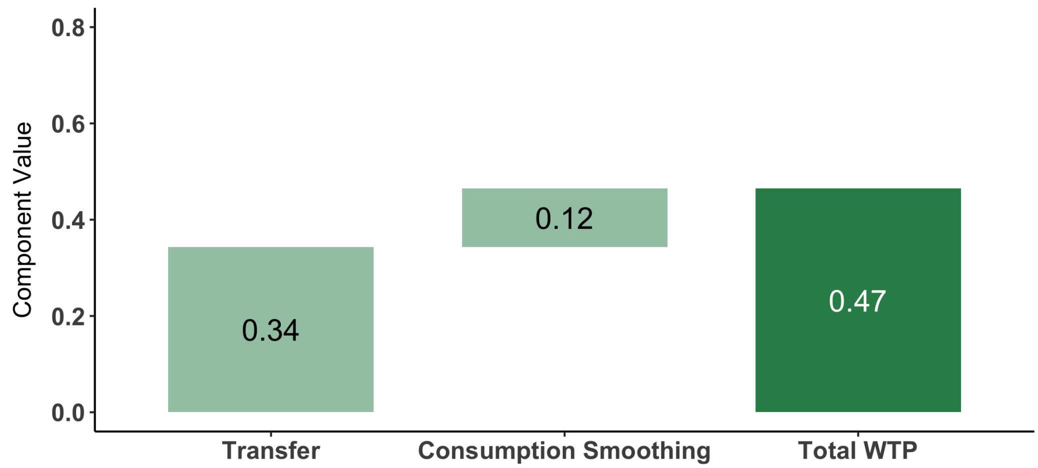


(A) Completion-Contingent Loan **(B) Employment-Contingent Loan** **(C) Dischargeable Loan**

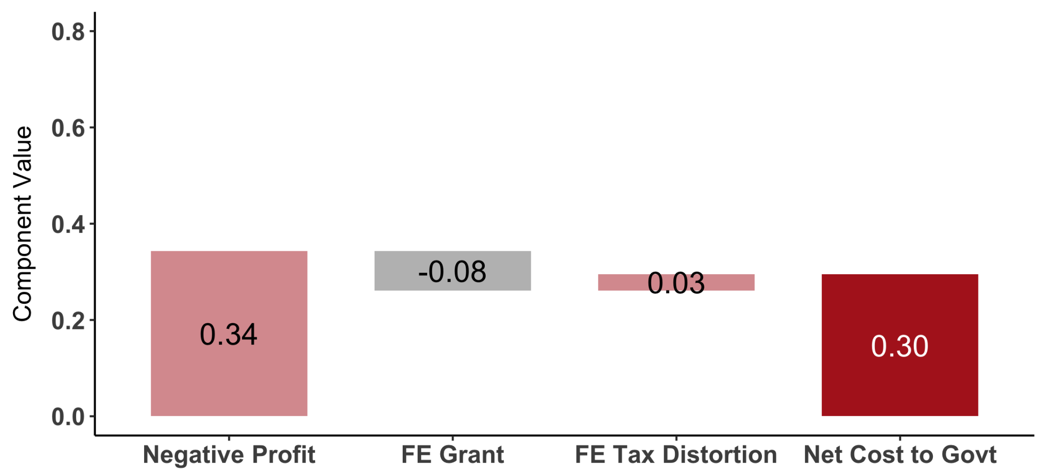
Note: This figure plots the willingness-to-accept and value curves for the three state-contingent loan markets. We plot each curve against the fraction of the market insured, θ, on the horizontal axis. The blue line plots the marginal value curve, $MV(\theta)$. The green line presents the average value curve, $AV(\theta)$. The red line presents the willingness-to-accept curve, $WTA(\theta)$. Panel A presents the results for the state-contingent debt market with repayment only if the borrower graduates, Panel B presents the results for the state-contingent debt market with repayment only in the event of employment, and Panel C presents the results for the dischargeable loan market requiring repayment only if not delinquent on traditional student loans. Results are conditional on academic category of public information, as defined in Appendix Table A1. The shaded region presents 95% confidence intervals constructed via bootstrap resampling. We also present the p-value for a test of the market unraveling condition in equation (7), which is given by the fraction of bootstrap draws for which there exists a value of θ such that $WTA(\theta) < AV(\theta)$. Note that this p-value accounts for correlated sampling error between the $WTA(\theta)$ and $AV(\theta)$ curves. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

Figure 6: MVPF Components for Earnings-Equity Subsidy

(A) Willingness to Pay Decomposition



(B) Net Government Cost Decomposition



Note: This figure reports components of the marginal value of public funds (MVPF) for subsidizing an earnings-equity contract under rational beliefs, defined in Section 6. The MVPF is calculated for a program offering one dollar of equity financing at the price that would be actuarially fair under no private information, $\lambda = E[y]$. Panel A decomposes aggregate willingness-to-pay (the MVPF numerator) into two components: a "transfer" component, which equals the average expected surplus contractees would receive, and a "consumption smoothing" component, which equals the added welfare from the contracts' insurance benefits. Panel B decomposes net government costs (the MVPF denominator) into three components: the contract's expected negative profits (i.e., expected transfer to individuals), the fiscal externality resulting from the provision of the education finance ("FE Grant"), and the fiscal externality resulting from the provision of the education finance ("FE Tax Distortion"). Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

Table 1: Summary Statistics: Elicitations and Realizations

Category	Variable	Mean	SD
Panel A: Ex-Ante Elicitations	Ever Completion Likelihood	9.314	1.838
	On-Time Completion Likelihood	8.413	2.103
	Expected Completion Year	2014.3	1.091
	Likelihood of Employment in Expected Occ.	8.154	1.734
	Exp. Occ. Employed	0.847	0.0937
	Expected Salary	64064.2	44800.8
	Highest Expected Salary	117110.8	142762.8
	Lowest Expected Salary	43923.5	26926.0
	Expected Salary if No College	17332.5	7823.6
	Exp. Occ. Salary	30073.1	8503.5
	Elicited Discount Factor	0.370	0.321
	Supportive Friends	4.372	0.971
	Supportive Classmates	4.226	1.071
	Supportive Parents	4.227	1.072
	Parent Financial Support	6463.8	9512.1
Panel B: Ex-Post Outcomes	Completed Degree	0.515	0.500
	Completed Degree On-Time	0.413	0.492
	On-Time Repayment	0.310	0.462
	Delinquent	0.620	0.485
	Default	0.165	0.371
	Employed	0.735	0.441
	Unemployed	0.123	0.328
	Realized Salary	32701.5	24345.6
	Number of Credit Cards	1.051	0.816
	Credit Card Balance	1234.9	3171.3
	Paid Credit Card Balance	0.604	0.489

Note: This table provides summary statistics for the complete set of outcomes and elicitations used in our non-parametric deconvolution, and maximum-likelihood exercises. Data are taken from the 2012-2017 Beginning Post-secondary Students (BPS) study. Elicitations are measured in winter and spring of 2012. Outcomes are measured in the spring of 2017. "Completed Degree" indicates whether the respondent had completed their intended degree as of June 2017. "Non-Repayment" indicates whether the respondent reported being in default, delinquency, or forbearance on their student loans at least once since beginning repayment. "Employed" indicates whether the respondent reported holding a job at some point between February and June of 2017. "Unemployed" indicates whether the respondent was not employed and looking for work for one or more months since leaving college. "Realized Salary" is the respondent's reported salary for their most recently held job since February 2017, excluding those without jobs. "Number of Credit Cards" and "Credit Card Balance" provides the self-reported total number and monthly balance on credit cards among respondents who held credit cards in 2017. "Paid Credit Card Balance" indicates credit-card holders said they do not usually carry a balance month to month. Elicitations are defined in Appendix C. Statistics are adjusted using cross-sectional BPS survey weights to reflect the national population of first-time college enrollees in 2012. Sample size is 22,530 individuals, rounded to the nearest ten. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

Table 2: Summary Statistics: Public Information

Category	Variable	Mean	SD
Academic	Age	20.54	5.948
	BA Program	0.472	0.499
	STEM Major	0.476	0.499
Institution	Four-Year	0.540	0.498
	Private	0.299	0.458
	For-Profit	0.128	0.334
	Enrollment	18218.3	34962.9
	Tuition	9620.2	10939.2
	Share Female	0.573	0.123
	Share Black	0.138	0.163
	Admissions Rate	0.633	0.199
	Completion Rate	0.411	0.245
	Avg. SAT Score	1102.0	137.5
	Md. Parent Income	32142.5	20580.4
	Md. 6-Yr Earnings	29530.3	8106.7
Performance	High School GPA	3.058	0.613
	SAT Score	1008.7	203.3
Demographics	US Citizen	0.945	0.228
	Married	0.0585	0.235
	Children	0.121	0.326
Parental	Parent has BA	0.386	0.487
	Parents Married	0.661	0.473
	Dependent	0.783	0.412
	Parental Income	77816.3	73684.7
	EFC	10245.3	16865.8
Protected Classes	Black	0.176	0.381
	Female	0.565	0.496

Note: This table provides summary statistics for the for key public-information and demographic variables used in our non-parametric deconvolution, and maximum-likelihood exercises. All variables in this table are classified as public information in our various control specifications with the exception of gender and race (these are protected classes and cannot be used in pricing or screening for financial products). Sample size is 22,530 individuals, rounded to the nearest ten. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

Table 3: Presence of Private Information

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Log Salary	β Log Expected Salary	0.113***	0.0594***	0.0446***	0.0428***	0.0425***	0.0414***	0.0451***	0.0373*	0.0348**
		(0.0159)	(0.0160)	(0.0161)	(0.0160)	(0.0160)	(0.0160)	(0.0150)	(0.0198)	(0.0149)
	N	12580	12580	12580	12580	12580	12580	12490	9470	12490
Panel B: Degree Completion	β On-Time Completion	0.0492***	0.0446***	0.0364***	0.0344***	0.0347***	0.0336***	0.0318***	0.0343***	0.0314***
	Likelihood	(0.00223)	(0.00229)	(0.00224)	(0.00225)	(0.00224)	(0.00222)	(0.00221)	(0.00248)	(0.00220)
	N	22340	22340	22340	22340	22340	22340	22310	19010	22310
Panel C: Employment	β Log Expected Salary	0.0313***	0.0231**	0.0212**	0.0197*	0.0187*	0.0180*	0.0119	0.0155	0.0103
	if No College	(0.0107)	(0.0107)	(0.0108)	(0.0107)	(0.0106)	(0.0106)	(0.0106)	(0.0124)	(0.0106)
	N	17480	17480	17480	17480	17480	17480	17430	14190	17430
Panel D: On-Time Repayment	β Supportive Parents	0.0635***	0.0440***	0.0336***	0.0304***	0.0300***	0.0282***	0.0264***	0.0222***	0.0265***
		(0.00505)	(0.00498)	(0.00497)	(0.00491)	(0.00491)	(0.00486)	(0.00471)	(0.00498)	(0.00469)
	N	15520	15520	15520	15520	15520	15520	15450	12450	15450
Control Categories	Academic		X	X	X	X	X	X	X	X
	Institution			X	X	X	X	X	X	X
	Performance				X	X	X	X	X	X
	Demographics					X	X	X	X	X
	Parental						X	X	X	X
	Institution FE							X	X	X
	Institution × Major FE								X	
	Protected									X

Note: This table reports estimated coefficients on elicitation variables with associated standard errors from OLS regressions of outcomes against elicitations and public information. Panels A through D correspond to regressions of log salary, degree completion, employment, and on-time repayment in 2017 against log elicited salary, elicited on-time completion likelihood, elicited log expected salary if no college, and elicited assessment of parental support in 2012, respectively. Columns (1)–(7) include an increasing set of controls for observable information that are classified in Appendix Table A1. Columns (1)–(7) include an increasing set of controls for observable information that are classified in Appendix Table A1. Column (1) includes no additional controls, Column (2) adds controls for academic characteristics, Column (3) adds institution fixed effects, Column (4) adds controls for high school performance, Column (5) adds controls for demographic information, Column (6) adds controls for parental information, and Column (7) adds race and gender dummies. Number of observations are roundedn to the nearest ten. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

Table 4: Lower Bound on Mean Magnitude and Presence of Private Information

		(1)	(2)	(3)	(4)	(5)
Panel A: Log Salary	$E[m^Z]$	.5256	.4319	.3247	.2691	.2413
	p-value	6.0e-60	3.4e-09	1.1e-08	5.0e-08	9.6e-10
	N	12580	12580	12580	12580	12490
Panel B: Degree Completion	$E[m^Z]$	.2175	.1496	.1245	.1101	.1113
	p-value	3.e-239	5.3e-90	8.8e-79	1.9e-74	1.8e-72
	N	22340	22340	22340	22340	22310
Panel C: Employment	$E[m^Z]$	.1162	.0961	.0643	.0502	.0466
	p-value	3.0e-05	.0198	.0145	.0136	.0793
	N	17480	17480	17480	17480	17430
Panel D: On-Time Repayment	$E[m^Z]$	.1201	.1059	.0613	.0418	.0403
	p-value	3.0e-55	4.0e-14	5.3e-13	5.9e-11	3.4e-10
	N	15520	15520	15520	15520	15450
Control Categories	Academic		X	X	X	X
	Institution		X	X	X	X
	Performance			X	X	X
	Demographics			X	X	X
	Parental				X	X
	Protected					X

Note: This table reports lower bounds on magnitude, $E\left[m^Z\right]$, and joint significance of private information found in elicitations. Rows labeled $E\left[m^Z\right]$ report estimates the lower bound on the average difference between the average value curve, $AV(\theta)$, and the marginal value curve, $MV(\theta) \equiv E[Y|\theta]$, for each of our four contracts. $E\left[m^Z\right]$ values are calculated from equation 28 using out-of-sample random-forest predictions $E[Y|X_i,Z_i]$ and $E[Y|X_i]$, where Z is the set of all eliciations and X_i includes publicly known observables corresponding to each column label. Rows labeled "p-value" report p-values from F-tests on the joint significance of all elicitations, Z, in OLS regressions of each outcome, Y, against Z and X. Column (1) includes no controls for observable variables. Column (2) adds controls for academic information. Column (3) adds controls for high school performance and demographic information. Column (4) adds controls for parental information. Column (5) adds information on race and gender. Z_i includes all private elicitations in Table 1, as well as any observable variables not included in the specified set of public information, X. These categories are defined in Table 2. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

Table 5: Former and Existing Income-Share Agreements (ISAs)

Provider	Type	Years	Status	Target Group	Notes
Yale University	University	1971 – 1978	Defunct	Undergraduate students	"Yale refunded the difference in payments...several years before most TPO groups were scheduled to stop contributing money" (Ladine, 2001).
My Rich Uncle	Private Company	2000 – 2009	Defunct	Undergraduate and graduate students	"In 2009, the company ran aground...[due to] a lack of investors" (Rudegeair, 2016).
Student Securities	Non-Profit Organization	2003 – 2006	Defunct	Undergraduate students	No website currently functions. The most recent page from internet archives is copyrighted 2005–06 (REEF, 2006).
Lumni USA	Private Company	2011 – 2014	Suspended	Various degrees and certificates	"at the moment, Lumni doesn't have new funds available to finance students through ISAs in the USA" (Lumni, 2022).
Make School	Vocational School	2013 – 2018	Defunct	Vocational students	"The ISA program hasn't turned a profit since 2014" (Berman, 2021).
Base Human Capital	Private Company	2015 – 2019	Defunct	Various degrees and certificates	No website currently functions. The most recently active URL found on internet archives is from January 2019 (Base Human Capital, 2019).
Better Future Forward	Non-Profit Organization	2016 – 2021	Suspended	Undergraduate students	"Currently, all our support dollars have been allocated to other students, and we are not able to review and approve new applications at this time" (BFF, 2022).
Purdue University	University	2016 – 2022	Suspended	Sophomores, juniors, and seniors only	"[The Purdue Research Foundation] decided to pause new ISA originations under Back a Boiler" (Moody, 2021).
Lambda School	Vocational School	2016 –	Continuing	Vocational students	"The Lambda School teaches information technology skills online...Students pay back 17 percent of their income from the first two years of work" (Cowen, 2019).
Mentorworks	Private Company	2016 –	Continuing	STEM juniors, seniors, and vocational students	Federally subsidized through the Community Development Financial Institutions Fund (MentorWorks, 2023).
Point Loma Nazarene University	University	2017 – 2018	Defunct	Undergraduate and vocational students	No reference to ISAs can be found on PLNU's website (Douglas-Gabriel, 2017).
Leif	Private Company	2017 –	Continuing	Primarily vocational students	Primarily serves training and vocational schools. More than 75 percent of applicants have more than a high school degree (Leif, 2021).
Houston Baptist University	University	2018 – 2022	Defunct	Undergraduate students	No reference to ISAs can be found on HBU's website. HBU's servicer, Vemo, collapsed in 2022 (Yoder, 2022).
Brenau University	University	2018 – 2022	Defunct	Undergraduate students	No reference to ISAs can be found on Brenau's website. HBU's servicer, Vemo, collapsed in 2022 (Yoder, 2022).
Colorado Mountain College	College	2018 – 2022	Suspended	DACA students	"Colorado Mountain College, which offered ISAs to undocumented students not eligible for federal aid, has suspended its program indefinitely" (Yoder, 2022).
Vemo	Private Company	2018 – 2022	Defunct	Various degrees and certificates	"One reason Back a Boiler has been suspended is that program servicer Vemo Education went out of business" (Yoder, 2022).

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Table 5 Continued from previous page

Provider	Type	Years	Status	Target Group	Notes
Clarkson University	University	2018 –	Continuing	Juniors and seniors only	"'I can see some risks," [Clarkson CFO] says, noting that...it's still too soon to say if the model will work" (Johnson, 2019).
Messiah University	University	2018 –	Continuing	Undergraduate students	Messiah subsidizes ISA to "guarantee students will never repay more than they were awarded" (Kerr, 2021).
Norwich University	University	2018 –	Continuing	Sophomores, juniors, and seniors only	ISA is designated as a "scholarship type" to which donors can give money. (Norwich University, 2021)
Stride	Private Company	2018 –	Continuing	Juniors and seniors; graduate students	"In order to qualify for an ISA with Stride Funding, you must...be within at least two years of graduation" (Bareham, 2022).
Flatiron School	Vocational School	2019 – 2021	Defunct	Vocational students	"Flatiron School no longer offers an income share agreement or ISA" (Gallinelli, 2019).
Kenzie Academy	Vocational School	2019 – 2022	Defunct	Vocational students	"Kenzie Academy no longer offers Income Share Agreements as a financial option" (Kenzie Academy, 2020).
Lackawanna College	College	2019 – 2022	Suspended	Juniors and seniors; vocational students	"So far the program has reached about 39 students who have 'tapped out all of their borrowing and no other financing options' " (Johnson, 2019).
Northeastern University	Vocational School	2019 – 2022	Defunct	Vocational students	Online application no longer functional. (Northeastern University, 2022)
Placement	Private Company	2019 – 2022	Defunct	Primarily vocational students	"I think the ISA experiment has failed...ISAs tend to have significant adverse selection problems" (Linehan, 2022).
San Diego Workforce Partnership	Non-Profit Organization	2019 – 2022	Suspended	Community college and vocational students	"SDWP's ISA is solely philanthropy funded, with $3.25 million raised so far" (Busta, 2019).
University of Utah	University	2019 – 2022	Suspended	Undergraduate students	"Invest in U...has awarded just 59 ISA contracts" (Johnson, 2019). Program was funded through "a combination of university funds, donations and impact investments from family foundations" (Busta, 2019).
Eastern Kentucky University	University	2020 – 2022	Defunct	Juniors and seniors in aviation and nursing	No website currently functions. The most recent internet archive is dated March, 2022 (EKU, 2022).
Pacific Lutheran University	University	2020 – 2022	Defunct	Undergraduate students	No website currently functions. The most recent internet archive is dated January, 2022 (PLU, 2022).
Rockhurst University	University	2020 – 2022	Suspended	Undergraduate students	No website currently functions. The most recently active URL found on internet archives is from December 2021 (Rockhurst University, 2021).
William Jessup University	University	2020 –	Continuing	Undergraduate students	Designed to crowd-out institutional grants and aid: "Income Share Agreements (ISA) are applied before any other Jessup Aid and will reduce your other scholarships that are subject to commuter limits or tuition limits" (Jessup, 2023).

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Table 5 Continued from previous page

Provider	Type	Years	Status	Target Group	Notes
Robert Morris University	University	2020 –	Continuing	Undergraduate students	"10 RMU students are now utilizing ISAs to help fund their education" (University, 2020).
Student Freedom Iniative	Non-Profit Organization	2021 –	Continuing	STEM junior and senior at HBCUs	Funded through philanthropic donations. "[Donors] contributed $50+ million in financial support...through our Income Contingent Alternative" (Initiative, 2023).
University of Colorado at Boulder	University	2022 – 2022	Defunct	Engineering students	No website currently functions. The most recent internet archive is dated June, 2022 (UC Boulder, 2022).
Stanford Law School	Graduate School	2022 –	Pre-Launch	Law Students	"Stanford Law will...subsidize payments...at a projected annual cost to the school of $200,000 to $300,000...[The ISA] will initially be limited to 20 students" (Sloan, 2022).

Note: This table reports a list of current and former Income-Share Agreement (ISA) programs. The "Provider" column lists the name of the institution offering the ISA. "Type" lists whether the institution is a college/university, vocational school, private company, or non-profit organization. "Years" reports the years in which the ISA was offered. "Status" reports whether the ISA is defunct, indefinitely suspended, or continuing to offer new contracts. "Targeted Group" lists the population that is eligible for each ISA. The "Notes" column reports additional information, such as sources of funding, eligibility criteria, and number of signed contracts.

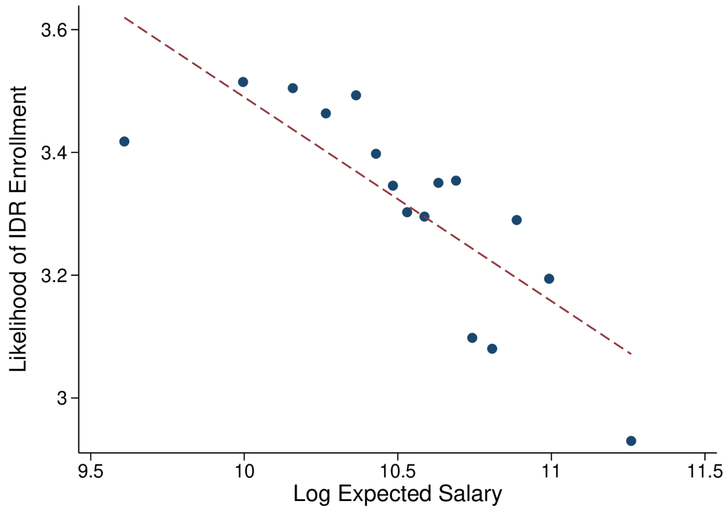
Table 6: MVPF Components

Selection On...		(1) Take-up	(2) Transfer	(3) Consumption Smoothing	(4) WTP	(5) FE Grant	(6) FE Tax Distortion	(7) Cost to Govt	(8) MVPF
Rational Beliefs	Earnings Equity	0.72	0.34	0.12	0.47	0.08	-0.03	0.30	1.58
		(0.01)	(0.03)	(0.01)	(0.03)	(0.00)	(0.00)	(0.03)	(0.10)
	Completion-Contingent Loan	0.52	0.31	0.10	0.41	0.09	-0.13	0.35	1.17
		(0.01)	(0.03)	(0.00)	(0.03)	(0.00)	(0.00)	(0.03)	(0.03)
	Employment-Contingent Loan	0.55	0.11	0.05	0.17	0.10	-0.10	0.12	1.44
		(0.03)	(0.05)	(0.00)	(0.05)	(0.00)	(0.00)	(0.05)	(0.12)
	Dischargeable Loan	0.46	0.55	0.03	0.58	0.09	-0.30	0.76	0.77
		(0.02)	(0.06)	(0.00)	(0.06)	(0.00)	(0.01)	(0.07)	(0.01)
	Grant	1.00	1.00	0.00	1.00	0.14	-0.00	0.86	1.17
		–	–	–	–	–	–	–	–
Biased Beliefs	Earnings Equity	0.52	0.45	0.13	0.58	0.07	-0.03	0.41	1.41
		(0.04)	(0.05)	(0.05)	(0.10)	(0.00)	(0.00)	(0.05)	(0.08)

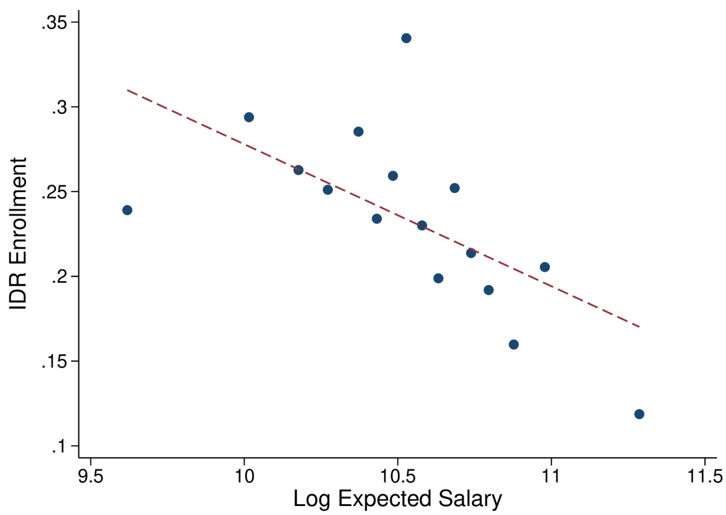
Note: This table reports components of the marginal value of public funds (MVPF), defined in Section 6. Components are reported for each of four hypothetical contracts: salary-based equity contract (row 1), and state-contingent debt contracts that are dischargeable in the event of dropout (row 2), non-employment (row 3), and non-repayment (row 4). For each contract, the MVPF is calculated at prices $\lambda = E[y]$ and $\kappa = \frac{1}{E[y]}$, so that the government would break even if there was no differential selection into the contract. Column (1) reports the "Take-up", which denotes the share of individuals who would accept the contract, column (2) reports the size of the "Transfer", which equals the average expected surplus contractees would receive (i.e., expected negative profits the financier would incur). Column (3) reports the "Consumption Smoothing" benefits individuals derive from the contract. Column (4) reports the willingness to pay by those who choose to take up the contract, which is the sum of the size of the transfer and consumption smoothing benefits. Columns (5)–(6) turn to the components of costs that arise from fiscal externalities from behavioral responses to the financing. Column (5) reports the size of the fiscal externality resulting from the provision of the education finance, "FE Grant". Column (6) reports the fiscal externality from the distortion associated with the implicit tax on earnings associated with the risk-mitigating contracts. Column (7) measures total cost, which equals the size of the transfer minus the two fiscal externality terms. Column (8) reports the MVPF, which is the ratio of WTP in Column (4) to net government Cost in Column 7. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

Appendix A Additional Figures and Tables

Figure A1: Log Expected Salary versus Planned and Actual IDR Enrollment



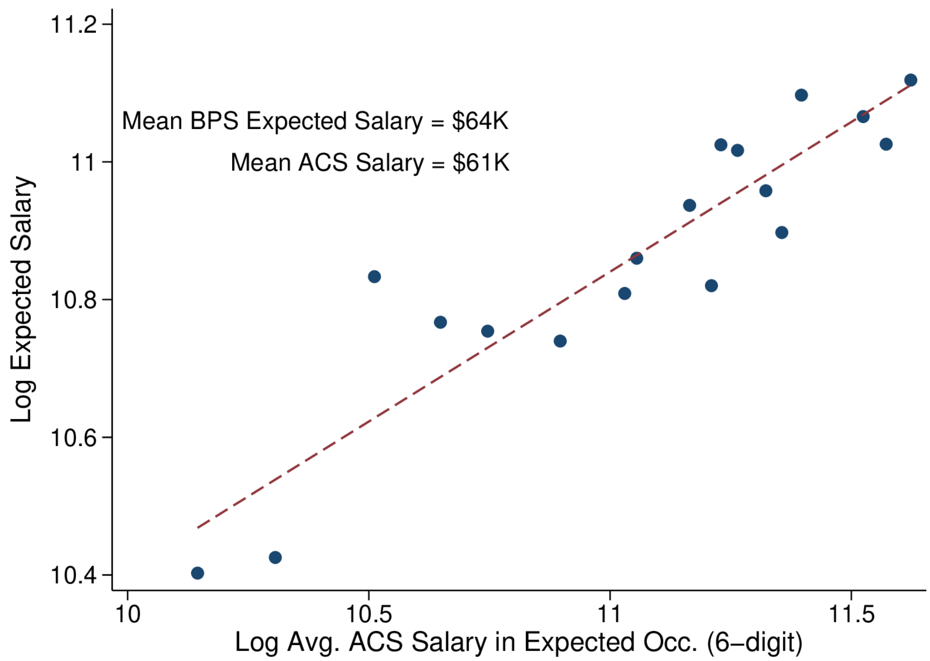
(A) Likelihood of Enrolling in IDR



(B) IDR Enrollment

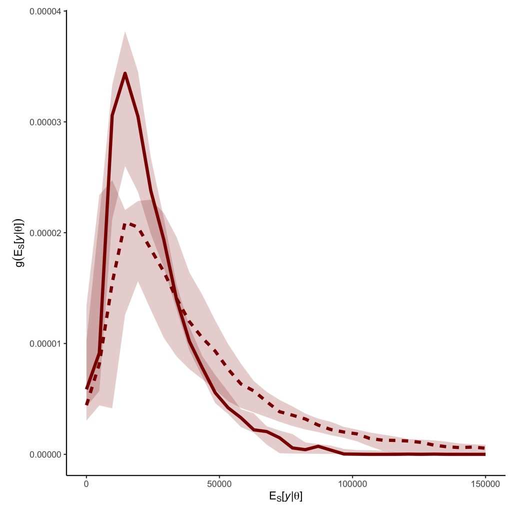
Note: This figure reports binned scatter plots of elicited and realized enrollment in income-driven repayment (IDR) against salary expectation elicitations for a representative sample of 2016 graduating seniors who borrowed student loans. The vertical axis in Panel A measures respondents' stated likelihoods of later enrolling in IDR. The vertical axis in Panel B measures actual IDR enrollment one year later. In both panels, the horizontal axis measures respondents' stated salary expectations. Both plots control for age, type of college, and major field of study. Source: U.S. Department of Education, National Center for Education Statistics, 2016 Baccalaureate and Beyond (B&B16) study, authors' calculations (September 2020)

Figure A2: Log ACS Average Earnings Among 35- to 45-year-old's by Log Expected Salary

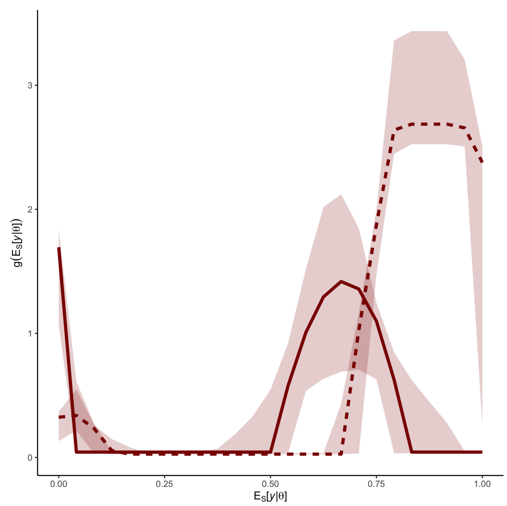


Note: This figure reports a binned scatter plot of respondents' log expected salary elicitations against the log mean realized earnings among 35- to 45-year-olds in the American Communities Survey (ACS) employed the their expected occupation. Dotted lines denote linear OLS predictions. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

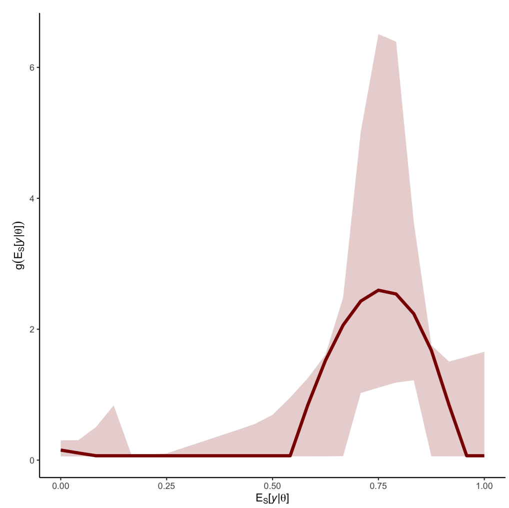
Figure A3: Estimates of Belief Distributions



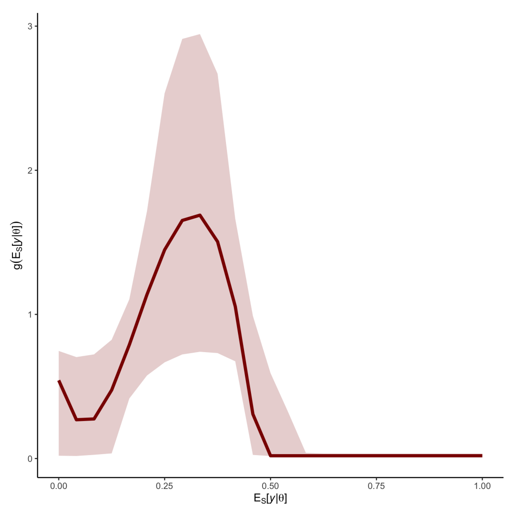
(A) Earnings



(B) Degree Completion



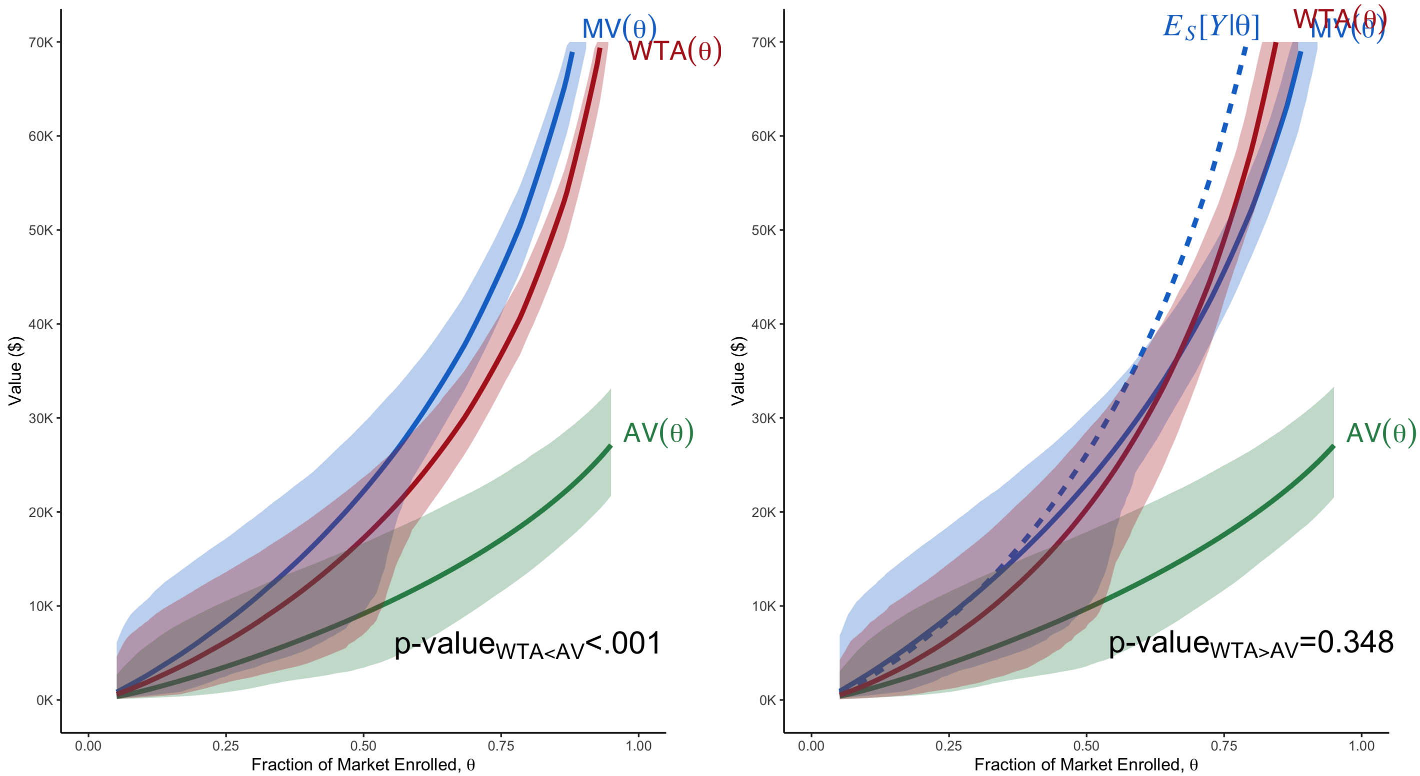
(C) Employment



(D) On-Time Repayment

Note: This figure plots the distributions of privately believed future outcomes, conditional on observables listed in academic and institution categories defined in Appendix Table A1. Solid lines plot estimated densities of rational beliefs, $E\left[Y|\theta,X=x\right]$, where $X=x$ denotes the population with observable characteristics such that $E[Y|X=x]=E[Y]$. Dotted lines plot estimated densities of potentially biased beliefs, $E_S\left[Y|\theta,X=x\right]$, which can only be estimated for earnings and completion outcomes. Panel A plots earnings beliefs, Panel B plots beliefs about college completion, Panel C plots employment beliefs, and Panel D plots beliefs about avoiding any delinquencies on existing student loans. The shaded region presents 95% confidence intervals constructed via bootstrap resampling. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

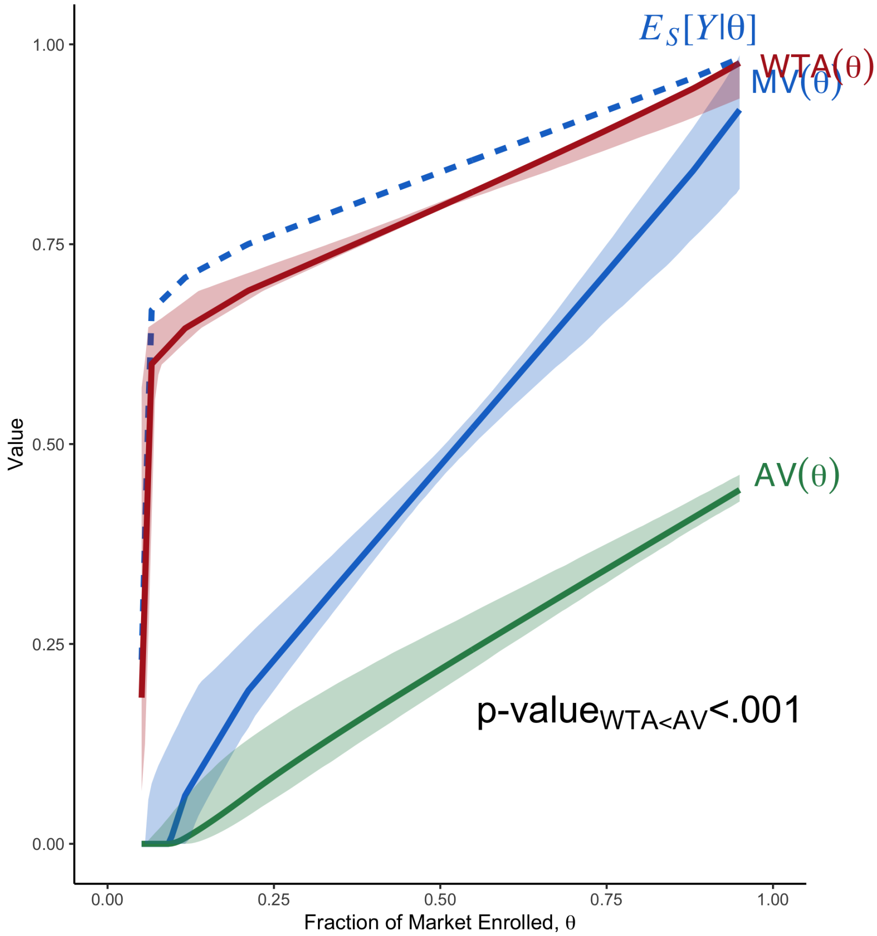
Figure A4: Market Unraveling for High-Potential Students: AV and WTA curves for the Top Quartile of $E[Y|X]$



(A) Rational Beliefs **(B) Biased Beliefs**

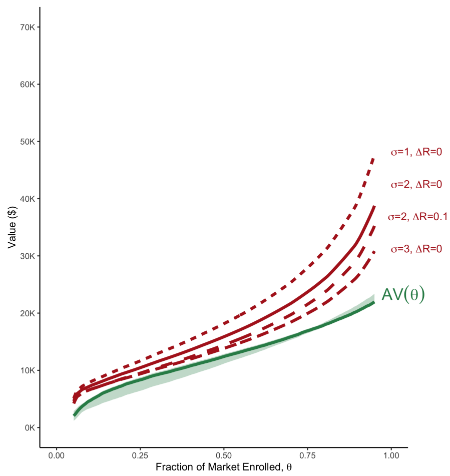
Note: This figure plots willingness-to-accept and value curves for the earnings-equity market for the subsample of individual in the top quartile of publicly predicted income, $E[y|X]$. We plot each curve against the fraction of the market insured, θ, on the horizontal axis. The solid blue line plots the marginal value curve, $MV(\theta)$. The green line presents the average value curve, $AV(\theta)$. The red line presents the willingness-to-accept curve, $WTA(\theta)$. Panel A plots the rational belief specification, in which $MV(\theta)$ corresponds to unbiased beliefs of future salary. Panel B plots the biased beliefs specification, in which the CDF of subjective salary expectations, $E_S[y|\theta]$, is given by the dashed blue line. Results are conditional on academic and insitution categories of public information, as defined in Appendix Table A1. The shaded region presents 95% confidence intervals constructed via bootstrap resampling. We also present the p-value for a test of the market unraveling condition in equation (7), which is given by the fraction of bootstrap draws for which there exists a value of θ such that $WTA(\theta) < AV(\theta)$. Note that this p-value accounts for correlated sampling error between the $WTA(\theta)$ and $AV(\theta)$ curves. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

Figure A5: Market Unraveling Under Biased Beliefs for Completion Contingent Loans

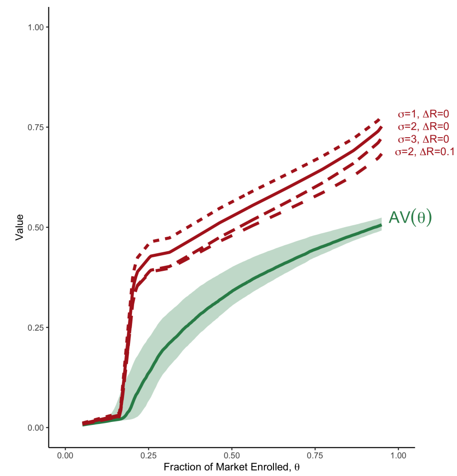


Note: This figure plots the willingness-to-accept and value curves for the state-contingent debt market with repayment only if the borrower graduates, allowing for potentially biased beliefs, $E_S[Y|\theta] \neq E[Y|\theta]$. We plot each curve against the fraction of the market insured, θ, on the horizontal axis. The blue line plots the marginal value curve, $MV(\theta)$. The green line presents the average value curve, $AV(\theta)$. The red line presents the willingness-to-accept curve, $WTA(\theta)$. Results are conditional on academic category of public information, as defined in Appendix Table A1. The shaded region presents 95% confidence intervals constructed via bootstrap resampling. We also present the p-value for a test of the market unraveling condition in equation (7), which is given by the fraction of bootstrap draws for which there exists a value of θ such that $WTA(\theta) < AV(\theta)$. Note that this p-value accounts for correlated sampling error between the $WTA(\theta)$ and $AV(\theta)$ curves. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

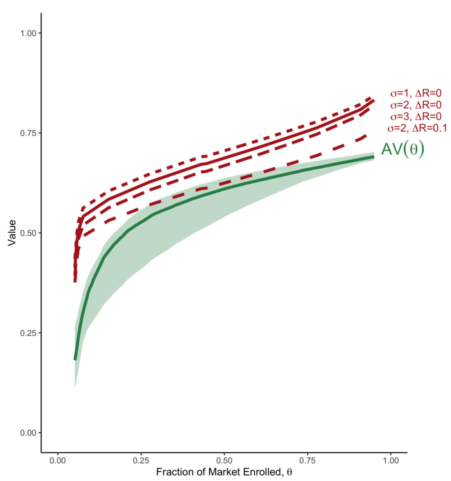
Figure A6: AV and WTA Curves Under Alternative WTA Specifications



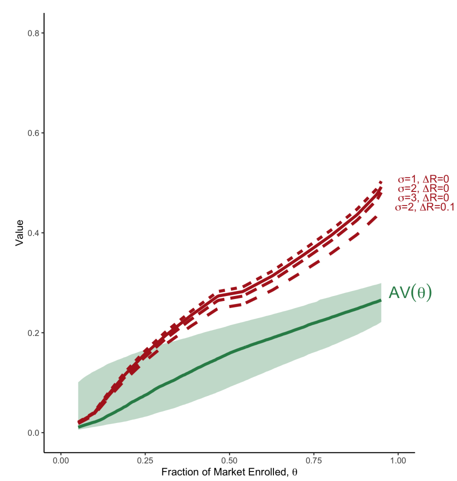
(A) Earnings Equity



(B) Completion-Contingent Loan



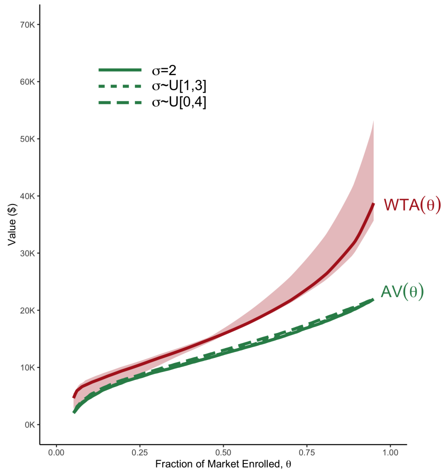
(C) Employment-Contingent Loan



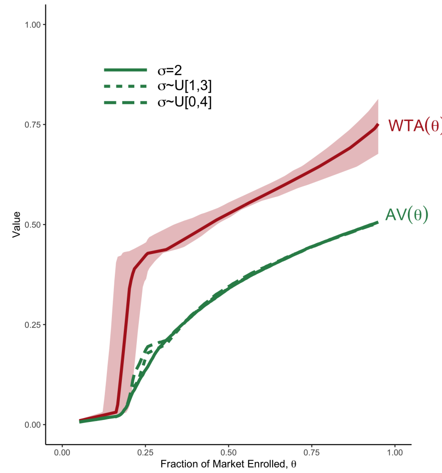
(D) Dischargeable Loan

Note: This figure plots alternative specifications for the willingness-to-accept curve, $WTA(\theta)$, for different values of the coefficient of relative risk aversion, σ, and assumptions about the difference between the interest rate faced by financiers and the implicit interest rate rationalizing the Euler equation of college-goers (ΔR). We plot each curve against the fraction of the market insured, θ, on the horizontal axis. For reference, the green line presents the average value curve, $AV(\theta)$, from the baseline specification. The solid red line presents the willingness-to-accept curve, $WTA(\theta)$, from the baseline specification. The three dashed red lines present alternative specifications for $WTA(\theta)$ using $\sigma = 1$ and $\sigma = 3$, and an alternative specification assuming college-goers face a 10pp higher implicit interest rate than financiers, $\Delta R = 0.10$. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

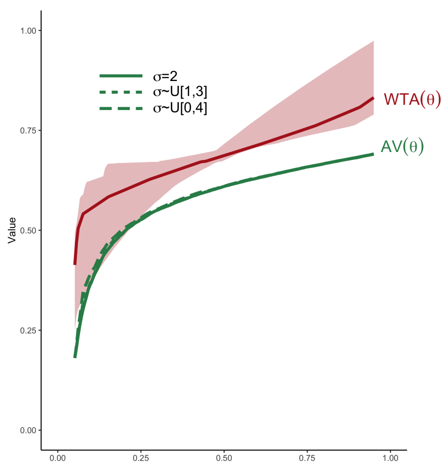
Figure A7: AV and WTA Curves Under Preference Heterogeneity



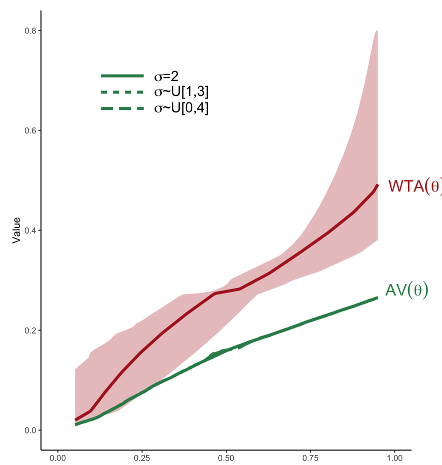
(A) Earnings Equity



(B) Completion-Contingent Loan



(C) Employment-Contingent Loan

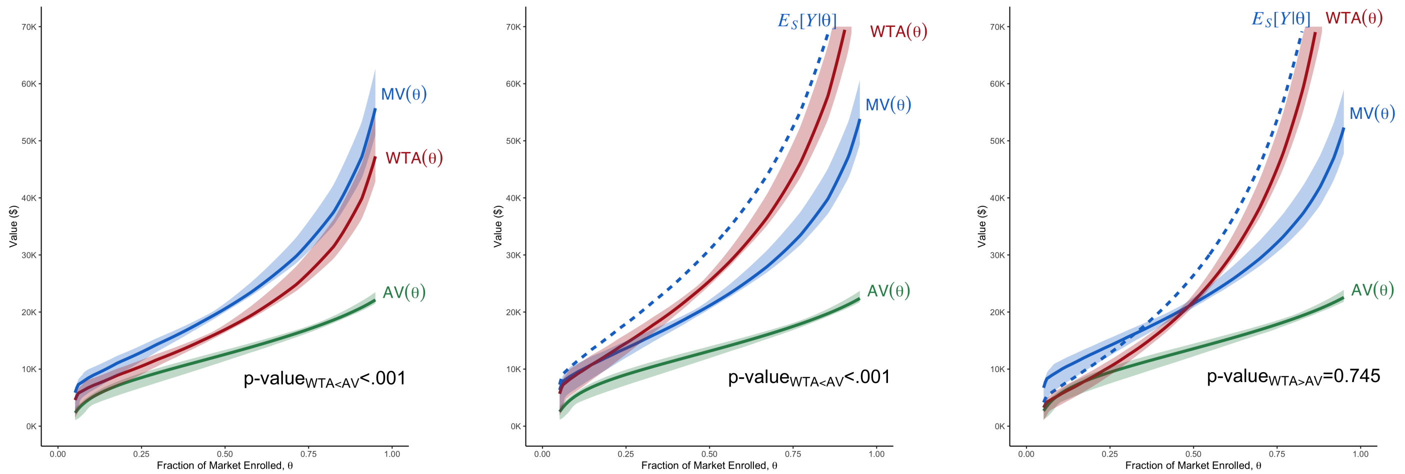


(D) Dischargeable Loan

Note: This figure compares average value and willingness-to-accept under alternative specifications that allow for heterogeneity in risk aversion, σ. The red line presents the quantiles of the willingness to accept from the baseline specification. The solid, dotted, and dashed green lines present average value curves, $AV(\theta)$, under each alternative specification. The $AV(\theta)$ curves using equation (5) as the average value of y for those who have a lower willingness to accept than the plotted value of the willingness to accept curve. For ease of comparison, the figure holds the levels of the $WTA(\theta)$ curve fixed from the baseline specification when computing the AV curve. This allows the figure to illustrate the no trade condition relative to a single standardized $WTA(\theta)$ curve, but the fraction of the market taking up the contract differs slightly from θ across specifications. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

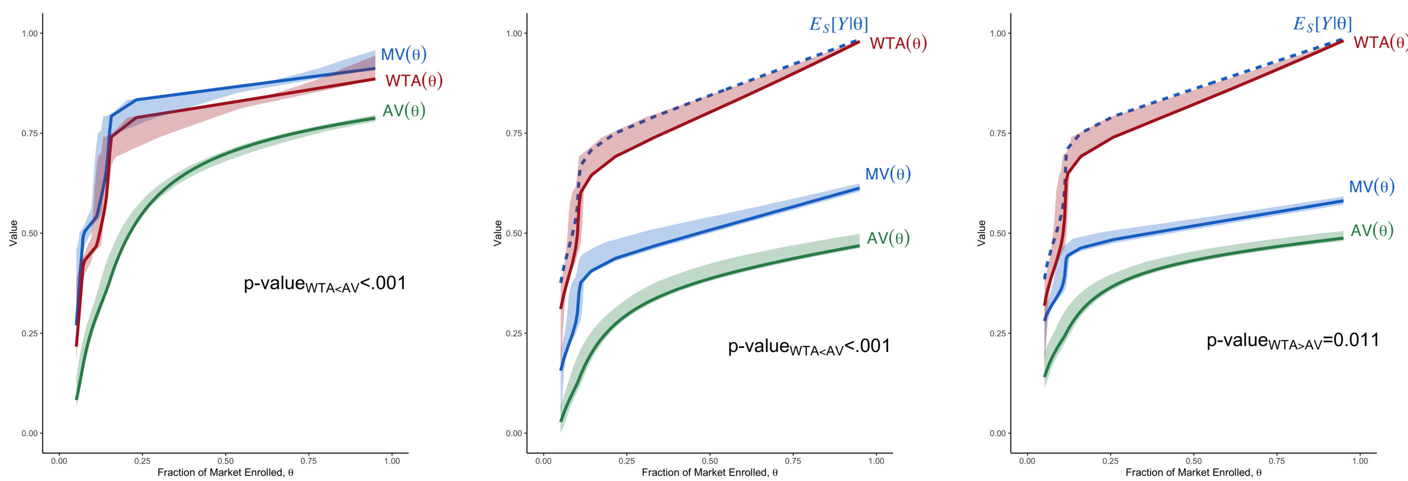
Figure A8: AV and WTA Curves Relaxing IV Assumptions and Using Calibrated γ and b

(I) Earnings Equity



(A) **Rational Beliefs,** $\gamma = 1$, $b = 1$ (B) **Biased Beliefs,** $\gamma = 1$, $b = .75$ (C) **Biased Beliefs,** $\gamma = 1$, $b = .5$

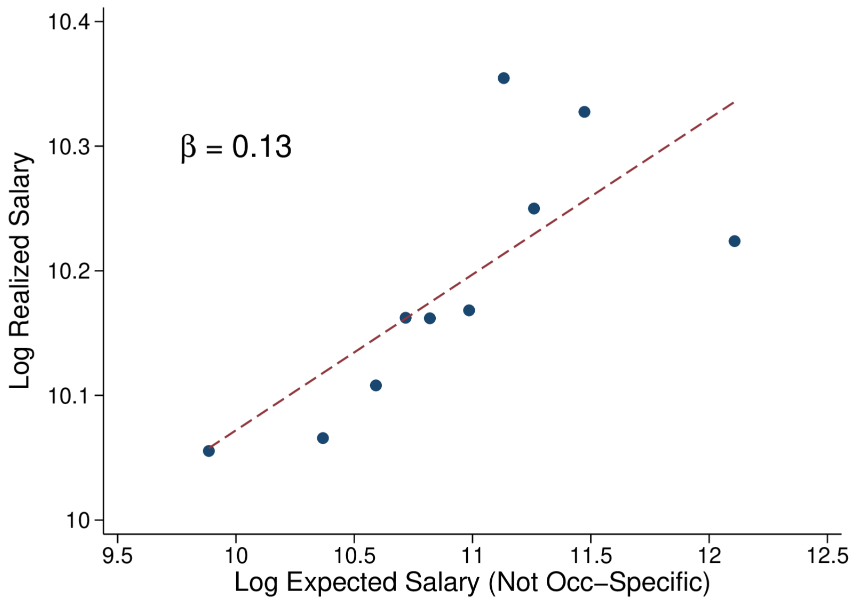
(II) Completion-Contingent Loan



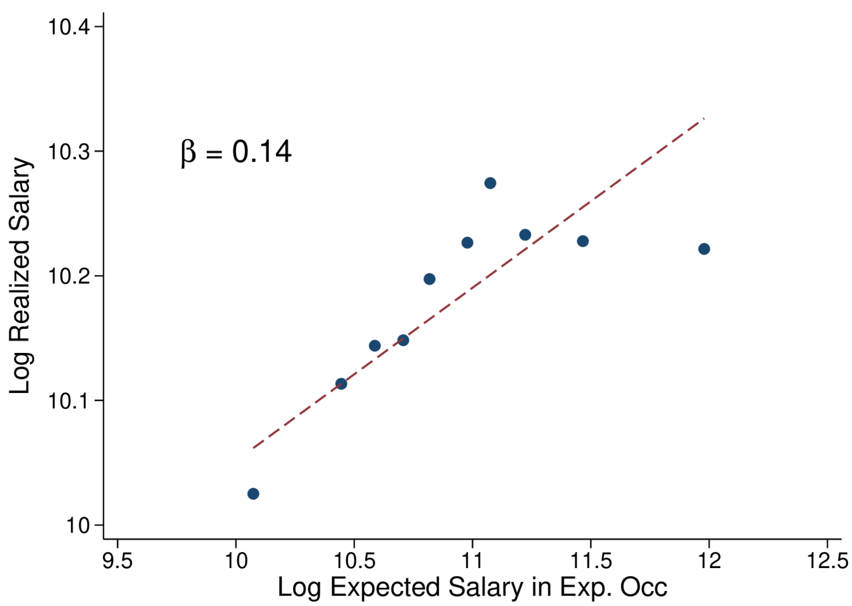
(A) Rational Beliefs, $\gamma = 1$, $b = 1$ **(B) Biased Beliefs,** $\gamma = 1$, $b = .75$ **(C) Biased Beliefs,** $\gamma = 1$, $b = .5$

Note: This figure plots willingness-to-accept and value curves for the earnings-equity and completion-contingent loan markets under different calibrations of γ and b. Curves are defined as in Figure 4. Results are conditional on academic and insitution categories of public information, as defined in Appendix Table A1. The shaded region presents 95% confidence intervals constructed via bootstrap resampling. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

Figure A9: Realizations Versus Elicitations: Abbreviated versus Non-Abbreviated Interviews



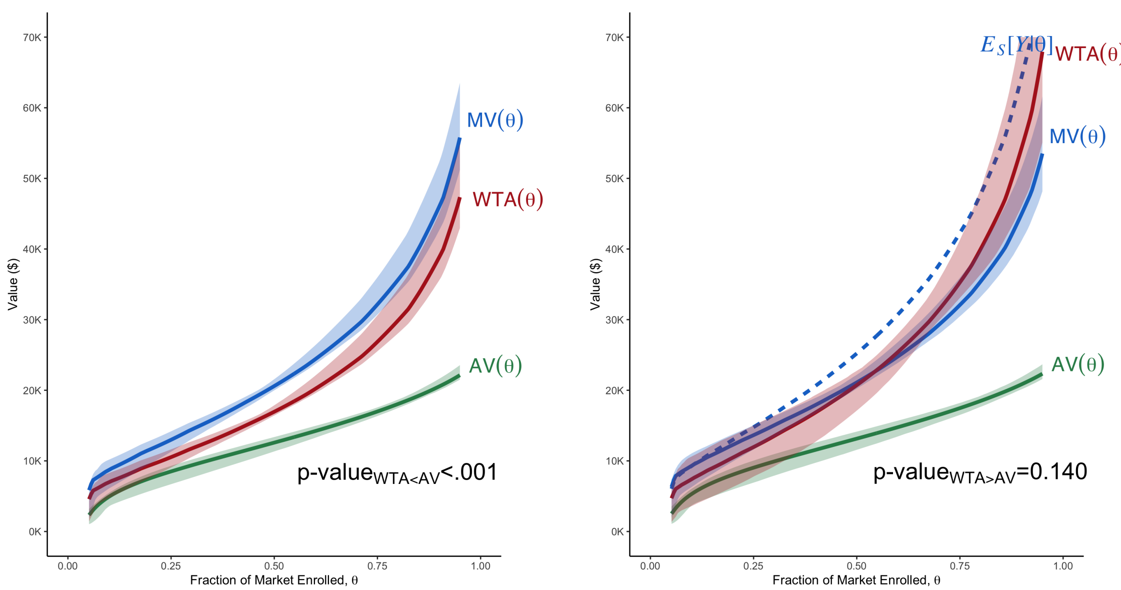
(A) Abbreviated Interview



(B) Unabbreviated Interview

Note: This figure plots binned scatter plots of log realized salary against the log of elicited salary expectations separately by questionnaire wording. Panel A plots the realization-elicitation relationship for a 10% subsample of respondents who received an "abbreviated interview," in which the salary elicitation question was worded as "What do you expect your salary to be once you finish your education?" Panel B plots the same relationship for the remaining 90% of respondents of the standard interview, in which the salary elicitation was worded as in Appendix C: "We have some questions about the range of salary you expect to make once you begin working a [EXPECTED OCCUPATION] job. What is...your expected yearly salary?"

Figure A10: AV and WTA Curves for Earnings-Equity Market using Composite Salary Elicitation

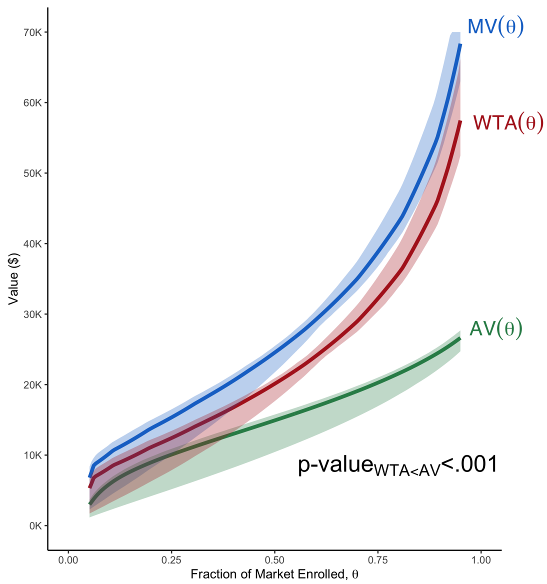


(A) Rational Beliefs **(B) Biased Beliefs**

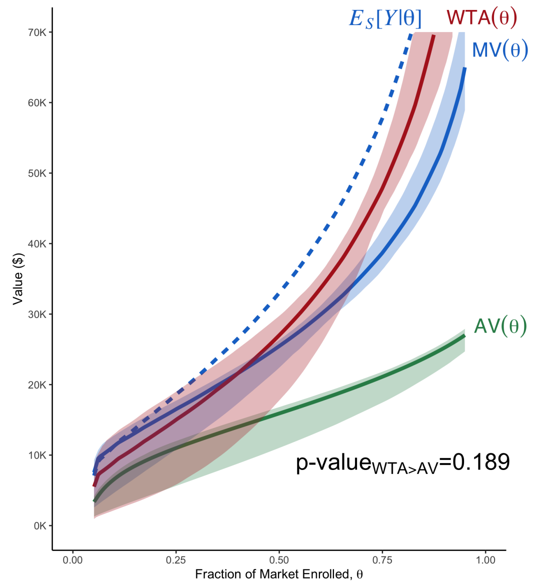
Note: This figure plots willingness-to-accept and value curves for the earnings-equity market using the composite elicitation defined in Equation 20. We plot each curve against the fraction of the market insured, θ, on the horizontal axis. The solid blue line plots the marginal value curve, $MV(\theta)$. The green line presents the average value curve, $AV(\theta)$. The red line presents the willingness-to-accept curve, $WTA(\theta)$. Panel A plots the rational belief specification, in which $MV(\theta)$ corresponds to unbiased beliefs of future salary. Panel B plots the biased beliefs specification, in which the CDF of subjective salary expectations, $E_S[y|\theta]$, is given by the dashed blue line. Results are conditional on academic and insitution categories of public information, as defined in Appendix Table A1. The shaded region presents 95% confidence intervals constructed via bootstrap resampling. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

Figure A11: AV and WTA Curves for Earnings-Equity Market by Gender

(I) Men

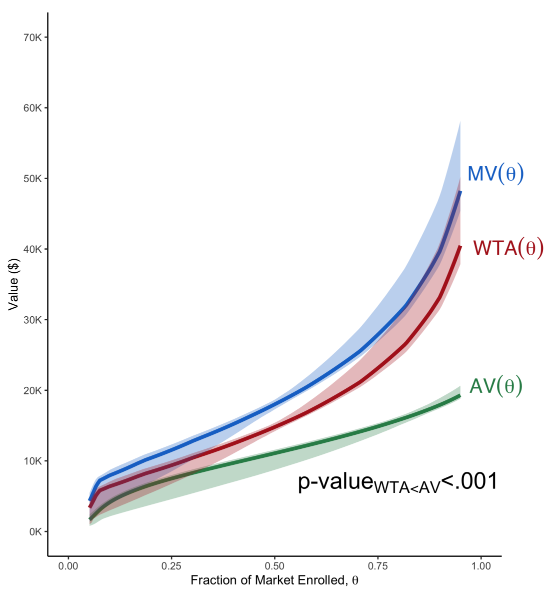


(A) Rational Beliefs

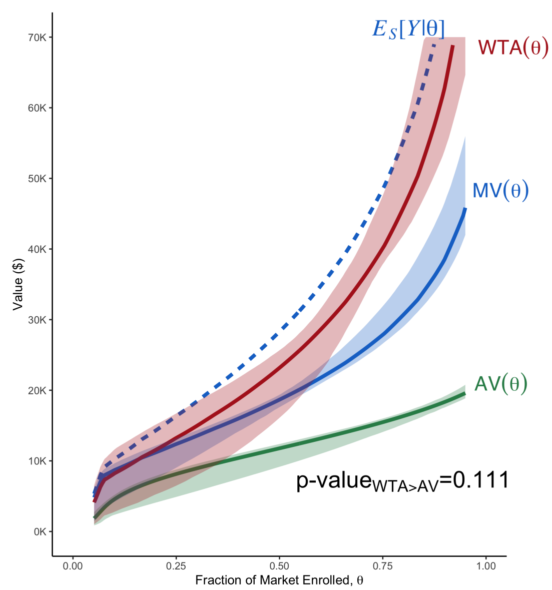


(B) Biased Beliefs

(II) Women



(A) Rational Beliefs

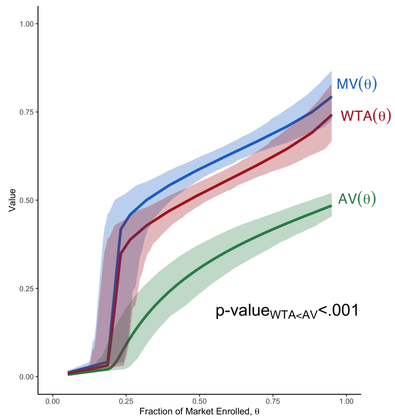


(B) Biased Beliefs

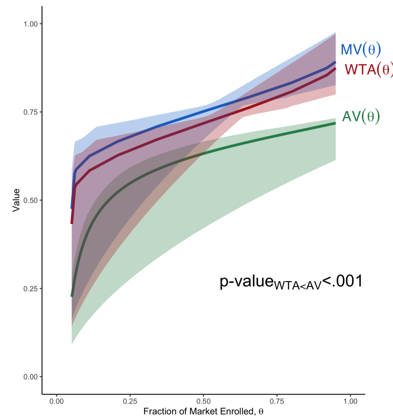
Note: This figure plots willingness-to-accept and value curves for the earnings-equity market separately for men and women. We plot each curve against the fraction of the market insured, θ, on the horizontal axis. The solid blue line plots the marginal value curve, $MV(\theta)$. The green line presents the average value curve, $AV(\theta)$. The red line presents the willingness-to-accept curve, $WTA(\theta)$. Panel A plots the rational belief specification, in which $MV(\theta)$ corresponds to unbiased beliefs of future salary. Panel B plots the biased beliefs specification, in which the CDF of subjective salary expectations, $E_S[y|\theta]$, is given by the dashed blue line. Results are conditional on academic and insitution categories of public information, as defined in Appendix Table A1. The shaded region presents 95% confidence intervals constructed via bootstrap resampling. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

Figure A12: AV and WTA Curves for State-Contingent Loan Markets by Gender

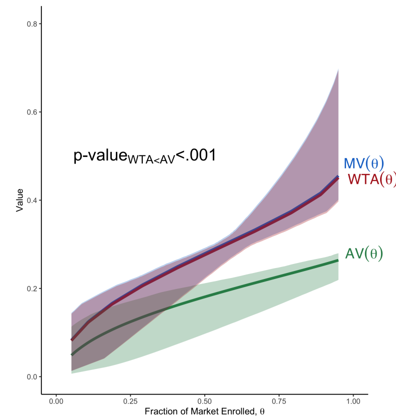
(I) Men



(A) **Completion-Contingent Loan**

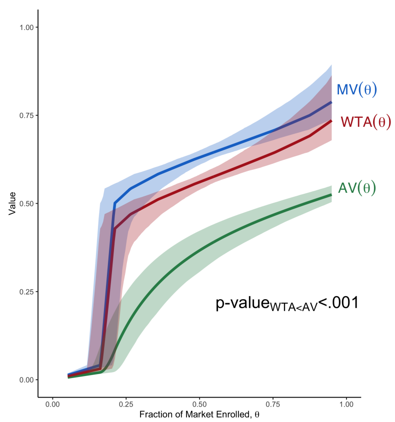


(B) **Employment-Contingent Loan**

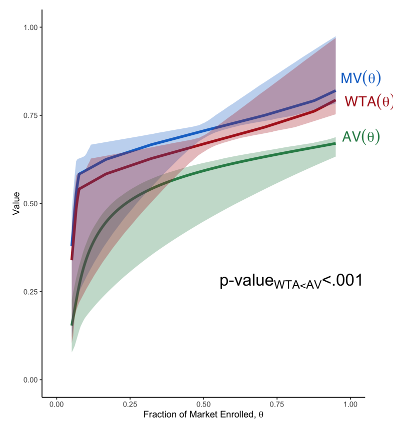


(C) **Dischargeable Loan**

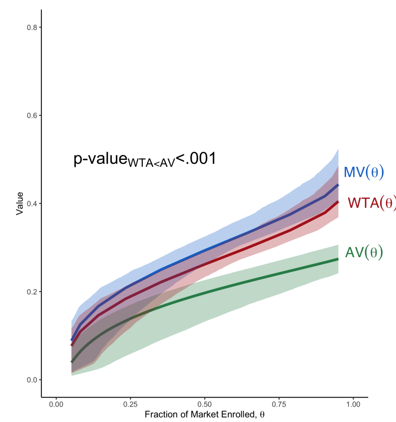
(II) Women



(A) **Completion-Contingent Loan**



(B) **Employment-Contingent Loan**

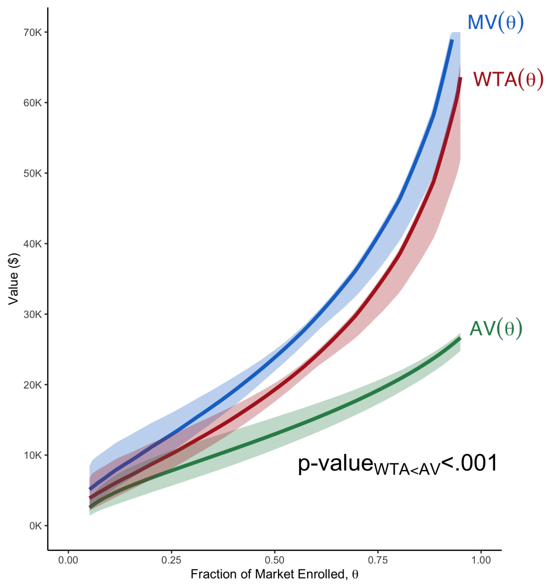


(C) **Dischargeable Loan**

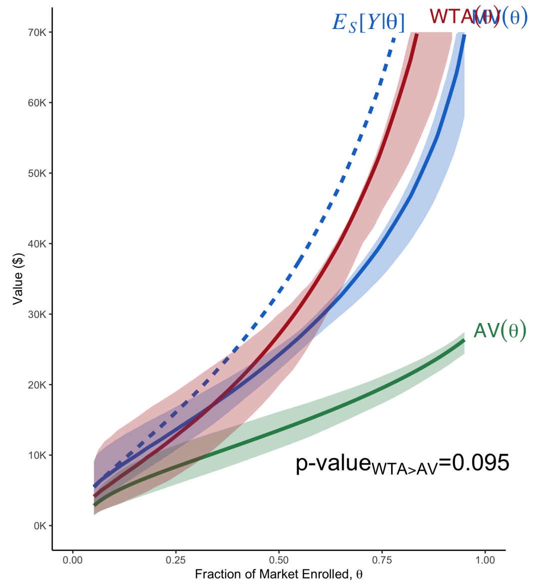
Note: This figure plots willingness-to-accept and value curves for the state-contingent loan markets separately for men and women. We plot each curve against the fraction of the market insured, θ, on the horizontal axis. The solid blue line plots the marginal value curve, $MV(\theta)$. The green line presents the average value curve, $AV(\theta)$. The red line presents the willingness-to-accept curve, $WTA(\theta)$. Results are conditional on academic and insitution categories of public information, as defined in Appendix Table A1. The shaded region presents 95% confidence intervals constructed via bootstrap resampling. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

Figure A13: AV and WTA Curves for Earnings-Equity Market by College Type

(I) Four-Year

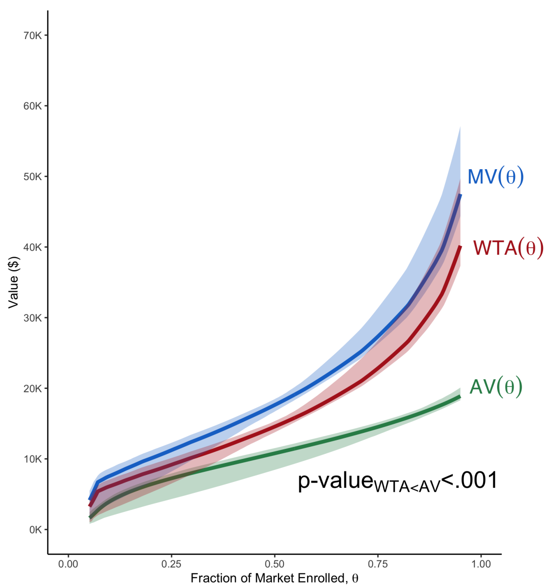


(A) **Rational Beliefs**

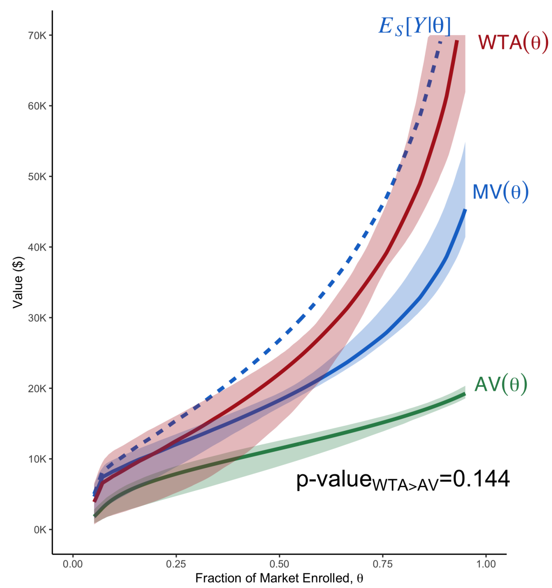


(B) **Biased Beliefs**

(II) Two-Year



(A) **Rational Beliefs**

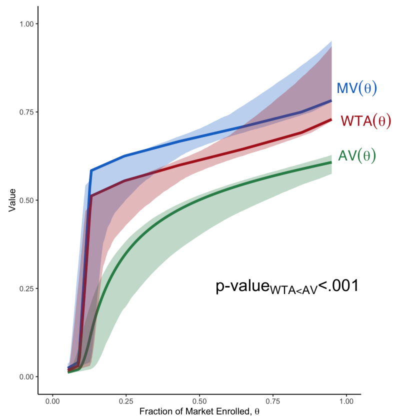


(B) **Biased Beliefs**

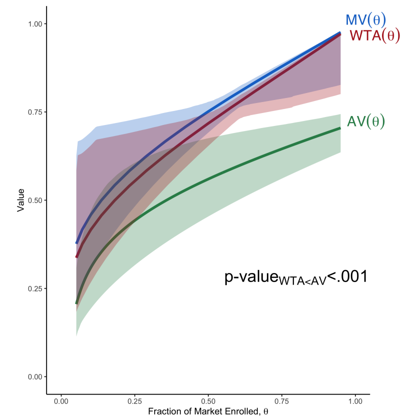
Note: This figure plots willingness-to-accept and value curves for the earnings-equity market for separate subsamples of two- versus four-year college attendees. We plot each curve against the fraction of the market insured, θ, on the horizontal axis. The solid blue line plots the marginal value curve, $MV(\theta)$. The green line presents the average value curve, $AV(\theta)$. The red line presents the willingness-to-accept curve, $WTA(\theta)$. Panel A plots the rational belief specification, in which $MV(\theta)$ corresponds to unbiased beliefs of future salary. Panel B plots the biased beliefs specification, in which the CDF of subjective salary expectations, $E_S[y|\theta]$, is given by the dashed blue line. Results are conditional on academic and insitution categories of public information, as defined in Appendix Table A1. The shaded region presents 95% confidence intervals constructed via bootstrap resampling. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

Figure A14: AV and WTA Curves for State-Contingent Loan Markets by College Type

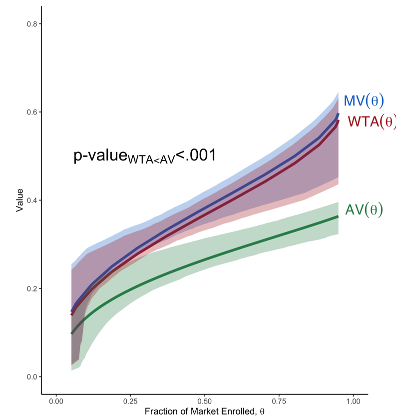
(I) Four-Year



(A) **Completion-Contingent Loan**

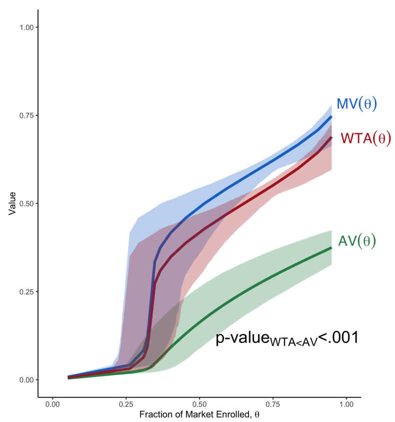


(B) **Employment-Contingent Loan**

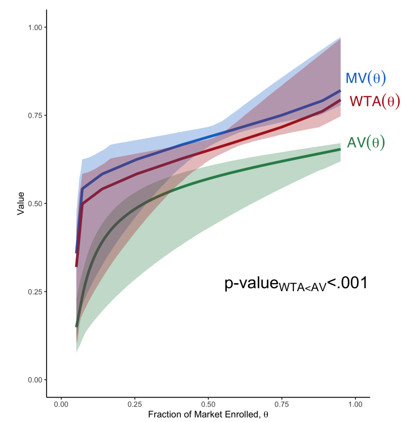


(C) **Dischargeable Loan**

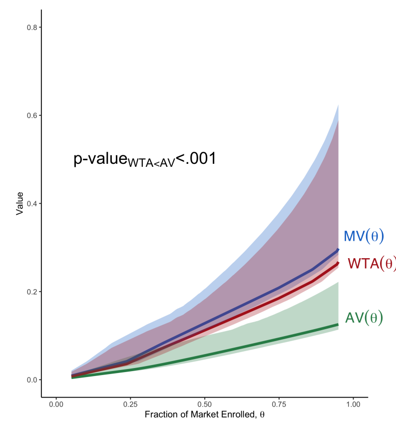
(II) Two-Year



(A) **Completion-Contingent Loan**



(B) **Employment-Contingent Loan**

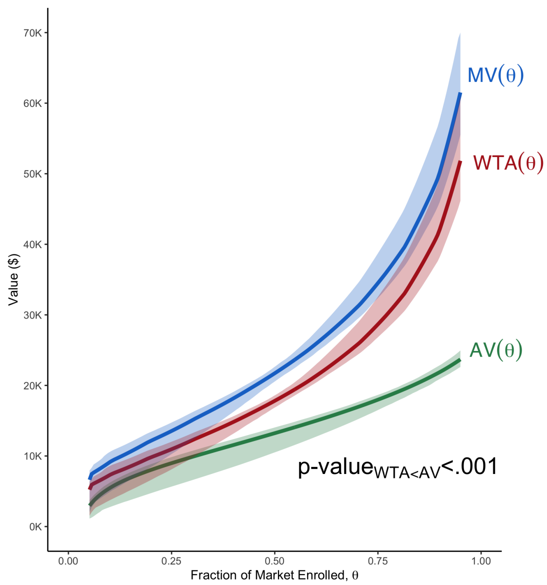


(C) **Dischargeable Loan**

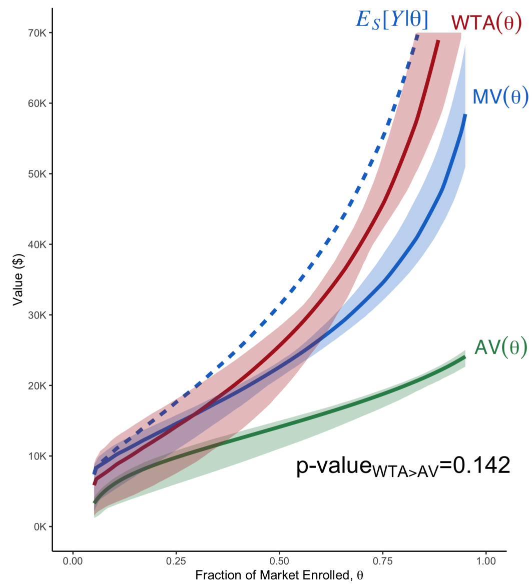
Note: This figure plots willingness-to-accept and value curves for the state-contingent loan markets for separate subsamples of two- versus four-year college attendees. We plot each curve against the fraction of the market insured, θ, on the horizontal axis. The solid blue line plots the marginal value curve, $MV(\theta)$. The green line presents the average value curve, $AV(\theta)$. The red line presents the willingness-to-accept curve, $WTA(\theta)$. Results are conditional on academic and insitution categories of public information, as defined in Appendix Table A1. The shaded region presents 95% confidence intervals constructed via bootstrap resampling. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

Figure A15: AV and WTA Curves for Earnings-Equity Market by STEM versus Non-STEM Fields

(I) STEM

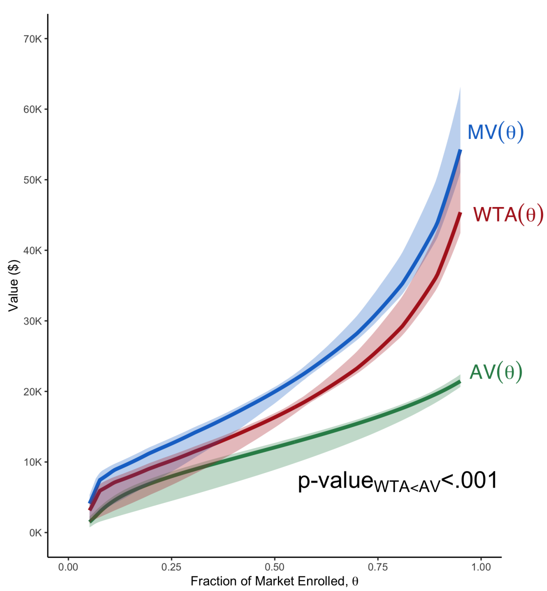


(A) Rational Beliefs

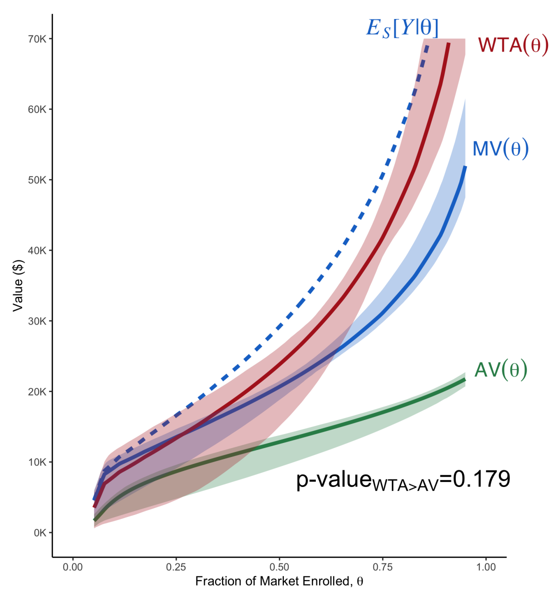


(B) Biased Beliefs

(II) Non-STEM



(A) Rational Beliefs

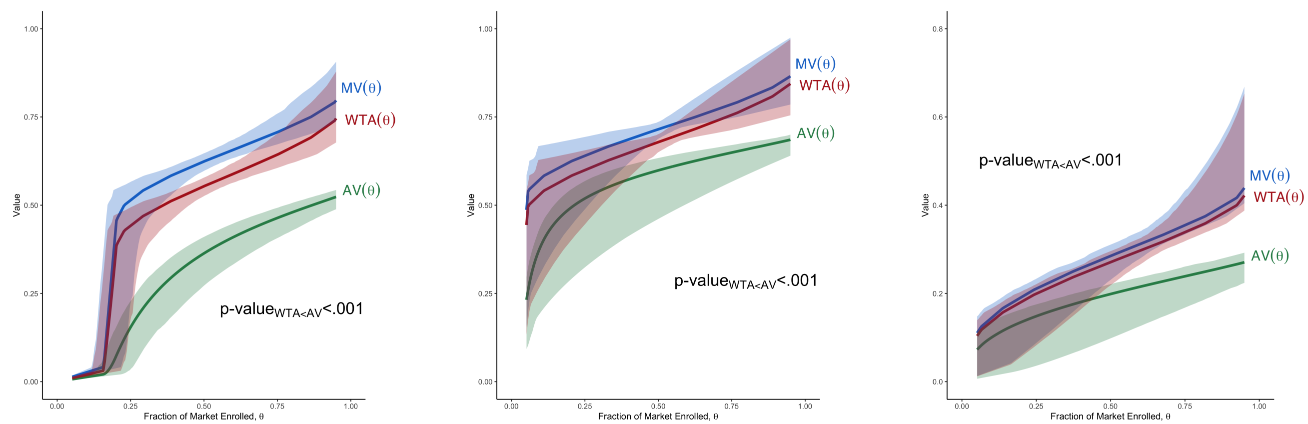


(B) Biased Beliefs

Note: This figure plots willingness-to-accept and value curves for the earnings-equity market for separate subsamples of students in STEM versus non-STEM majors. We plot each curve against the fraction of the market insured, θ, on the horizontal axis. The solid blue line plots the marginal value curve, $MV(\theta)$. The green line presents the average value curve, $AV(\theta)$. The red line presents the willingness-to-accept curve, $WTA(\theta)$. Panel A plots the rational belief specification, in which $MV(\theta)$ corresponds to unbiased beliefs of future salary. Panel B plots the biased beliefs specification, in which the CDF of subjective salary expectations, $E_S[y|\theta]$, is given by the dashed blue line. Results are conditional on academic and insitution categories of public information, as defined in Appendix Table A1. The shaded region presents 95% confidence intervals constructed via bootstrap resampling. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

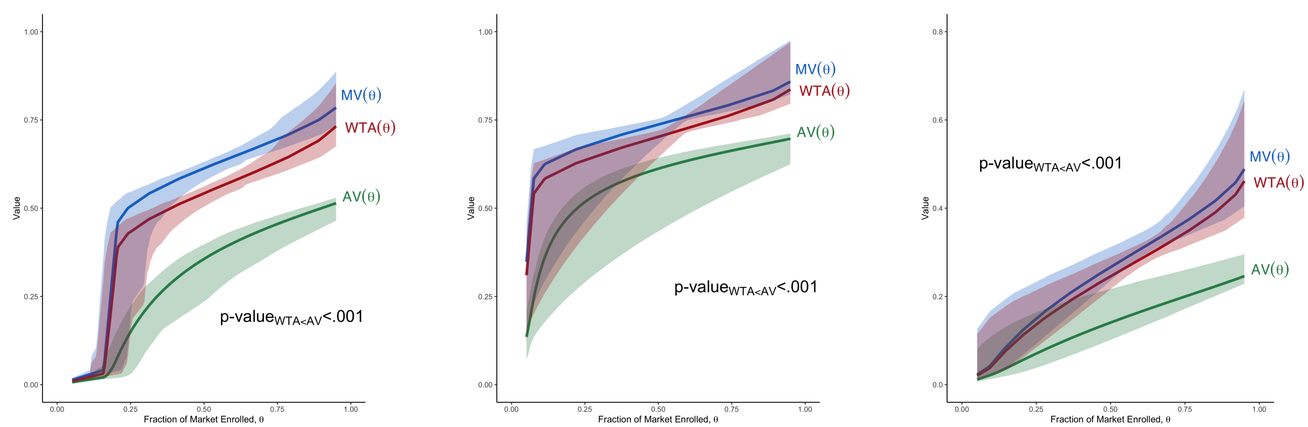
Figure A16: AV and WTA Curves for State-Contingent Loan Markets by STEM versus Non-STEM Fields

(I) STEM



(A) **Completion-Contingent Loan** (B) **Employment-Contingent Loan** (C) **Dischargeable Loan**

(II) Non-STEM



(A) **Completion-Contingent Loan** (B) **Employment-Contingent Loan** (C) **Dischargeable Loan**

Note: This figure plots willingness-to-accept and value curves for the state-contingent loan markets for separate subsamples of students in STEM versus non-STEM majors. We plot each curve against the fraction of the market insured, θ, on the horizontal axis. The solid blue line plots the marginal value curve, $MV(\theta)$. The green line presents the average value curve, $AV(\theta)$. The red line presents the willingness-to-accept curve, $WTA(\theta)$. Results are conditional on academic and insitution categories of public information, as defined in Appendix Table A1. The shaded region presents 95% confidence intervals constructed via bootstrap resampling. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

Table A1: Categorization and Description of Publicly Observable Information, X

Category	Variable
Academic Characteristics	Age at Enrollment Type of Degree (BA, AA) Field of Study (14 Categories)
Institution Characteristics	Four-Year College Private/Public Status For-Profit Region (8 Categories) Enrollment Size Share Black Share Female Admissions Rate Completion Rate Average SAT Score Median Parental Income Median 6-Year Salary
Performance	High School GPA SAT Score
Demographics	Citizenship Status Marital Status Number of Dependents
Parental Characteristics	Parents' Highest Education Parents' Marital Status Student's Dependency Status Parents' Income Expected Family Contribution (FAFSA)
Protected Classes	Race Gender

Note: This table lists names and categories for all variables used as observable characteristics in our analysis. The right column provides the variable name. The left column provides category names for each group of variables. More detailed variable definitions can be found at the National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study website: https://nces.ed.gov/surveys/bps/.

Table A2: IV Estimation Details and γ Estimates

(1) Outcome	(2) Elicitation	(3) Instrument	(4) γ-Estimate
Salary	*Log Expected Salary*	*Log Avg. Salary Expected Occ.*	0.69
			(0.16)
Completion	*On-Time Completion Likelihood*	*Supportive Parents*	3.20
			(0.23)
Employment	*Log Expected Salary if No College*	*Avg. Employment Expected Occ.*	0.59
			(0.29)
On-Time Repayment	*Supportive Parents*	*Parents' Financial Support*	2.28
			(0.47)

Note: This table summarizes the specifications used for each outcome in our IV estimation of the elicitation-belief relationship, γ, in equations (13) and (32) of the text. Column (1) lists the names of the outcome variables, y. Column (2) lists the names of the focal elicitations, z, used as dependent variables. Column (3) lists the names of instrumental variables, z', used to instrument for z in each regression. Column (4) reports point estimates of γ for each outcome-elicitation pair. Standard errors are reported in parentheses. Full elicitation descriptions are provided in Appendix C. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

Table A3: IV Estimation Details and b-Estimates

(1) Outcome	(2) Elicitation	(3) Instrument	(4) b-Estimate
Salary	*Log Expected Salary*	*Log Avg. Salary Expected Occ.*	0.70
			(0.17)
Completion	*On-Time Completion Likelihood*	*Supportive Parents*	3.13
			(0.22)

Note: This table summarizes the specifications used for each outcome in our IV estimation of the elicitation-belief relationship, β, in equations (13) and (32) of the text. Column (1) lists the names of the outcome variables, y. Column (2) lists the names of the focal elicitations, z, used as dependent variables. Column (3) lists the names of instrumental variables, z', used to instrument for z in each regression. Column (4) reports point estimates of β for each outcome-elicitation pair. Standard errors are reported in parentheses. Full elicitation descriptions are provided in Appendix C. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

Table A4: Mean Magnitude of Private Information: Point Estimates versus Lower Bounds

Contract	(1) $E[m(\theta)]$	(2) $E[m^Z]$
Earnings Equity	14049	4319
Completion-Contingent Loan	0.23	0.15
Employment-Contingent Loan	0.15	0.096
Dischargeable Loan	0.11	0.11

Note: This table reports structural point estimates and non-parametric lower bounds on the mean magnitude of private information, defined as the average difference between the average value curve, $AV(\theta)$, and the marginal value curve, $MV(\theta) \equiv E[Y|\theta]$, for each of our four contracts. Column (1) reports point estimates of the mean magnitude, $E[m(\theta)]$, derived from our sturctural estimates of average and marginal value curves in Section 5. Column (2) reports non-parametric estimates of the lower bound on mean magnitude, $E\left[m^Z\right]$, derived from the predictive power of elicitations in Section D.

Table A5: IV Estimation Details and γ-Estimates: Alternative Specifications

(1) Outcome	(2) Elicitation	(3) Alternative Instrument	(4) γ-Estimate
Salary	*Log Expected Salary*	*Log Expected Salary if No College*	0.77
			(0.10)
Completion	*On-Time Completion Likelihood*	*Parents' Financial Support*	1.72
			(0.17)
Employment	*Log Expected Salary if No College*	*Likelihood Employed in Expected Occ.*	1.34
			(0.62)
On-Time Repayment	*Supportive Parents*	*Avg. Employment Expected Occ.*	1.86
			(0.70)

Note: This table summarizes the alternative specifications used for each outcome in our secondary IV estimation of the elicitation-belief relationship, γ. Column (1) lists the names of the outcome variables, y. Column (2) lists the names of the focal elicitations, z, used as dependent variables. Column (3) lists the names of instrumental variables used to instrument for z in each regression. Column (4) reports point estimates of γ for each outcome-elicitation pair. Standard errors are reported in parentheses. Full elicitation descriptions are provided in Appendix C. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

Table A6: IV Estimation Details and b-Estimates: Alternative Specifications

(1) Outcome	(2) Elicitation	(3) Alternative Instrument	(4) b-Estimate
Salary	*Log Expected Salary*	*Log Expected Salary if No College*	1.31
			(0.18)
Completion	*On-Time Completion Likelihood*	*Parents' Financial Support*	5.83
			(0.57)

Note: This table summarizes the alternative specifications used for each outcome in our secondary IV estimation of the outcome-belief relationship, b. Column (1) lists the names of the outcome variables, y. Column (2) lists the names of the focal elicitations, z, used as dependent variables. Column (3) lists the names of instrumental variables used to instrument for z in each regression. Column (4) reports point estimates of b for each outcome-elicitation pair. Standard errors are reported in parentheses. Full elicitation descriptions are provided in Appendix C. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

Table A7: Lower-Bound and Presence of Private Information By Subgroup

		(1) Male	(2) Female	(3) Four-Year	(4) Two-Year	(5) Stem	(6) Non-Stem
Panel A: Log Salary	$E[m^Z]$	4493	4109	5246	3141	4557	4145
	p-value	9.6e-05	4.2e-10	3.4e-05	3.6e-06	9.7e-07	2.2e-05
	N	5430	7140	7700	4870	6310	6160
Panel B: Degree Completion	$E[m^Z]$	.1486	.1506	.1469	.1498	.155	.1445
	p-value	5.7e-39	2.8e-44	2.3e-63	2.1e-29	5.2e-53	1.3e-38
	N	9380	12970	13110	9230	11630	10710
Panel C: Employment	$E[m^Z]$	.0965	.0957	.1078	.0824	.099	.0943
	p-value	1.0e-09	2.2e-06	4.4e-30	.0709	9.3e-17	.0455
	N	7410	10070	10510	6970	8940	8390
Panel D: On-Time Repayment	$E[m^Z]$	.1082	.1045	.1294	.0705	.1064	.1067
	p-value	2.2e-12	2.3e-06	1.0e-16	8.3e-09	4.0e-12	2.6e-07
	N	6050	9470	10040	5490	8240	7220

Note: This table documents the statistical significance of private elicitations conditional on public information separately by subgroup. Each panel reports lower-bound estimates as well as p-values from F-tests of joint significance of elicitations in regressions of the outcome against all private elicitations in Table 1 and institution and academic observables listed Appendix Table A1. Each column designates the subgroup.

Appendix B Dynamic Model with College Decision and Life Cycle Earnings

This section extends the baseline model to allow the contract (η,λ) to affect the decision of whether to go to college and to allow for dynamic consumption and effort choices over the life cycle. The model provides two clarifications about how one should interpret our WTA and AV curves in the two-period model in the main text.

First, because we envision that the contract is offered only to college-goers, the model shows that we need to estimate the distribution of beliefs about future outcomes amongst those who are enrolled in college when they are asked to enroll and obtain $\lambda d\eta$. This means using the BPS survey of first-year college students aligns well with the theory. In the model, offering contracts can cause more people to go to college. But when assessing market existence, the envelope theorem allows us to ignore the causal effect of the contract offering on college attendance when computing the WTA and AV curves, just as we can ignore other behavioral responses (however, these become important when thinking about the normative conclusions about optimal policy interventions in Section 6).

Second, the model provides a precise way of thinking about "period 2" in the 2-period model in the main text: it is the period in which individuals are asked to repay the small contract, $yd\eta$. So, in our setting, because we observe earnings six years after enrollment in college, we can use our approach to assess whether a market can exist that enables individuals to pay back proportionally to their earnings six years after enrollment. This particular time frame is highly policy relevant because much of the uncertainty about future earnings and graduation has been revealed and those not obtaining sufficiently good jobs are currently likely to be defaulting on student debt contacts. The model below also makes clear that one could easily apply our approach to other repayment periods or other contracts (e.g. equity contracts 7, 8, or 9 years after, or a weighted average of incomes across multiple years). To do so, one would need to observe these other outcomes.

Willingness to Accept Curve

A set of individuals live for $N+1$ periods, $t = 0,...,N$. In each period, they consume $c_t \in \mathbb{R}$ and take a vector of actions, $a_t \in \mathbb{R}^{k_t}$, where k_t indexes the number of decisions people make in each period t. Uncertainty is realized in each period, which we denote by a random variable, ζ_t. Each individual observes an iid draw of ζ_t in each period and can take actions that depend on the realization of uncertainty up to time t. We let θ_t denote the history of realizations up through period t, $\theta_t = \{\zeta_1,...,\zeta_t\}$, omitting individual subscripts for brevity but recognizing that this realization varies across the population. We let $\alpha_t = (a_1,...,a_t)$ denote the history of actions taken up through period t. In period 0, individuals choose whether or not to apply to college based on information θ_0. We let period 1 denote the first year of college (i.e. the time when our survey is administered), and we denote college enrollment as an indicator $e(\theta_0) \in \{0,1\}$. As in the model in the main text, individuals who choose to enroll are able to potentially decide to purchase a risk-mitigating contract that provides $\lambda\eta$ in period 1 in exchange for paying back $Y_r(\theta_r,\alpha_r)\eta$ in some period $r > 1$, where $Y_r(\theta_r,\alpha_r)$ is a realized outcome in period r that is affected both by uncertainty θ_r and by actions taken up through and including period r, α_r. We assume individuals are able to make this choice after observing the uncertainty realized in period 1, so that we let $d(\theta_1;\eta,\lambda) \in \{0,1\}$ denote an indicator for taking up the contract with terms η and λ. Note that we model the repayment occurring in a single period, r, as this will most readily nest how to think about our two period model in the main text. But the analysis below is readily extended to the case where payments $Y_t(\theta_t,\alpha_t)\eta$ are made in a range of future periods, $t > 1$. Note that we allow the choice of whether to take up the contract, (η,λ), to be an element of the set of actions chosen in period 1, a_1.

In each period, individuals observe a personal realization of uncertainty and then choose consumption and actions.[71] To accommodate a wide range of potential budget / financial constraints, we write the constraints in a general form. Let $c_t(\theta_t)$ and $a_t(\theta_t)$ denote the consumption and actions chosen in each period j after realizing a history of uncertainty through period t, θ_t. We assume these choices are made subject to constraints in each period t that are given by:

$$c_t(\theta_t) \quad \leq \quad B_t^c\left(\{c_k(\theta_k)\}_{k<t}, \{a_k(\theta_k)\}_{k\leq t}; \theta_t\right) + \eta\lambda 1\{t=1,d=1\} - \eta Y_r(\theta_r,\alpha_r) 1\{t=r,d=1\} \quad (21)$$

$$a_t(\theta_t) \in B_t^a\left(\{c_k(\theta_k)\}_{k<t}, \{a_k(\theta_k)\}_{k\leq t}; \theta_t\right) \quad (22)$$

where $B_t^c \in \mathbb{R}$ is the consumption constraint and $B_t^a \subset \mathbb{R}^{k_t}$ is the set constraint on action choices in the status quo world with $\eta = 0$. This constraint describes how past consumption decisions (e.g. savings/borrowing), current and past actions, and realizations of uncertainty affect available consumption in period t. In addition to this status quo budget constraint, the risk-mitigating financial contract provides additional opportunities. If individuals attend college ($e = 1$) and they choose to take up the financial contract, $d = 1$, then they receive η in period 1 and agree to repay λY_r in period $t = r$. The constraint $B_t^a \subset \mathbb{R}^{k_t}$ describes how past actions, current and past consumption, and realizations of uncertainty affect the types of actions one can choose in period t.

Note that we allow for rich interactions between actions and budget constraints. For example, studying hard in high school in period 0 can be an element of a_0, $a_{0,i}$, which in turn increases earnings and thus expands the consumption availabilities in future period $\frac{\partial B_t^c}{\partial a_{0,i}} > 0$. As a result, this specification nests most common dynamic models of investment in human capital – for example, the shape of B_t^c and impact of uncertainty, θ_t, on B_t^c captures arbitrary credit constraints and other financial opportunities available to the individual.

We assume individuals experience a realized utility in each period given by $u_t(c_t,\alpha_t;\theta_t)$ in each period t, so that utility depends on consumption today, the set of actions up through period t, $\alpha_t = (a_0,...,a_t)$, and the set of uncertainty realized up through period t, $\theta_t = (\zeta_0,...,\zeta_t)$. For $t = 1$,

[71] We assume no aggregate risk and rational expectations by the financier. This means taht the the population distribution of θ_t corresponds to the distribution of ex-ante risk perceived by the financier.

individuals may be enrolled in college, given by the indicator $e(\theta_1)$. We note that this utility function choice enables us to nest cases where utility depends on college attendance. Suppose utility in period 1 is given by $\tilde{u}_1(c_1,e,a_1)$; we can rewrite this as $u_1(c_1,\{a_0,a_1\};\theta_1) = \tilde{u}_1(c_1,e(a_0;\theta_1),a_1;\theta_1)$. We let β denote the discount factor of individuals and E_S denote their subjective expectation about future outcomes (i.e. realizations of ζ_t for $t > 0$). We assume that individuals hold a set of beliefs that satisfy the axioms of probability, but we do not require they accord with reality (we assume ex-ante contingent plans align with ex-post choices, but the core results easily extend to the case where individuals adjust their beliefs over time in response to learning about their biases). Individuals maximize their expected present-discounted value of utility:

$$\begin{aligned} max \qquad & E_S\left[\sum_{t=0}^{N}\beta^t u\left(c_t(\theta_t),\{a_i(\theta_i)\}_{i\le t};\theta_t\right)\right] \\ s.t. \qquad & ((21)),((22)) \end{aligned}$$

The availability of risk-mitigating financial contracts at terms (η,λ) affects the constraint set of individuals and therefore their realized ex-ante expected utility. We can use the optimization assumption to assess what types, θ_1, will choose to take a contract (η,λ). Let $V(\eta,\lambda;\theta_1)$ denote the realized expected utility if a type θ_1 chooses to accept the contract, (η,λ) so that they face the constraints imposed when $d(\eta,\lambda;\theta_1) = 1$. We can now consider the marginal welfare gain from taking up a small contract by asking how η affects $V(\eta,\lambda;\theta_1)$. The key insight is that η and λ affect utility only through their relaxation of the constraints – i.e. they expand or contract the availability of additional consumption in different states of the world. The constraints satisfy the Milgrom-Segal conditions for the envelope theorem to be valid when differentiating with respect to η. For those not enrolled in college when $\eta = 0$, the constraints are not directly affected. An increase in η could cause some individuals to enroll in college, but they will have $\frac{\partial V}{\partial \eta}|_{\eta=0} = 0$. We discuss the impact of these "marginal" types below when discussing the profits of the financier. For those enrolled in college, an increase in η can strictly increase welfare. To see this, let $\kappa_t(\theta_t;\eta,\lambda)$ denote the Lagrange multiplier on the consumption constraint in period t given history θ_t. The envelope theorem implies:

$$\frac{\partial V}{\partial \eta}|_{\eta=0} = \kappa_1(\theta_1) - \sum_{\theta_r}\kappa_r(\theta_r)\,Y_r^{\eta=0}(\theta_r) \tag{23}$$

where $d(\theta_1;0,\lambda)$ denotes an indicator that an individual with history θ_1 will choose a small contract, $d\eta$, at valuation $\lambda$and $Y_r^{\eta=0}(\theta_r) = Y_r(\theta_r,\alpha_r(\theta_r;0,\lambda))$ is the realization of Y_r in the status quo world where $\eta = 0$ and people make a sequence of choices, $\alpha_r(\theta_r;0,\lambda)$.[72] Note that the model allows

[72]Note that equations (21) and (22) imply that the constraints are not affected by λ when $\eta = 0$ so that WLOG we can consider $\alpha_r(\theta_r;0,\lambda)$ to be the actions taken by the individual in the $\eta = 0$ world regardless of the value of λ.

individuals to change their decisions about whether to go to college based on any other choice of α_1. But the key insight of equation (23) (which is the result of the envelope theorem) is that the behavioral response of going to college does not affect utility directly – rather, the marginal value of the financial contract is given solely by the status quo distribution of take-up when $\eta = 0$.

The additive separability of the contract in the budget constraint implies that the Lagrange multipliers on the consumption constraint are equal to the marginal utilities of consumption in each period:

$$\begin{aligned}
\kappa_1(\theta_1) &= \beta \frac{\partial u_1}{\partial c} f_1(\theta_1) \\
\kappa_r(\theta_r) &= \beta^r \frac{\partial u_r}{\partial c} f_r(\theta_r)
\end{aligned}$$

where $f_1(\theta_1)$ is the subjective pdf of θ_1 occurring and $f_r(\theta_r)$ is the subjective pdf of θ_r occurring. The marginal utilities in period 1 and period r are evaluated under the status quo world with $\eta = 0$ and are functions of θ_1 and θ_r, respectively. Combining, we have

$$\frac{\partial V}{\partial \eta}|_{\eta=0} = \beta \frac{\partial u_1}{\partial c} d(\theta_1; 0, \lambda) f_1(\theta_1) - \sum_{\theta_r} \beta^r \frac{\partial u_r}{\partial c} Y_r^{\eta=0}(\theta_r) d(\theta_1; 0, \lambda) f_r(\theta_r),$$

which means that a college-goer will choose to take up the contract if and only if

$$\beta \frac{\partial u_1}{\partial c} \lambda [f_1(\theta_1)] \geq \sum_{\theta_r} \beta^r \frac{\partial u_r}{\partial c}(\theta_r)[f_r(\theta_r)]$$

Importantly, we can evaluate these marginal utilities, $\frac{\partial u_1}{\partial c}$ and $\frac{\partial u_r}{\partial c}$, under the status quo world with $\eta = 0$. The take-up decision for college enrollees can be expressed as:

$$\lambda \geq \frac{E_S\left[\beta^r \frac{\partial u_r}{\partial c} Y_r(\theta_r, \alpha_r) | \theta_1\right]}{\beta \frac{\partial u_1}{\partial c}(\theta_1)}$$

The term $E_S\left[\beta^r \frac{\partial u_r}{\partial c} Y_r(\theta_r, \alpha_r) | \theta_1\right]$ is the expected marginal disutility of repayment amongst those who are enrolled in college and $\beta \frac{\partial u_1}{\partial c}(\theta_1)$ is the valuation of this in units of first period utility. If this ratio is less than the valuation, λ, they choose to take up the contract.

Note that this ratio corresponds to the WTA equation in Section 2 with the clarification that one needs to condition on the set of people who are in college, since those are the people who are eligible to take the contract. Following our definitions in the text, we can now define the willingness to accept of an individual college-goer with type θ_1 by multiplying by the rate of return available to the financier between period 1 and period r, R^{r-1}.

$$WTA(\theta_1) = \frac{(\beta R)^{r-1} E_S\left[\frac{\partial u_r}{\partial c} Y_r(\theta_r,\alpha_r)|\theta_1\right]}{\frac{\partial u_1}{\partial c}(\theta_1)},$$

so that the take up decision then corresponds to $WTA(\theta_1) \leq R^{r-1}\lambda$. In our baseline case, we assume financiers face the same risk-free rate interest rate so that $\frac{\partial u_1}{\partial c}(\theta_1) = (\beta R)^{r-1} E\left[\frac{\partial u_r}{\partial c}|\theta_1\right]$. This in turn implies that

$$WTA(\theta_1) = \frac{E_S\left[\frac{\partial u_r}{\partial c} Y_r(\theta_r,\alpha_r)|\theta_1\right]}{E\left[\frac{\partial u_r}{\partial c}|\theta_1\right]},$$

which is the dynamic analogue to our WTA curve in the main text. Note that in the presence of credit constraints, one would expect that the risk-free interest rate faced by individuals would differ from the one faced by firms. There are two cases here. First, suppose individuals face a risk-free interest rate between periods 1 and r of $R(\theta_1) \neq R$. In this case, the WTA curve becomes

$$WTA(\theta_1) = \left(\frac{R(\theta_1)}{R}\right)^{r-1} \frac{E_S\left[\frac{\partial u_r}{\partial c} Y_r(\theta_r,\alpha_r)|\theta_1\right]}{E\left[\frac{\partial u_r}{\partial c}|\theta_1\right]}$$

so that we can multiply the ratio of expected marginal utilities by the ratio of the interest rate relative to the firms' interest rate, taken to the $r-1$ power. Second, suppose individuals are borrowing constrained only when in college so that they face interest rate R after graduation (periods 2+) but interest rate $R(\theta)$ for trading between period 1 and 2. In this case, the WTA curve becomes

$$WTA(\theta_1) = \frac{R(\theta_1)}{R} \frac{E_S\left[\frac{\partial u_r}{\partial c} Y_r(\theta_r,\alpha_r)|\theta_1\right]}{E\left[\frac{\partial u_r}{\partial c}|\theta_1\right]}$$

and we multiply the ratio of expected marginal utilities by the ratio of the interest rate to the gross interest rate.

Average Value Curve

Now we can consider how the average value curve differs in this setup. To begin, note that the period-0 present discounted value of profits per person who takes up the contract is given by:

$$\Pi(\eta,\lambda) = \left(\eta E\left[Y_r(\theta_r,\alpha_r(\theta_r;\eta,\lambda))|d(\theta_1;\eta,\lambda)=1\right] R^{-r} - \eta\lambda R^{-1}\right)$$

where we assume profits are discounted at the real risk-free interest rate, $R > 1$. Profits per person who takes up the contract are equal to the difference between the (discounted) revenue they obtain from repayments in the future, $\eta E\left[y_r(\theta_r,\alpha_r)|d(\theta_1;\eta,\lambda)=1,\right] R^{-r}$, and the upfront payments they make in period 1, $\eta\lambda R^{-1}$. To assess whether it is potentially profitable to offer a contract, we can differentiate the profit function w.r.t. η and evaluate at $\eta = 0$ (under our maintained assumption that profitability is concave in the size of the contract, η):

$$
\begin{aligned}
\frac{d\Pi}{d\eta} &= E\left[Y_r\left(\theta_r,\alpha_r\right)|d\left(\theta_1;\eta,\lambda\right)=1\right]R^{-r}-\lambda R^{-1} \\
&+\eta E\left[\frac{dY_r\left(\theta_r,\alpha_r\right)}{d\eta}|d\left(\theta_1;\eta,\lambda\right)=1\right] \\
&+\frac{d\Pr\left\{d\left(\theta_1;\eta,\lambda\right)=1\right\}}{d\eta}\left(\eta\left(E\left[Y_r\left(\theta_r,\alpha_r\right)|\theta_1\in D_E\left(\eta,\lambda\right)\right]-E\left[Y_r\left(\theta_r,\alpha_r\right)|d\left(\theta_1;\eta,\lambda\right)=1\right]\right)\right)
\end{aligned}
$$

where $D_E(\eta,\lambda)$ is the boundary of types, θ_1, who are indifferent to taking the contract. Importantly, the term $E\left[Y_r\left(\theta_r,\alpha_r\right)|\theta_1\in D_E\left(\eta,\lambda\right)\right]$ includes people who are on the margin of deciding to go to college in response to the increase in the availability of risk-mitigating financing. However, now we can evaluate this term at $\eta=0$ to consider the marginal profitability of the first dollar of the contract provision starting from the status quo environment where $\eta=0$. In doing so, note that the second and third terms are second order and equal to zero. The intuition is that the people who choose to go to college do affect the financier profits, but a small η contract causes a small amount of people to go to college. In turn, these people have a small effect on costs when η is small, so that the effects are second order. At $\eta=0$, the marginal profit function can be calculated on the subset of people who choose to go to college:

$$\frac{d\Pi}{d\eta}|_{\eta=0}=\left(E\left[Y_r\left(\theta_r,\alpha_r\right)|WTA\left(\theta_1\right)\leq R^{(r-1)}\lambda\right]R^{-r}-\lambda R^{-1}\right)$$

so that marginal profits are non-negative at a given λ if and only if

$$E\left[Y_r\left(\theta_r,\alpha_r\right)|WTA\left(\theta_1\right)\leq R^{(r-1)}\lambda\right]\geq\lambda R^{r-1}$$

Because take-up is determined by $WTA\left(\theta_1\right)\leq R^{r-1}\lambda$, there exists a λ such that marginal profits are non-negative if and only if

$$E\left[Y_r\left(\theta_r,\alpha_r\right)|WTA\left(\theta_1\right)\leq R^{(r-1)}\lambda\right]\geq WTA\left(\theta_1\right)$$

which corresponds to exactly the equation in the main text. The dynamic model clarifies that the relevant distribution of income, Y_r, is amongst those who take up the contract in the status quo ($\eta=0$) world (i.e. we can ignore the impact of offering the contract on college enrollment decisions). However, college enrollment decisions may have externalities on the government and others, and these need to be taken into account for welfare analysis —- as we discuss in Section 6.

Appendix C Descriptions of Elicitation Variables

The elicitation variables we use are the recorded responses to first-wave survey questions from the 2012/17 Beginning Postsecondary Students (BPS) study. The question text corresponding to each elicitation is provided below. Where applicable, we also include the alternative survey-question wording used for the roughly 10% subsample of BPS respondents who received an "abbreviated interview."

- *Expected Occupation*: "What is the title of the job you want to have after you complete your education?" [Response options correspond to 2010–13 Occupational Information Network-Standard Occupational Classification (O*NET-SOC) codes.]
- *Expected Salary*: "We have some questions about the range of salary you expect to make once you begin working a [EXPECTED OCCUPATION] job. What is...your expected yearly salary?"
  - Abbreviated wording: "What do you expect your salary to be once you finish your education?"
- *Likelihood Employed in Expected Occupation*: "On a scale from 0–10, how likely do you think it is that, five years from now you will hold your intended occupation?"
- *On-Time Completion Likelihood*: "On a scale from 0–10, how likely is it you will finish your degree by [EXPECTED DATE]?"
- *Supportive Parents*: "On a scale of 1–5, how much do you agree with the following statement: 'My parents encourage me to stay in college.'?"
- *Expected Salary if No College*: "How much do you think you would have earned at all your jobs together if you had not attended college in the 2011–2012 school year?"
- *Parents' Financial Support*: "Through the end of the 2011–2012 school year, about how much will your parents (or guardians) have helped you pay for any of your education and living expenses while you are enrolled in school?"

More information on the survey design and implementation can be found at https://nces.ed.gov/surveys/bps/.

In addition to the elicitations above, we construct two additional Z-variables—*Log Average Salary in Expected Occupation* and *Average Employment in Expected Occupation*—using responses to the *Expected Occupation* question. Specifically, for each individual i, we take averages of outcomes among college graduates (j) who had worked in individual i's expected occupation (occ_i) as of the BPS 2012 survey:

$$\textit{Log Avg. Salary Expected Occ.} = \log \frac{1}{N^{BB}_{occ_i}} \sum_{j \in occ_i} y^{BB}_j \tag{24}$$

$$\textit{Avg. Employment Expected Occ.} = \frac{1}{N^{BB}_{occ_i}} \sum_{j \in occ_i} e^{BB}_j . \tag{25}$$

Post-graduate salaries and employment (y^{BB}_j and e^{BB}_j), and cell-sizes ($N^{BB}_{occ_i}$) are taken from the 2008 Baccalaureate and Beyond (B&B08) study, which we match to BPS occupation elicitations (occ_i) using three-digit occupation codes. The B&B08 data include survey responses for a representative sample of four-year college graduates in the spring of 2008, followed up on in 2011–2012. More information can be found at https://nces.ed.gov/surveys/b&b/.

Appendix D Derivation and Estimation of Lower-Bound Magnitudes

This appendix provides formal derivation of how the predictive power of the elicitations, Z, for the outcome Y, conditional on X, provides a lower bound of the average difference between the marginal and average value curves. To form these bounds, we rely on benchmark assumptions of rational beliefs and unidimensional heterogeneity.

Let $m(\theta)$ denote the discount an individual of type θ would need to accept below their marginal value to cover the financier's cost of adverse selection,

$$m(\theta) \equiv MV(\theta) - AV(\theta). \tag{26}$$

We refer to $m(\theta)$ as the magnitude of private information. Assuming rational beliefs and unidimensional heterogeneity, the AV curve is equal to the average realization of Y for those with weakly lower expected outcomes (equation (8)). So we can rewrite equation (26) as

$$m(\theta) = MV(\theta) - E\left[MV(\theta')|MV(\theta') \leq MV(\theta)\right]. \tag{27}$$

Under these assumptions, the magnitude of type θ's information, $m(\theta)$, is the difference between their marginal value and the average of all marginal values worse than their own. Without observing $MV(\theta)$, we cannot estimate $m(\theta)$. So instead of estimating the magnitude of all private information in θ, we construct an analagous measure using just the information contained in Z.

For each individual, i, let r_i be the difference between their predicted outcome conditional on both publicly observable information and elicitations, $E[Y|X = X_i, Z = Z_i]$, and their predicted outcome given only publicly observable information, $E[Y|X = X_i]$:

$$r_i \equiv E[Y|X = X_i, Z = Z_i] - E[Y|X = X_i]. \tag{28}$$

The value of r_i measures the extent to which an individual's elicitation predicts them to have a different realization of Y, conditional on their observables, X. Using r_i in place of $MV(\theta)$ in equation (27), we can define the magnitude of the discount implied by the elicitations, m_i^Z, as the average r among all individuals with $r < r_i$:

$$m_i^Z \equiv r_i - E[r|r < r_i]. \tag{29}$$

The value of m_i^Z measures the magnitude of private information in a world where all of the borrowers' knowledge were limited to the information in Z and X. Under our maintained assumptions that (i) the elicitations are no more predictive than beliefs themselves, $E[Y|\theta,X,Z] = E[Y|\theta,X]$, and (ii) belief are rational, we can apply Proposition 2 from Hendren (2013) to obtain a lower bound on the average magnitude of private information:

$$E_\theta\left[m\left(\theta\right)\right] \geq E_i\left[m_i^Z\right]. \tag{30}$$

The left-hand side of inequality (30) is the (unobserved) average difference between the marginal value curve, $MV(\theta)$, and average value curve, $AV\left(\theta\right)$. The right-hand side is a lower bound that can be estimated using the distribution of predicted values of Y given X and Z. Importantly, inequality (30) only relies on the predictive power of Z for Y conditional on X, so we do not need to specify a structural relationship between beliefs and elicitations.

Estimation To calculate $E\left[m_i^Z\right]$, we use a random-forest algorithm to separately estimate $E\left[Y|X\right]$ and $E\left[Y|X,Z\right]$, where $\{X\}$ denotes the set of public information, and $\{X,Z\}$ denotes the set of both public and private information.

For each binary outcome, we train an eight-fold cross-validated random forest model with 2000 trees on a 70% sample of our data and measure its predictive performance using the 30% holdout sample.[73] We repeat this procedure for each subset of predictor variables given by the categories listed at the top of Appendix Table D8, using the first three subsets to estimate $E[Y|X]$ under alternative definitions of X, and using the final subset, "All Public + Elicitations", to estimate $E[Y|X,Z]$.

For log salary, we follow the same procedure as we do for binary outcomes, but adapt the random forest algorithm to predict not just the conditional mean of y, $E[y|X]$, but also its conditional quantile function, $F^{-1}(\alpha|X)$ for all $\alpha \in [0,1]$, a technique known as quantile regression forests (Meinshausen, 2006). We use these estimated quantile functions to form predicted level salary conditional on employment, $E\left[\widehat{e^{\log(y^S)}|Y} > 0,X,Z\right]$, which we then combine with employment predictions, $Pr(\widehat{Y > 0}|X,Z)$ to form predicted unconditional level salary:

$$E\,[\widehat{y^S|X},Z] = Pr(\widehat{Y > 0}|X,Z) * E\left[\widehat{e^{\log(y^S)}|Y} > 0,X,Z\right]. \tag{31}$$

We repeat this procedure for five different specifications of $\{X\}$: (1) a benchmark case with no public information, in which $E[Y|X] = E[Y]$, (2) allowing $\{X\}$ to include only institutional and academic characteristics, (3) adding performance and demographic characteristics, (4) adding parental background characteristics, and (5) adding race and gender.[74]

[73] For an overview of the random forest algorithm and other machine-learning approaches to applied econometrics, see Mullainathan and Spiess (2017).

[74] In theory, $\{X,Z\}$ should contain all information an individual might use to predict outcomes at the time of the interview. To be conservative, we restrict this information set to include only elicitations, Z, plus those variables observable to the firm, X (e.g., individuals cannot make predictions using their own SAT scores unless financiers can). In Appendix Table D9, we allow private information to also include any observable variables not included in the specified set of public information, so that $E\left[Y|X,Z\right]$ does not vary across specifications. We find larger, but

Appendix Table D8 reports out-of-sample performance statistics from our random-forest estimates of $E[Y|X]$ and $E[Y|X,Z]$. Consistent with the results in Table 3, we find that predictive metrics improve when adding elicitations, Z, to the model, even after conditioning on our full set of observables.

qualitatively similar lower-bound estimates.

Table D8: Predictive Performance With and Without Elicitations

Outcome	Statistic	Category				
		(1) *Academic + Institution*	(2) *Academic + Institution + Performance + Demographics*	(3) *Academic + Institution + Performance + Demographics + Parental*	(4) *Academic + Institution + Performance + Demographics + Parental + Protected*	(5) *All Public + Elicitations*
Panel A: Log Salary	R^2	0.071	0.070	0.077	0.094	0.109
		(0.010)	(0.010)	(0.009)	(0.010)	(0.011)
	RMSE	0.640	0.640	0.638	0.631	0.626
		(0.012)	(0.013)	(0.012)	(0.012)	(0.012)
	MAE	0.464	0.462	0.462	0.455	0.453
		(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Panel B: Dropout	Pseudo R^2	0.101	0.157	0.166	0.169	0.231
		(0.011)	(0.008)	(0.007)	(0.007)	(0.007)
	ROC	0.741	0.761	0.767	0.770	0.813
		(0.006)	(0.006)	(0.006)	(0.006)	(0.005)
	Accuracy	0.684	0.699	0.701	0.702	0.739
		(0.006)	(0.006)	(0.006)	(0.006)	(0.005)
Panel C: On-Time Repayment	Pseudo R^2	0.058	0.131	0.152	0.155	0.168
		(0.014)	(0.011)	(0.010)	(0.010)	(0.009)
	ROC	0.721	0.753	0.769	0.772	0.782
		(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
	Accuracy	0.754	0.759	0.760	0.763	0.766
		(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Panel D: Employment	Pseudo R^2	-0.127	-0.001	0.019	0.023	0.041
		(0.027)	(0.007)	(0.006)	(0.006)	(0.005)
	ROC	0.567	0.586	0.606	0.614	0.637
		(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
	Accuracy	0.697	0.717	0.719	0.720	0.724
		(0.006)	(0.006)	(0.006)	(0.006)	(0.006)

Note: This table reports out-of-sample prediction performance statistics for each outcome. Each column corresponds to an increasing set of predictor variables that are included in a random forest model trained on a 70% sample. Column (1) includes academic variables. Column (2) adds performance and demographics. Column (3) adds parental characteristics. Column (4) adds information on race and gender. Each of these categories is defined in Appendix Table A1. Finally, column (5) adds in the elicitations. Numbers in parentheses denote standard deviations of prediction statistics calculated over 1000 bootstrap samples of the 30% holdout sample. Pseudo-R^2 is calculated as $1 - \frac{\ln L_M}{\ln L_0}$, where L_M and L_0 denote the likelihood of observed outcomes given predictions from the random forest model and sample mean, respectively. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

Table D9: Lower-Bound on the Magnitude of Private Information, Including Non-Public Observables as Private Information

	Category				
	(1) *No Public Info*	(2) *Academic + Institution*	(3) *Academic + Institution + Performance + Demographics*	(4) *Academic + Institution + Performance + Demographics + Parental*	(5) *Academic + Institution + Performance + Demographics + Parental + Protected*
Earnings Equity	5833	4845	4242	3281	2500
Completion-Contingent Loan	0.20	0.16	0.13	0.11	0.11
Employment-Contingent Loan	0.09	0.11	0.08	0.05	0.05
Dischargeable Loan	0.14	0.13	0.08	0.05	0.04

Note: This table provides lower-bound estimates, $E\left[m^Z\right]$, under the assumption that $\{X,Z\}$ contains all information that would be available to the individual at the time of the interview, so that $E\left[Y|X,Z\right]$ does not vary across specifications. In other words, we allow private information, Z, to include all elicitations variables listed in Appendix C as well as any observable variables not included in the specified set of public information, X. Values are calculated from equation 28 using random-forest estimates of $E\left[y|X_i,Z_i\right]$ and $E\left[y|X_i\right]$. X_i includes the set of publicly known variables corresponding to each column label. Column (1) includes no controls for observable variables. Column (2) adds controls for institutional and academic information. Column (3) adds controls for high school performance and demographic information. Column (4) adds controls for parental information. Column (5) adds information on race and gender. These categories are defined in Table 2. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

Appendix E Additional Estimation Details

This appendix provides further details on our empirical estimation in Section 5. We begin by discussing our empirical approach for the case when the outcome is binary. We then discuss how we combine estimates for log salary and employment to obtain the full distribution of expected salary. Third, we discuss how we residualize the variables to incorporate controls for observable characteristics. Lastly, we provide further details on how we apply the deconvolution estimator from Bonhomme and Robin (2010) in our setting.

Estimating Beliefs about Binary Outcomes

Because employment is a binary outcome, the identification result and deconvolution estimator in Bonhomme and Robin (2010) cannot be applied (a deconvolution of the distribution of a binary outcome into a continuous distribution of beliefs would violate the rank condition). However, we show here that one can use a flexible maximum likelihood estimator that is motivated by the non-parametric identification results in Hu and Schennach (2008). We focus our discussion on the case of rational beliefs, but discuss below how we modify our approach to allow for biased beliefs, which we apply for the on-time completion completion outcome.

Let d_i denote an indicator for some binary outcome, and z_i denote an elicitation containing private information about that outcome. As in the salary case, we use an instrumental variable, w_i, to identify the relationship between the elicitations and true beliefs. Appendix Table A2 lists the variables we use as z_i and w_i for each outcome in our baseline specification.[75]

As in the salary case, we let μ_i denote the rational belief i would form about d_i, $\mu_i \equiv E[d_i|\theta]$. We assume that we can write the elicitation, z_i, as a linear function of μ_i:

$$z_i = \alpha + \gamma\mu_i + \nu_i, \quad \nu_i \sim N\left(0,\sigma^2\right), \tag{32}$$

for some unknown variance, σ^2. We estimate γ as in the continuous case above: we regress z_i on the binary outcome, d_i, instrumented with w_i. As described in Section 5, the key identification assumption is that measurement error is independent, so that w_i is correlated with z_i only through its correlation with beliefs. Appendix Table A2 reports the IV estimates of γ.[76]

In cases where z_i could plausibly serve as an unbiased measure of respondents' subjective beliefs, $E[z_i|\theta] = \Pr_S[d_i|\theta]$, we can modify the approach above to allow for potentially biased beliefs. Specifically, we can impose $\alpha = 0$ and $\gamma = 1$ in equation (32), $z_i = \mu_{S_i} + \nu_i$, and allow $d_i = a + b\mu_{S_i} + \xi_i$, where $\mu_{S_i} \equiv \Pr_S[d_i|\theta]$. For employment and loan-repayment outcomes, elicitations are only indirectly related to beliefs, making this approach impossible. For degree completion, however,

[75] Appendix Table A5 lists alternative instruments used for robustness estimates of γ.

[76] Appendix Table A5 shows that these estimates are similar using alternative variables as instruments, w_i.

we can plausibly satisfy the unbiased-elicitation assumption by setting z_i equal to respondents' self-reported completion likelihoods on a 0 to 10 scale, divided by 10. We report these results in Appendix Figure A5.

Dropping i subscripts, consider the joint distribution of elicitations, z, and binary outcome d, $f_{d,z}(d,z)$. We can expand the observed density of d and z, $f_{d,z}(d,z)$, by conditioning on beliefs, μ:

$$f_{d,z}(d,z) = \int \mu^d (1-\mu)^{1-d} f_{z|\mu}(z|\mu)\, g(\mu)\, d\mu, \tag{33}$$

where $f_{y|\mu} = \mu^d (1-\mu)^{1-d}$ is the p.m.f. of e given μ, $f_{z|\mu}$ is the distribution of the elicitations given μ, and $g(\mu)$ is the distribution of beliefs. Our estimates for α and γ and σ in equation (32) provide an estimate of $f_{z|\mu}$. The distribution of beliefs, $g(\mu)$, can then be inferred from the joint distribution of y and z.[77] We flexibly specify the belief distribution, $g(\mu)$, as a grid of discrete point masses, so that it's c.d.f., $G(\mu)$, is given by

$$G(\mu) = \sum_j \delta_j \mathbb{1}\{\mu \leq a_j\}, \tag{34}$$

where $\{a_j\}$ is a set of twenty-five evenly-spaced point masses in [0,1]. Combining the flexible density function in (34) with the elicitation error distribution given by (32), we estimate $g(\mu)$ from the joint distribution of z and d by maximizing the likelihood given by equation (33).[78]

Constructing the Expected Salary Distribution

Section describes our method for identifying the distribution of private beliefs about log earnings conditional on employment, $\mu_S \equiv E_S[y|\theta, Y > 0]$. To form beliefs about the distribution about unconditional earnings in levels, $\mu_S \equiv E_S[Y|\theta]$, we transform this estimated belief distribution for conditional log-salary and combine it with the estimated belief distribution for employment.

To transform rational beliefs about logs into rational beliefs about levels, we use our estimated belief distributions for both mean log salary, μ, and residual uncertainty, ϵ, to construct conditional

[77] Hu and Schennach (2008) show that a sufficient set of requirements for $g(\mu)$ to be non-parametrically identified is that the linear mapping from $g(\circ)$ to $\int \theta^y (1-\theta)^{1-y} f_{Z|\theta}(z|\theta)\, g(\mu)\, d\theta$ is injective and that the distribution of z given θ has a known mapping, $E[m(z)|\theta] = \theta$. In our setting, when the elicitations are uncorrelated, γ_j is identified through an IV regression of the elicitation on the outcome, which corresponds to the required mapping. Because the elicitations are discrete, we are formally identified to some extent from the functional form choice of g and $f_{Z|\theta}$.

[78] In order to condition on observable characteristics, X, we augment equation (33) to allow for an additional point mass that varies with $E[y|X]$:

$$G(\mu) = w\mathbb{1}\{\mu \leq E[d|X] - a\} + (1-w)\sum_i \delta_i \mathbb{1}\{\mu \leq a_i\}. \tag{35}$$

expectations of level salary:

$$E[Y|\theta,Y>0] \;=\; E[e^{\mu+\epsilon}|\theta] \tag{36}$$

$$= \; e^{\mu}E[e^{\epsilon}], \tag{37}$$

$$\tag{38}$$

where the $E[e^{\epsilon}]$ is calculated using the estimated distribution of expectational error, f_{ϵ}. In the biased-belief specification, equation (38) is instead written as $E_S[Y|\theta,Y>0] = e^{\mu_S}E[e^{\xi}]$, where $E[e^{\xi}]$ is calculated using the estimated distribution of expectational error plus idiosyncratic bias, f_{ξ}.

To combine beliefs about mean level salary, $E_S[Y|\theta,Y>0]$, with beliefs about employment, $E_S[Y>0|\theta]$, we make a single index assumption that those with higher beliefs about employment also have higher expected salaries.[79] Specifically, we assume the α-quantile of the distribution of $E_S[Y|\theta]$, $Q_{\alpha}(E_S[Y|\theta])$, is given by the product of the two quantiles:

$$Q_{\alpha}(E_S[Y|\theta]) = Q_{\alpha}(E_S[Y|Y>0,\theta])\,Q_{\alpha}(\Pr[Y>0|\theta]) \tag{39}$$

Estimates of equation (39) will vary depending on whether we assume rational beliefs ($E_S[Y|Y>0,\theta] = E[Y|Y>0,\theta]$) or biased beliefs, ($E_S[Y|Y>0,\theta] = E[Z|\theta]$). Beliefs about employment, on the other hand, are assumed unbiased under both specifications, $\Pr_S[Y>0|\theta] = \Pr[Y>0|\theta]$. To the extent to which beliefs about employment prospects are also optimistic, this would further reinforce our central conclusion that biased beliefs are amplifying the market unraveling.

Conditioning on X

In this section, we discuss how we condition on observables, X, in our structural estimation to simulate markets in which firms can price contracts using observable information.

Conditioning with rational beliefs First we consider the distribution of residual rational beliefs. We let $\tilde{\mu}_i \equiv \mu_i - E[y|X]$, the residual belief individual i would hold after removing the prediction they would make if they held rational beliefs but only held public information. In this case, we can rewrite equations (12) and (14) as

$$y_i \;=\; E[y|X] + \tilde{\mu} + \epsilon_i \tag{40}$$

$$z_i \;=\; \alpha + \gamma\tilde{\mu} + \gamma E[y|X] + \nu_i' \tag{41}$$

[79] This assumption is consistent with the empirical literature suggesting that those with higher salaries also have stronger labor force attachment.

where $\nu_i' = \gamma(\mu_{Si} - \mu_i) + \nu_i$. With equations (40) and (41), we can estimate the distribution of residualized rational beliefs, $f(\tilde{\mu})$, by simply performing our deconvolution procedure on $\tilde{y} \equiv y - E[y|X]$ and $\tilde{z} \equiv z - \gamma E[y|X]$.

Conditioning with biased beliefs Next, we consider the distribution of residual beliefs allowing belief formation to be biased. Let $\tilde{\mu_S}_i \equiv \mu_{Si} - E_S[y|X]$, the residual belief after removing the subjective prediction individual i would make using only public information. We assume subjective beliefs, while potentially biased, obey the law of iterated expectations, so

$$\begin{aligned} E[\mu_{Si}|X] &\equiv E[E_S[y|\theta]|X] && (42)\\ &= E_S[y|X], && (43)\end{aligned}$$

which implies $E[\tilde{\mu_S}_i|X] = 0$.

Using equation (16), we have:

$$\begin{aligned} y_i &= a + b\mu_S + \xi_i && (44)\\ &= a + b(\tilde{\mu_S} + E_S[y|X]) + \xi_i && (45)\\ E[y_i|X] &= a + bE_S[y|X], && (46)\end{aligned}$$

which means we can relate empirical and subjective predictions of y using X as $E_S[y|X] = \frac{E[y|X]-a}{b}$. Using this relationship, we can then rewrite equations (16) and (15) in terms of residual private beliefs $\tilde{\mu_S}$:

$$\begin{aligned} y_i &= E[y|X] + b\tilde{\mu_S} + \xi_i && (47)\\ z_i &= \frac{E[y|X]-a}{b} + \bar{\alpha} + \tilde{\mu_S} + \nu_i. && (48)\end{aligned}$$

With equations (47) and (48), we can estimate the distribution of residualized biased beliefs, $f(\tilde{\mu_S})$, by performing our deconvolution procedure on $\tilde{y} \equiv y - E[y|X]$ and $\tilde{z}^S \equiv z - \frac{E[y|X]-a}{b}$.

Deconvolution Details

Bonhomme and Robin (2010) deconvolve linear independent multi-factor models of the form $\boldsymbol{Y} = \boldsymbol{AX}$, where $\boldsymbol{Y}$ is a vector of observed measurements, $\boldsymbol{X}$ is a vector of latent variables, and A is a matrix of factor loadings, assumed to be known. We adapt this framework to estimate rational beliefs using equations (12) and (14) and defining $\boldsymbol{Y}$, A, and $\boldsymbol{X}$ as

$$\boldsymbol{Y} = \begin{bmatrix} \tilde{y} \\ \tilde{z} \end{bmatrix}, A = \begin{bmatrix} 1 & 1 & 0 \\ \gamma & 0 & 1 \end{bmatrix}, \text{and } \boldsymbol{X} = \begin{bmatrix} \mu \\ \epsilon \\ \nu \end{bmatrix},$$

where $\tilde{y}$ and $\tilde{z}$ are log realized salary and log expected salary, residualized as in Appendix E. The belief-elicitation relationship, γ, is estimated prior to the deconvolution following the instrumental-variables procedure in Section E. Since rational beliefs (μ), expectational error (ϵ), and elicitation error (ν) are mutually independent, we can use the Bonhomme-Robin framework to non-parametrically estimate density of believed mean log income across individuals, f_μ, the density of expectational error within type, f_ϵ, and the density of elicitation error, f_ν.

To estimate latent factors under our biased-belief specification, we map equations (16) and (15) into the Bonhomme and Robin (2010) framework by simply replacing A and redefining the vector of latent factors, $\boldsymbol{X}$:

$$\boldsymbol{Y} = \begin{bmatrix} \tilde{y} \\ \tilde{z}^S \end{bmatrix}, A = \begin{bmatrix} b & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix}, \text{and } \boldsymbol{X} = \begin{bmatrix} \mu_S \\ \xi \\ \nu' \end{bmatrix}.$$

Under this specification, the deconvolution identifies the density of subjective beliefs of mean log income across individuals, f_{μ_S}, the density of expectational error and idiosyncratic bias within type, f_ξ, and the density of elicitation error, $f_{\nu'}$.

In both specifications, the deconvolution procedure uses empirical characteristic functions of observed measurements to uncover the empirical characteristic functions of unobserved latent factors. These characteristic functions are then transformed into density functions through inverse Fourier transformation. This transformation requires kernel and bandwidth choice to facilitate smoothing. We use the second-order kernel specified in Bonhomme and Robin (2010). To select bandwidth, we use the recommended bandwidth selector from Delaigle and Gijbels (2004).

WTA for Binary Outcomes

For binary contracts, the WTA in equation (19) reduces to:

$$WTA(\theta) = \frac{1}{1 + \frac{1-E[Y|\theta]}{E[Y|\theta]} \left(1 + (\Delta c)^\rho\right)}$$

where Δc is the percentage difference in consumption if $Y = 1$ versus $Y = 0$ and ρ is defined as in the text as the relationship between income and consumption. We calibrate Δc separately for each outcome.[80] For the completion-contingent loan contract, we approximate the increased consumption arising from degree completion using estimates from Zimmerman (2014). Relative to a base of non-enrollee incomes, Zimmerman (2014) estimates a 90% earnings increase from earning a BA degree, compared to a 22% increase from attendance alone. This implies a difference in earnings for those who complete versus do not of 68%. We translate this into the consumption difference by multiplying by $\rho = 0.23$ to obtain a consumption effect of $\Delta c = .16$.

For the employment-contingent loan contract, we approximate the increased consumption arising from employment using estimates from Hendren (2017) and Ganong and Noel (2019). Hendren (2017) estimates a causal effect of unemployment on consumption ranging from 7% to 9%, while Ganong and Noel (2019) estimate values between 6% and 12%. To be conservative, we let $\Delta c = .09$.

Finally, for the non-dischargeable loan contract, we approximate the increased consumption arising from non-delinquency as follows.[81] We run a two-stage least-squares regression of realized salary against delinquency status and the "Expected Salary" elicitation, instrumenting for "Expected Salary" using the log of average earnings by occupation as in Section E. Assuming independent measurement error of the elicitations, the instrumented elicitation controls for the portion of salary that is ex-ante known to the borrower, so that the residual correlation between delinquency and salary captures a causal effect of one on the other. This procedure yields an estimated earnings increase of 20%, which we multiply by $\rho = 0.23$ to obtain a consumption effect of $\Delta c = .05$.

Appendix F Mumford (2022) and the Purdue ISA

In this Appendix, we discuss the relationship between our results and Mumford (2022), which investigates adverse selection and moral hazard among applicants to the "Back-a-Boiler" program, an income share agreement (ISA) at Purdue University. Mumford's analysis compares baseline characteristics and post-college outcomes between ISA enrollees and students who completed ISA applications but did not ultimately enroll. The core results of Mumford (2022) can be summarized as follows: First, the paper finds that ISA enrollees major in fields with significantly lower starting starting salaries than non-enrolling applicants (Table 3, row 3). Conditional on their major, however, the two groups earn SAT scores and first-year GPAs that are not statistically different (Table 3, rows 5–7). Second, using an original survey conducted on a subsample of ISA applicants, Mumford (2022) finds that ISA enrollees expect to earn roughly $5K less than those who applied but did not enroll in the ISA (Table 5, row 2). Third, the paper finds that realized post-college

[80]Note that for binary contracts, equation (19) reduces to

$$WTA(\theta) = \left(1 + \frac{1 - E[y|\theta]}{E[y|\theta]} (1 + \Delta c^{\sigma})\right)^{-1}. \tag{49}$$

where Δc is the percentage difference in consumption if $y = 1$ versus $y = 0$.

[81]To our knowledge, there does not exist existing estimates of the income or consumption difference between those who have and have not defaulted on their student debt.

salaries of ISA enrollees are between \$5K and \$7K lower than non-enrolling applicants, even after conditioning on observable characteristics (Table 9, row 1)—remarkably close to the difference in ex-ante believed future salaries from the survey.

In interpreting his results, Mumford (2022) is agnostic about the source of post-college salary differences, writing "The lower starting salary could be the result of moral hazard...or could be due to adverse selection that is still unaccounted for after conditioning on the observables. I suspect that the truth is some mix of the two mechanisms." He does, however, argue that the magnitude of this difference—roughly \$5K—is inconsistent with the unraveling hypothesis in our paper, writing "While this difference is highly statistically significant, I find it striking how small the difference in actual salary is between the two groups. Again, this suggests that there is less adverse selection on private information than in Herbst and Hendren (2021)." Later, he concludes, "even if the the entire difference was due to unobserved adverse selection, \$5,000 is a relatively small difference that would not cause the college ISA market to unravel." While we are grateful to Mumford (2022) for providing a transparent and informative analysis of the Purdue ISA, we draw somewhat different conclusions from his results.

First, while we agree that the observed \$5K difference in ex-post salaries could arise from some mix of both adverse selection and moral hazard, we think adverse selection is the primary mechanism. For one thing, attributing the difference to moral hazard would imply an implausibly high elasticity of taxable income—a \$5K earnings response to Purdue's ISA terms would correspond to an elasticity of roughly 2,[82] which is several times larger than consensus estimates of around 0.3 (Saez et al., 2012). Moreover, Mumford's finding that those in lower-earning majors are more likely to enroll in ISAs is consistent with adverse selection, not moral hazard. The apparent lack of selection on first-year GPA and SAT scores conditional on major (Table 3, rows 5-7) is also entirely consistent with our results, which suggest adverse selection would occur among students with observably similar academic performance. In Table F10 below, we regress first-year GPA and composite SAT scores against log expected future salary in the BPS data, controlling for institutional factors and major field of study. Conditional on these baseline controls, neither measure is significantly correlated with the elicitation, suggesting the private information driving our results is independent of observable academic performance.

Second, we view the magnitude of the earnings difference in Mumford (2022) to be entirely consistent with unraveled equity markets. One reason why this difference is only \$5,000 could lie in Mumford's institutional setting. Several features of the Purdue ISA differ from the earnings-equity contracts we consider, often in ways that would lead to less adverse selection. Most notably, our paper concerns contract markets among entering college students, who are more likely to hold private information than their older counterparts and would be ineligible for the Purdue ISA. In fact,

[82] A \$5,000 earnings reduction corresponds to a 10% decrease relative to a mean of roughly \$50K. ISA enrollees pay 3.73% of their pre-tax income on average (Table 2), which would equal roughly 5% of after-tax income.

Mumford (2022) appears to agree that equity contracts like the ones we consider might unravel, writing "allow[ing] first-year students to participate...would dramatically increase the adverse selection and would make it very difficult to offer different income share rates based on expected future earnings."

More importantly, however, Mumford (2022) compares earnings between ISA enrollees and non-enrollees who applied to the ISA but did not enroll. Non-enrolling applicants likely earn only \$5K more than applicants because the true "high types" never applied for the ISA—those with knowledge of high earnings potential should expect to gain little from income-contingent contracts.[83] In fact, Mumford (2022) shows that non-applicants' SAT scores, GPAs, and earnings-by-major compare favorably to those of ISA applicants (Table 2), who compose less than 2% of sophomores, juniors, and seniors at Purdue.[84] So while a \$5,000 difference between participants and non-participants is indeed smaller than our results would predict for an earnings-equity contract with 50% take-up, the true pool of non-participants is larger and likely higher-earning than the pool non-enrolling applicants. If we account for an adversely selected applicant pool, our results can easily be reconciled with Mumford's \$5K estimate. For example, if the bottom 25% of individuals in Figure 4 applied for the ISA, and the bottom half of those applicants enrolled, we would expect the difference in earnings between enrollees and non-enrolling applicants to be $2\left(AV(.25) - AV(.125)\right) \approx \$5K$.

In other words, what Mumford (2022) observes as a small magnitude of adverse selection is likely masked by larger adverse selection into the study sample. It is quite plausible the terms of the Purdue ISA were immediately unattractive to all but a small portion of eligible students, only half of whom ultimately enrolled. Rather than conclude that unraveling cannot occur because earnings differences are small, we argue that earnings differences are small because much of the market has already largely unraveled. Why "Back-a-Boiler" and similar ISAs have not completely unraveled is a separate question. We discuss several potential answers in Section 5.5, though recent developments might make the question irrelevant: as of September 2022, Purdue has indefinitely paused all new ISA contracts (Moody, 2021).

Appendix G MVPF Derivation

Continuous Contracts

We begin the construction of the MVPF with the costs. Let $C(\eta,\lambda)$ denote the net cost to the government of offering a contract of size η at valuation, λ. The marginal cost, $\frac{\partial C(\eta,\lambda)}{\partial \eta}$, of providing the first dollar of equity financing at valuation at price λ is given by the sum of two terms. First, there is the marginal cost of subsidizing an adversely-selected contract. Let θ_λ denote the type

[83] Purdue ISA terms were publicly available, so students would not need to apply to learn the contract's potential payoffs. See Purdue's Program Descriptionand ISA Comparison Tool.

[84] This comparison does not control for ISA eligibility, which Mumford (2022) does not observe.

Table F10: OLS Regressions of First-Year GPA and Composite SAT Scores versus Log Expected Salary

	(1) SAT Score	(2) SAT Score	(3) First-Year GPA	(4) First-Year GPA
Log Expected Salary	8.783	7.872	-0.00187	0.0133
	(5.876)	(6.857)	(0.0300)	(0.0328)
Institution	Yes	Yes	Yes	Yes
Institution FE	No	Yes	No	Yes
Major FE	Yes	Yes	Yes	Yes
Mean Dep. Var.	1046	1047	3	3
N	2310	2220	2320	2230

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Note: This table reports estimated coefficients from OLS regressions of first-year GPAs and composite SAT scores against log expected salary among first-year students in four-year colleges who have exhausted their federal student loan limits (and would therefore be plausibly eligible for an ISA). Data are taken from the 2012-2017 Beginning Postsecondary Students (BPS) study. Sample size is rounded to the nearest ten. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations (September 2020).

that is indifferent to the contract at valuation λ so that all types $\theta \leq \theta_\lambda$ select the contract. These (negative) profits are given by:

$$\Pi(\lambda) = \Pr[\theta \leq \theta_\lambda] \left(E[Y|\theta \leq \theta_\lambda] - \lambda\right). \tag{50}$$

Note that if $\lambda = E[Y]$, the contract would break even in the absence of adverse selection. But the fact that the no trade condition holds above implies that $\Pi(\lambda)$ is negative for all possible values of λ and thus subsidies are needed for the market to exist.

In contrast to a private financier, the government also incurs any fiscal externalities from changes in individuals' (lifetime) earnings in response to the contract.[85] To capture these effects, we conceptualize the equity contract as the sum of two components: an increase in college funding, g, given by $\frac{dg}{d\eta} = \lambda$, and an increase in future tax rates, τ, given by $\frac{d\tau}{d\eta} = 1$. To fully estimate the net costs of any subsidy for risk-mitigating financing for college, we need to know it's impact on government tax revenue. We let Y^L denote lifetime PDV of earnings so that τY^L is the lifetime tax payments. We can write lifetime earnings as a function of both college funding, g, and tax rates, τ, $Y^L(g,\tau)$. The net effect of financing options is ambiguous. On the one hand, the increased up-front funding might improve future earnings by relaxing credit constraints and increasing human capital investments (g may increase Y^L). On the other hand, higher post-college tax rates may reduce earnings (τ may decrease Y^L). We assume here that the tax increase only has an impact on earnings in the year the taxes are collected (i.e. repayments made), but this is easily generalized with suitable empirical

[85] Hendren and Sprung-Keyser (2020) shows that these behavioral responses have only second order effects on financier profits. But these effects are first order to the government because of pre-existing tax distortions.

estimates. We can then express the equity contract's net effect on earnings for each type θ as the sum of these two effects:

$$FE(\lambda) \equiv \tau \frac{dE\left[Y^L\right]}{d\eta} = -\underbrace{\frac{\tau}{1-\tau} E\left[Y|\theta \le \theta_\lambda\right] \epsilon_{Y,1-\tau}(\theta_\lambda)}_{\text{Tax Distortion}} + \underbrace{\tau \frac{dE\left[Y^L\right]}{dg}}_{\text{Impact on Earnings via Grant}}, \tag{51}$$

where $\epsilon_{Y,1-\tau} = \frac{1-\tau}{E[Y|\theta \le \theta_\lambda]} \frac{dE[Y|\theta \le \theta_\lambda]}{d(1-\tau)}$ is the elasticity of taxable income at the time repayment is required (i.e. six years after college enrollment using our estimates), and $\tau \frac{dE\left[Y^L\right]}{dg}$ is the impact of a $1 grant for college financing on lifetime tax payments.

Putting these terms together, the total marginal cost to the government is the sum of the negative profits from the contract and the fiscal externality on tax revenue,

$$\begin{aligned} \frac{dC(\eta,\lambda)}{d\eta}\Big|_{\eta=0} &= -\Pi(\lambda) - FE(\lambda) \qquad (52) \\ &= \Pr\{\theta \le \theta_\lambda\} \left[\lambda - E\left[Y|\theta \le \theta_\lambda\right] - \tau \frac{dE\left[Y^L\right]}{dg} \frac{1}{\Pr\{\theta \le \theta_\lambda\}} + \frac{\tau}{1-\tau} E\left[Y|\theta \le \theta_\lambda\right] \epsilon_{Y,1-\tau}\right] \end{aligned}$$

Next we turn to the aggregate willingness to pay among enrollees. The value of contract λ for an individual of type θ equals its impact on expected utility, $\lambda u_1(\theta) - E(Yu_2|\theta)$, divided by the marginal utility of income at the time financing is received, $u_1(\theta)$.

An individual of type θ who takes up the contract has a willingness to pay for being given the option to take up the contract of:

$$\begin{aligned} wtp(\theta) &= \frac{\frac{dU}{d\eta}}{u_1(\theta)} \\ &= \lambda - \frac{E(Yu_2|\theta)}{u_1(\theta)} && (53) \\ &= \lambda - WTA(\theta) && (54) \\ &= \underbrace{\lambda - E\left[Y|\theta\right]}_{\text{Transfer}} + \underbrace{E\left[Y|\theta\right] - WTA(\theta)}_{\text{Consumption Smoothing}}, && (55) \end{aligned}$$

The third line makes clear that the WTP for the contract is given by the difference between the valuation and the valuation they would have accepted, $\lambda - WTA(\theta)$. Integrating over all types θ who choose to take up the contract, $\theta \le \theta_\lambda$, and dividing by the government's net marginal cost,

$\frac{dC(\eta,\lambda)}{d\eta}$, yields the MVPF:

$$
\begin{aligned}
MVPF(\lambda) &= \frac{\int_0^{\theta_\lambda} wtp(\theta)df(\mu)}{-\Pi(\lambda) - FE(\lambda)} \\
&= \frac{\lambda - E[WTA(\theta)|\theta \le \theta_\lambda]}{\lambda - E[Y|\theta \le \theta_\lambda] - \tau\lambda \frac{dE[Y^L]}{dg}\frac{1}{\Pr\{\theta \le \theta_\lambda\}} + \frac{\tau}{1-\tau}E[Y|\theta \le \theta_\lambda]\epsilon_{Y,1-\tau}} \qquad (56) \\
&= \frac{\lambda - E[Y|\theta \le \theta_\lambda] + (E[Y|\theta \le \theta_\lambda] - E[WTA(\theta)|\theta \le \theta_\lambda])}{\lambda - E[Y|\theta \le \theta_\lambda] - \tau\lambda \frac{dE[Y^L]}{dg}\frac{1}{\Pr\{\theta \le \theta_\lambda\}} + \frac{\tau}{1-\tau}E[Y|\theta \le \theta_\lambda]\epsilon_{Y,1-\tau}}. \qquad (57)
\end{aligned}
$$

Binary Contracts

This section derives the MVPF for our binary contract in which $Y = 1$ corresponds to repayment at valuation κ. To begin, note that the willingness to pay out of today's income for the contract by a type θ is given by:

$$
\begin{aligned}
wtp^d(\theta) &= \lambda - Pr\{Y = 1|\theta\} E\left[\frac{u_2}{u_1}|Y = 1,\theta\right] \\
&= \lambda - WTA(\theta)
\end{aligned}
$$

As noted in the main text, we set $\lambda = E[Y]$ and we let θ_λ denote the marginal type indifferent to taking up the contract, so that all types $\theta \le \theta_\lambda$. The aggregate willingness to pay is then

$$
WTP^{binary}(\lambda) = \Pr\{\theta \le \theta_\lambda\}[\lambda - E[WTA(\theta)|\theta \le \theta_\lambda]]
$$

The marginal cost to the government follows a similar pattern to that of the equity contract. The lost profits to the financier is the cost of the $\$\lambda$ provision minus the repayment for those that repay. In addition, we have fiscal externalities arising from two sources: the upfront grant of η and the repayment of $\eta\kappa$ in the event of non-default. Similar to the equity contract, the upfront grant increases tax revenue by $\tau\frac{dE[Y^L]}{dg}$. But the repayment mechanisms are now different than the equity contract. Debt repayment in adulthood likely reduces tax revenue by $-\kappa\tau\frac{dE[Y^L]}{dD}$, where $\tau\frac{dE[Y^L]}{dD}$ is the impact of \$1 additional debt burden on tax revenue. Summing,

$$
\frac{dC^{debt}(\kappa)}{d\eta}|_{\eta=0} = \Pr\{\theta \le \theta_\kappa\}(\lambda - \kappa E[Y|\theta \le \theta_\kappa]) - \lambda\tau\frac{dE[Y^L]}{dg} - \tau\frac{dE[Y^L]}{dD}
$$

So, the MVPF of a debt contract that requires repayment of κ is

$$
MVPF^{debt}(\kappa) \approx \frac{1 - \frac{1}{\lambda}E[Y|\theta \le \theta_k] + \frac{1}{\lambda}\sigma var(Y|\theta \le \theta_\kappa)\frac{\Delta c}{c}}{1 - \frac{1}{\lambda}E[Y|\theta \le \theta_\kappa] - \tau\frac{1}{\Pr\{\theta \le \theta_\kappa\}}\frac{dE[Y^L]}{dg} - \frac{\tau}{\lambda}\frac{1}{\Pr\{\theta \le \theta_\kappa\}}\frac{dE[Y^L]}{dD}}
$$

The distinction relative to the earnings-equity contract is that the behavioral response due to higher implicit tax rates from the equity contract is replaced with the causal effect of the debt repayment incentives on earnings, $\frac{\tau}{\lambda}\frac{1}{\Pr\{\theta\leq\theta_\kappa\}}\frac{dE\left[Y^L\right]}{dD}$. For the employment-contingent loan contract, we draw upon the literature on UI that shows behavioral responses to UI mean that every \$1 of UI spending actually costs the government around \$1.50 (Schmieder and Von Wachter (2016)). Since the odds of being unemployed are 12.3%, this implies every \$1 of financing that only requires repayment in the event of employment has an additional cost of $\frac{0.123}{1-0.123}0.5 = .07$ to the government. To the best of our knowledge, there does not exist empirical evidence on the impact of dischargeable loans and completion-based repayment contracts on taxable income. We therefore assume for simplicity that this fiscal externality per person taking up the contract is equal to the fiscal externality from the earning-based repayment disincentive.[86]

The resulting components of the MVPF are presented in Table 6.

[86]In principle, the fiscal externalities reflect not only any earnings effects, but also any effects on loan repayments that lead the government to not fully recoup their existing base of student loan spending.