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

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Abstract

Investing in college delivers 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 investigates whether 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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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. 28% of student borrowers default on their debt within five years of repayment.[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 constrained the supply of 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 explore the hypothesis that markets for risk-mitigating college financing have unraveled due to adverse selection.

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)

[1] Employment and completion statistics are calculated six years from enrollment using the 2012 Beginning Post-secondary 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). Five-year default rates are taken from the 2009 repayment cohort in Table 8 of Looney and Yannelis (2015).

[2] In Section 5.5, we discuss private attempts to offer equity-like contracts called income-share agreements (ISAs) for financing college.

curve, which corresponds to the minimum amount an individual is willing to accept today to sell a 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 the subset of borrowers with better expected outcomes to exit the market, so that profits are negative at any price. 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 default 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 \$3,000 to \$4,000 higher than those of observationally identical peers with lower elicitation-predicted earnings. 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.

Second, we estimate a structural model of beliefs and survey elicitations, allowing us to measure the AV and WTA curves in each setting. Motivated by likely measurement error in elicitations and the potential for biased beliefs, 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, 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 the joint distribution of what is known to individuals (their elicitations) and

[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 study.

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 that would mitigate post-college earnings risk. Under rational beliefs, the median individual expects to earn \$20,397, but the average earnings of those willing to accept lower valuations are just \$12,471 = $AV(0.5)$. 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 \$17,024 = $WTA(0.5)$. At this valuation, the financier would lose \$0.27 for every dollar they finance. We show that the WTA curve lies everywhere above the AV curve, so the market unravels. When we allow college-goers to hold potentially biased beliefs, we find that respondents' over-optimism can amplify the forces of market unraveling. But this bias cannot explain missing markets independently of adverse selection—in the absence of private information, a sizable fraction of college-goers with biased beliefs would accept actuarially fair equity contracts. We also discuss how the presence of outside financing or credit constraints affects our results. Our baseline results assume college-goers can access existing forms of credit, like federally subsidized student loans. If such loans were not available, those college-goers might be more likely to accept alternatives like equity contracts. However, our results suggest the market continues to unravel when we assume reasonable limits on the availability of outside credit.

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) default 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 default risk.[4]

If market unraveling is leaving Pareto-improving exchanges on the table, should the government step in to facilitate these exchanges? 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 risk-mitigating financial contracts. While earnings-equity contracts provide a consumption-smoothing benefit to college-goers, they can also reduce future tax revenue by discouraging work. While these moral hazard effects are second order to the financier's profits, they impose first-order costs on the government due to pre-existing taxes on earnings. Nonetheless, we show that for plausible elasticities of taxable income (ETI of 0.3 (Saez, Slemrod and Giertz, 2012)) and coefficients of relative risk aversion (CRRA of 2), the value of risk reduction is more than twice as large as the distortion induced by higher implicit taxes on future earnings. This comparison suggests that subsidizing an

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

earnings-equity contract has an MVPF in excess of 1, even if it does nothing to improve enrollment, persistence, or performance in college.[5] That said, we also show that a subsidy's potential to increase earnings through greater human capital investment can have dramatic welfare effects. If equity contracts induce credit-constrained or risk-averse individuals to invest in more education, the resulting increases in future tax revenue could more than offset the costs of the subsidies, leading to an infinite MVPF.

Our broad conclusions come with two important caveats. First, the set of contracts we consider in this paper is restricted by the specific outcomes we observe in the data. While we show that short-term contracts like completion-contingent loans and equity contracts on post-college earnings would likely unravel, we cannot currently consider longer-term contracts that require repayment after the BPS follow-up in 2017. Second, we cannot claim to reject every alternative explanation for missing markets. Other factors like borrower confusion, legal constraints, and regulatory uncertainty might also prevent the proliferation of earnings-equity or state-contingent debt. Even with these caveats, however, our normative results suggest that providing risk-mitigating financing options to college-goers could yield significant welfare gains.

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; Jacobs, 2021).[6] Broadly speaking, these papers consider the optimal design of income-based financing in higher education, balancing its insurance value against the distortionary costs of state-contingent contracts. Empirical studies of these distortionary costs include Britton and Gruber (2019) and de Silva (2023), who estimate the earnings disincentives of income-contingent repayment programs in the UK and Australia, respectively. We also relate to Evans, Boatman and Soliz (2019), who find that student take-up of income-contingent contracts is sensitive to how they are framed, and Madonia and Smith (2019), who document the distortionary effects of these contracts among professional poker players. Most closely related, 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, Einav and Levin, 2009; Einav, Jenkins and Levin, 2012), credit cards (Ausubel, 1999; Agarwal, Chomsisengphet and Liu, 2010), and personal loans (Dobbie and Skiba, 2013; Karlan and Zinman, 2009).

[5]By contrast, subsidizing the three state-contingent debt contracts we consider comes with distortionary costs that exceed the value of risk reduction, although we note these estimates rely on stronger assumptions about the moral hazard response.

[6]These studies form part of a larger literature on student loans and optimal human-capital financing (Jacobs and van Wijnbergen, 2007; Stinebrickner and Stinebrickner, 2008; Lochner and Monge-Naranjo, 2011; Stantcheva, 2017; Abbott et al., 2019). See Lochner and Monge-Naranjo (2016) for a review.

[7]In Appendix G, we offer a more detailed discussion of Mumford (2022) and show our results are broadly consistent.

Methodologically, our paper complements a large literature using subjective information to measure expectations and uncertainty (Manski, 2004; Jappelli and Pistaferri, 2010; d'Haultfoeuille, Gaillac and Maurel, 2021; Mueller, Spinnewijn and Topa, 2021), especially those concerning earnings risk (Dominitz, 1998; Manski and Straub, 2000; Van der Klaauw, 2012; Conlon et al., 2018; Mueller, Spinnewijn and Topa, 2021) or college-goers' beliefs about the future (Attanasio and Kaufmann, 2009; Hoxby and Turner, 2015; Gong, Stinebrickner and Stinebrickner, 2019; Crossley et al., 2021; Wiswall and Zafar, 2021).[8] We also relate to several papers in the behavioral economics literature, particularly those studying the impact of informational interventions in higher education (Bettinger et al., 2012; Wiswall and Zafar, 2015; Baker et al., 2018; Marx and Turner, 2019; Dynarski et al., 2021) and those documenting the interaction between biased beliefs and adverse selection (Handel, 2013; Spinnewijn, 2015). Our empirical approach builds upon strategies from Hendren (2013, 2017), who uses 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 the influence of private information in markets for higher education financing. Building upon existing models of insurance markets (Einav, Finkelstein and Cullen, 2010), we place this evidence in a framework that provides testable conditions for unraveled financial markets under adverse selection, moral hazard, biased beliefs, and outside credit options. Our paper also quantifies the 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, Finkelstein and Cullen (2010) to provide conditions for market unraveling for college

[8] The *Handbook of Economic Expectations* (Bachmann, Topa and van der Klaauw, 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.

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, $Y = f\left(a,\zeta\right)$, 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 $Y = \mathbb{1}\left\{Complete\right\}$ corresponds to a completion-contingent loan requiring repayment of η only if the borrower graduates.[10]

Individuals are observationally identical to the financier,[11] but may hold private information about their own future Y. This private information is 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 a vector of 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 (mean) beliefs about their realization of 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 held unbiased beliefs using all of their private information, their subjective beliefs would correspond to the mean realization of Y conditional on

[9] In Appendix C, we extend our theoretical analysis to a dynamic stochastic life-cycle model with biased beliefs and endogenous college enrollment, nesting several models from previous literature (Abbott et al., 2019; Lochner and Monge-Naranjo, 2011). The key lesson is that period 1 in our simple model corresponds to the time contracts are offered and period 2 is when the outcome triggering repayment, Y, is observed.

[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 readily 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 how X relates to outcomes, Y, could be one source of bias in beliefs.

θ, $E_S[Y|\theta] = E[Y|\theta]$.

In this environment, when can risk-neutral financiers profitably exchange risk-mitigating contracts with college-goers? 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

$$\lambda u_1(\theta) - \beta E_S[Yu_2|\theta] \geq 0, \tag{2}$$

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 ($\eta = 0$) allocations, (c_1,c_2,a), and any behavioral changes in a are not included in equation (2).[13]

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,

$$WTA(\theta) = \frac{\beta E_S[Yu_2|\theta]}{u_1(\theta)} R, \tag{3}$$

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 $R_\theta \equiv \frac{u_1}{\beta E_S[u_2|\theta]}$ 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:

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

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 for a type θ. The second term, $E_S[Y|\theta] - E[Y|\theta]$, denotes the borrower's

[12]While we allow beliefs to be biased, we assume borrowers' behavior is rational given their (potentially biased) beliefs. One could 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 C.

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 try to make 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 $WTA(\theta) \leq WTA(\theta_\lambda)$. The financier's 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 generate 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

[14]Inequality (7) characterizes when the financier can profitably sell a small contract, $\eta \approx 0$. In general, the marginal profits to the financier are declining in the size of the contract, η, so that 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 rules out the profitability of menus, $\{(\eta_\theta,\lambda_\theta)\}_\theta$.

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.

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 $E_S[Y|\theta] = E[Y|\theta] \equiv MV(\theta)$. 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 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,

[15] Appendix C 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.

$E[Y|\theta]$, 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 $\lambda =$ \$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. Now suppose that the financier sets the same valuation ($\lambda =$ \$30,000) to again attract the median borrower who expects to earn 50,000.[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 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 $E[Y|\theta]$ (e.g. we exploit this in Section 4.2). 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

[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.

[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.

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

Quantifying adverse selection for contracts that do not exist is not straightforward because we cannot readily observe data on individuals' contract decisions. Our empirical strategy, therefore, uses imperfect measures of their beliefs to test for private information and quantify the WTA and AV curves outlined above. We use data from the 2012/2017 Beginning Postsecondary Students (BPS) longitudinal study, a dataset from the National Center for Education Statistics.[18] 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 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 the level of financial support individuals expect to receive from their parents. Summary statistics, adjusted with BPS survey weights, are provided for key outcomes and elicitations in Table 1 and for public information in Table 2.

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.[19] The average salary six years after enrollment is $24,032, with a standard deviation of $25,376.[20] Over 40 percent of those with positive earnings report annual

[18]We provide more details on BPS survey questions and data-collection procedures in Appendix D. A comprehensive guide to BPS study design can be found at `https://nces.ed.gov/surveys/bps` (NCES, 2023).

[19]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.

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

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 default on their existing student loans, ($Y = \mathbb{1}\{No\ Default\}$). This last contract can be thought of as debt that is dischargeable in times of financial distress, where financial distress is proxied by default 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, 17% have already defaulted on their debt.[21]

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 classify these observables into five groups: (1) academic characteristics, which include the college-goer's degree type, major field of study (14 categories), 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;[22] (3) high school performance measures, which include high school GPA and SAT/ACT scores;[23] (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.[24] Controlling for these different sets of observable characteristics allows us to simulate how private information might change with the financier's underwriting capabilities.[25]

[21]Repayment outcomes measure the incidence of any delinquency/default through 2017. We exclude borrowers who are still enrolled in a degree program and therefore do not require repayment. 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.

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

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

[24]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.

[25]To the best of our knowledge, 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, 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 detailed in Appendix D, including the level of financial support they expect to receive from their parents. 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 the relationship between elicitations and outcomes. In particular, we use observed patterns in this relationship to (i) test for private information, (ii) assess the magnitude of this private information, (iii) determine whether this information would be used to adversely select state-contingent contracts, and (iv) explore evidence for potentially biased beliefs.

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). The key assumption underlying this test is that the elicitations are no more informative about Y than true beliefs, $E\left[Y|X,\theta,Z\right] = E\left[Y|X,\theta\right]$.[26] This means any predictive information found in Z must reflect predictive information in θ.[27] We therefore regress Y on Z controlling for X:

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

We establish the presence of private information by rejecting the null hypothesis $H_0 : \beta = 0$.

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.

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

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

In Figure 3A, we plot employed individuals' log salary in 2017 against the log of the "expected future salary" they reported in 2012.[28] 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 $\hat{\beta} = 0.176$ (SE=0.023).[29] Much of this relationship is explained by observable characteristics—adding academic and institutional controls reduces this point estimate to 0.079 (SE=0.024) in Column (3). Conditional on these academic and institutional characteristics, however, adding more covariates in Columns (4) through (9) has a comparatively small impact on estimates of β. We find a slope of 0.075 (SE=0.024) after adding controls for student performance and demographics, and a slope of 0.084 (SE=0.022) when further adding parental characteristics 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 $\hat{\beta} = 0.086$ (SE=0.028, p=0.002).

Turning to our next market setting, Figure 3B displays the relationship between six-year graduation status and respondents' reported likelihood of completing their degree "on-time", which we normalize to a [0,1] scale. Those reporting higher completion likelihoods in 2012 are more likely to have graduated by 2017 ($\hat{\beta}$=0.492, SE=0.022). 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 ($\hat{\beta}$=0.359, SE=0.022), but it remains relatively stable when adding further controls in Columns (3) through (9).

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 is valid as long as it does not contain information about Y that is not known to the individual (i.e. we require $E[Y|X,\theta,Z] = E[Y|X,\theta]$). 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 ($\hat{\beta}$=0.022, SE=0.0107). 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

[28] Not everyone responds in a serious manner to subjective elicitations. In an effort to purge the sample of potential "knucklehead responses" that do not reflect true beliefs, we drop salary elicitations that fall below $12,000 or above $130,000 (this corresponds to the bottom 2% and top 5% of responses, respectively). Appendix Table A2 reports the coefficients on the full sample, and Appendix Figure A1 reports coefficients across a variety of trimming specifications. With the exception of the specification controlling for both institution-by-major fixed effects and protected-class information, estimated coefficients in untrimmed specifications remain statistically significant, albeit with smaller magnitudes than those in Table 3. We discuss this attenuation from outlier responses in Section 4.4.

[29] Note that an estimated slope of $\hat{\beta} < 1$ could reflect biased beliefs, measurement error in elicitations, or both. We discuss these potential explanations in Section 4.4.

the employment outcome, individuals are not directly asked about their likelihood of default, but they are asked how much their parents support their education, which potentially relates to their ability to repay student debts. Figure 3D shows that student borrowers who report greater parental encouragement for college are more likely to make timely payments on their federal student loans (no defaults) through 2017. Conditional on academic and institution characteristics, Table 3D shows the slope of this relationship to be $\hat{\beta}$=0.115 (SE=0.0211), which remains statistically significant even after including our full set of control variables.[30]

Overall, results from Table 3 reveal a consistent pattern: Unconditionally, elicitations contain a substantial amount of predictive information about future outcomes, suggesting that uniformly priced contracts would face a considerable threat of adverse selection. Controlling for academic and institutional characteristics reduces this predictive power—sometimes considerably. But, with the exception of the employment outcome, adding more control variables beyond these categories does little to weaken the conditional relationship between elicitations and outcomes.[31] So while a financier might mitigate the threat of adverse selection by pricing on observables like age, field of study, or institutional rank, observably equivalent individuals would likely still retain some residual private information they could potentially use in contract decisions. In the following sections, we try to determine whether this residual private information is enough to unravel markets.

4.2 Magnitude of Private Information

Table 3 establishes the existence of private information says little about its magnitude. It also relies on a single elicitation in a simple linear model, instead of measuring the full predictive power of the elicitations.[32] We next try to infer something about the magnitude of the threat of adverse selection. A full quantification of the AV and WTA curves will require the structural model in Section 5. Here, we provide a lower bound on these frictions using the predictive power of the full set of elicitations combined with our benchmark assumptions in Section 2. Borrowing from Hendren (2013), we define the *magnitude of information in Z* as

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

[30]In Appendix Table A3, we present regression coefficients for alternative loan-repayment outcomes (no $Y = No\ Delinquencies$ and $Y = No\ Delinquencies\ or\ Forbearances$).

[31] While this relationship suggests that private information can help predict outcomes, it does not speak to the precision of those predictions relative to overall earnings uncertainty. In Appendix Table A4 we find that adding private elicitations to public observables can improve out-of-sample predictions, but the R-squared (R^2) and root-mean-square error (RMSE) of those predictions still imply a considerable amount of residual uncertainty. As we discuss in Section 5, this residual uncertainty is precisely why state-contingent contracts are valuable—they insure college-goers against unforeseen risks. At the same time, it raises concerns that the elicitations or true beliefs contain error and bias, which motivates our empirical approach to address these potential concerns.

[32]Correlating each outcome with a single elicitation will fail to capture all the private information in the survey if that elicitation is measured with error. Appendix Table A5 regresses realized salaries against two elicitations—expected future salary and expected degree completion–and finds significant coefficients on both.

where $r_i \equiv E[Y|X = X_i,Z = Z_i] - E[Y|X = X_i]$. The magnitude, m_i^Z, measures difference between an individual's expected outcome given Z and those of observationally-identical peers with lower elicitation-predicted outcomes. In other words, m_i^Z is a measure of the size of adverse selection if contract choice were determined by the predicted outcomes given elicitations and observables, $E[Y|Z,X]$. Under our model's benchmark assumptions of rational beliefs, $E[Y|X,\theta,Z] = E[Y|\theta]$, and unidimensional heterogeneity, Hendren (2013) shows that averaging these magnitudes forms a lower bound on the average difference between the true marginal and average value curves:

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

We construct $E[Y|X,Z]$ and $E[Y|X]$ using a machine learning procedure applied to the elicitations and observables in Tables 2 and 1, described in detail in Appendix E. 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 (10). To reflect the entire body of private information contained in surveys, we let Z_i include all elicitations.[33] In each specification, public information, X, includes the set of observable variables designated by the column label. The second row of each panel presents p-values for tests of joint significance of elicitations conditional on public information in a linear regression. Rejecting the null hypothesis $H_0 : E[Y|X,Z] = E[Y|X]$ in this test establishes the presence of private information using multiple elicitations, as opposed to the single elicitations in Table 3.

Panel A considers the earnings-equity market case when Y is salary.[34] 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. Relative to a mean earnings of \$24,032, these results imply that the average individual would have to be willing to accept a valuation that is at least 10% to 22% lower than their expected future income to cover the cost of worse risks if they adversely selected the contract.

In our state-contingent debt markets, we find similarly large frictions imposed by asymmetric information. Panel B of Table 4 shows that the average college-goer has a completion probability that is at least 11.0pp to 21.8pp higher than those who are observationally identical but whose private elicitations imply they are less likely to complete college, with the range depending on the controls used for public information. If contract choices were determined rational beliefs, college-

[33] To be conservative, we include only elicitations, Z, and the firm's observables, X, in individuals' information set. In Appendix Table A6, we allow private information to also include any observable variables not included in the specified set of public information, so that $E[Y|X,Z]$ does not vary across specifications. We find larger, but qualitatively similar lower-bound estimates.

[34] Note that for the equity contract, equation (11) 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 E.

goers would have to be willing to accept a level of financing that is at least 22% to 43% below their actuarially fair value for a completion-contingent loan market to exist.

Panels C–D of Table 4 show that the average college-goer is 4.7pp to 11.6pp more likely to find employment and 4.8pp to 12.1pp more likely to avoid default on their federal student loans than observationally-identical peers with private knowledge of worse risks. These values imply that, on average, individuals would have to accept financing that is 6–16% and 28–71% below actuarially fair values in order to sustain these respective state-contingent debt markets.

In principle, a financier could try to avoid adverse selection in the overall population by targeting subgroups with less private information, as is common in health-related insurance markets (Hendren, 2013). To assess this, Appendix Table A7 explores how these lower-bound estimates, $E_i\left[m_i^Z\right]$, vary by subgroups of the data, including by gender, degree type (STEM versus non-STEM), and type of school (2- versus 4-year). Broadly, we find significant magnitudes of private information within each of these subgroups, suggesting it would be difficult for a financier to evade private information by targeting a particular subpopulation. In summary, these results suggest that the elicitations contain enough information to pose a potential threat of adverse selection if these contracts were offered.

4.3 Do Elicitations Reflect Information Used for Financial Decisions?

Would individuals select contracts based on the information in their elicitations? Existing research suggests that subjective expectations may inform related decisions. For example, Arcidiacono et al. (2020) and Arcidiacono, Hotz and Kang (2012) provide evidence that college students sort into majors based on the expected returns implied by their subjective elicitations. Our model assumes individuals would behave similarly when opting into hypothetical contracts, so that those expecting higher realizations of Y would require a higher valuation to accept the contract as in equation (2). While we cannot directly test this assumption, we can test whether elicitations predict choices 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.

In Appendix B, we investigate the relationship between elicitations, realized salaries, and IDR take-up using data from the 2016 Baccalaureate and Beyond (B&B16) study, which asks college seniors both their self-reported likelihood of IDR enrollment after graduation and their expected salary after graduation. We show that student borrowers who expect higher salaries report significantly lower likelihoods of enrolling in IDR, even conditioning on age, college major, and a variety of institutional controls. We also show that they are also less likely to actually enroll in IDR when they begin loan repayment.[35] These patterns suggest the elicitations contain information individuals would use in deciding whether to take up our hypothetical contracts.[36]

4.4 Biased Beliefs versus Elicitation Error

The previous subsection suggests borrowers use their beliefs to make strategic financial decisions. But those beliefs could potentially reflect biased expectations of the future. College-goers report expected salaries of $56,637 on average, but employed graduates earn only $32,701 on average in 2017. They also report an average on-time completion likelihood of 8.4 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. Unless this over-optimism is subdued when making contract decisions, it would lead individuals to overvalue their own earnings prospects, making markets less likely to exist. On the other hand, the slope less than one in Figure 3A suggests this bias could be heterogeneous across the population, potentially attenuating the regression coefficient. In theory, such heterogeneity could make a market more likely to exist—there could be enough pessimists who undervalue their earnings prospects to make a market profitable. Importantly, our identification approach in Section 5 will allow for this heterogeneity in the degree of bias in beliefs.

Instead of biased beliefs, an alternative explanation for the observed relationship between elicitations and outcomes is that the elicitations contain large amounts of measurement error. In other words, respondents might make contract choices using unbiased beliefs about 2017 outcomes ($E_S[Y|\theta] = E[Y|\theta]$) but report something different in survey questionnaires ($Z \neq E_S[Y|\theta]$). 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.[37] This kind of elicitation error generates variation in Z that can attenuate estimates of β in Figure 3.

Elicitation error might also arise from systematic misinterpretations of survey questions or mis-

[35] These patterns are broadly consistent with findings in previous literature. Mumford (2022) finds that participants in an income-share agreement reported higher self-reported 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, Perry and Yannelis (2020) show that high-balance, low-income borrowers are more likely to opt into IDR.

[36] Later in Appendix B, we connect these patterns more closely to our model by assuming that people who have a greater desire for IDR enrollment also have a greater desire for an earnings-equity contract.The AV and MV curves implied by this exercise are qualitatively consistent with our baseline results.

[37] 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, Gneezy and Rasocha (2021) discuss a range of more advanced methods for eliciting beliefs and discuss the tradeoffs.

representations of true beliefs. For example, the BPS questionnaire does not specify a time period when asking about salary expectations, so rather than reporting beliefs about earnings immediately after college, some respondents may answer the question "What is...your expected yearly salary?" with their beliefs about earnings later in life.[38] 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 \$56,637 average expected salary reported in the BPS.[39] Moreover, even if survey-takers interpret the expected-salary question correctly, some might enjoy reporting higher future salaries than what they truly expect. Existing research suggests surveys often fail to elicit truthful responses, especially to questions concerning subjective beliefs (Tourangeau and Yan, 2007; Stephens-Davidowitz, 2013). And because BPS respondents are not rewarded for accuracy, embellishing one's own earning potential is costless. This kind of willful exaggeration might explain the sensitivity of our β estimates to extreme-valued earnings expectations. As noted in Footnote 28, our main sample drops these outlier responses, and including them attenuates our estimates considerably (see Appendix Figure A1).

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. 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. If it were possible to perfectly elicit people's beliefs through surveys, we would solely focus our efforts on these beliefs. However, as we noted above, elicited beliefs likely suffer from biased responses and non-classical measurement error.[40] Estimating these two distributions allows us to test for unraveling under two scenarios—one in which individuals hold rational beliefs or "rationalize" their beliefs before deciding whether

[38]See Appendix D 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.

[39]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.

[40]A more subtle point arises from the fact that even if survey questions elicited true beliefs, college-goers may subdue their biases or acquire public information in face of high-stakes financial decisions. 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). This provides a potential further rationale for the rational beliefs specification.

to accept a contract, and another in which they hold potentially biased beliefs but the reader needs to accept stronger assumptions on the distribution of measurement error that arises when eliciting beliefs.

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.[41] In Appendix F, we provide details on the residualization process and how we adapt our method for degree completion, loan repayment, and employment outcomes.

For each individual i, let $y_i = log\left(Y_i\right)$ denote the log of their realized salary and θ_i denote their type, which corresponds to the information they have about their future earnings. A log specification allows us to model uncertainty in the earnings process as a proportional shock, as is common in previous literature (Guvenen, 2007).[42] We assume the realization y_i is the sum of rational beliefs about y_i, which we denote by $\mu_i \equiv E\left[y_i|\theta_i\right]$, and a mean-zero homoskedastic error term, $\epsilon_i \sim f_\epsilon\left(\epsilon_i\right)$, which captures i's uncertainty around y:

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

Let $\mu_{Si} = E_S\left[y_i|\theta_i\right]$ denote θ_i's belief about y_i and let $z_i = log\left(Z_i\right)$ denote the log of the individuals' elicited expected salary. We assume z_i is a noisy and potentially biased measure of true beliefs,

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

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

5.1.1 Rational Expectations, μ

To estimate the distribution of rational beliefs, $f_\mu\left(\mu_i\right)$, we seek to decompose the observed distribution of y_i into μ_i and ϵ_i in equation (12). Substituting $\mu_{Si} = \mu_i - \left(\mu_{Si} - \mu_i\right)$ into equation (13) yields

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

[41]This set of observables is similar to those typically used by existing ISA providers; while our 14-category major-field-of-study variable cannot perfectly capture major-specific pricing, ISA providers have historically used similarly coarse field-of-study measures to price contracts (Purdue's ISA used just 8 categories) (Purdue University, 2022; Hartley, 2016). Moreover, Table 3 shows that conditioning on academic and institutional characteristics reduces the residual information contained in the elicitations, but adding further observables beyond these categories does not significantly change this relationship.

[42]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 F.

where $\alpha' \equiv \alpha + \gamma E[\mu_{Si} - \mu_i]$ and $\nu_i' = \gamma(\mu_{Si} - \mu_i) - \gamma E[\mu_{Si} - \mu_i] + \nu_i$. 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 $cov(w_i,\nu_i') = 0$.[43] This exclusion restriction would be violated if any idiosyncratic variation in biased beliefs or elicitation error captured in z_i 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_i.

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.[44] 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.[45] 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. While this assumption could plausibly be violated, Section 5.3 shows that we obtain similar results when using alternative instruments or simply calibrating $\gamma = 1$ so that a one-unit higher belief corresponds to a one-unit higher elicitation on average as in Hendren (2013, 2017). The key substantive restrictions in our structural model is log additivity with homoskedastic distributions of ϵ_i and ν_i'.

Using w_i to instrument for beliefs about log salary, we estimate γ=0.75 (SE=0.16) in equation (14).[46] 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.[47] 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'*

[43]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 $cov(w_i,\epsilon_i) = 0$.

[44]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. Note that post-graduate salaries of this B&B cohort are measured shortly before the initial BPS survey containing our elicitations, Z_i, ensuring that w_i only reflects information that is knowable at the time elicitations are measured. Details in Appendix D.

[45]One potential violation of the exclusion restriction would be if individuals shade their elicitations towards the occupation-specific mean earnings so that the measurement error in the elicitation is correlated with the occupation-specific mean conditional on true beliefs.

[46]Appendix Table A8 reports estimates of γ for all four outcomes, as well as the associated elicitation and instrument used in each estimation.

[47]We provide details on the deconvolution method in Appendix F.

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 beliefs. The strategy exploits the fact that realizations of y_i are unbiased measures of rational beliefs, $\mu_i \equiv E[y_i|\theta_i]$, while allowing elicitations, z_i, to be noisy and potentially biased measures of true beliefs, $\mu_{Si} \equiv E_S[y_i|\theta_i]$.

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 salary elicitations are unbiased measures of true beliefs so that the average realization of Z_i for a type θ_i equals their true beliefs, $E[Z_i|\theta_i] = E_S[Y_i|\theta_i, Y_i > 0]$.[48] 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 $\bar{\alpha} \equiv log\left(E_S\left[e^{\epsilon_i}|\theta_i\right]\right) - log\left(E\left[e^{\nu_i}\right]\right)$ ensures Z_i is unbiased in levels, $E[Z_i|\theta] = E_S[Y_i|\theta, Y_i > 0]$. 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 the average y_i for those with beliefs μ_{Si} and a homoskedastic error term:

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

where the second line follows from taking expectations in equation (12). We assume a linear approximation to this conditional expectation function, $E[\mu_i|\mu_{Si}] = a + b\mu_{Si}$, 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.[49] We then write (16) as

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

[48] Note we condition on $Y_i > 0$ because Z is asked about salary when working after college. As in the reduced-form analysis, we reduce the impact of outliers by removing the bottom 2% (below $12,000) and top 5% (above $130,000) of salary elicitations when estimating the biased-belief distribution.

[49] 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 $\Pr_S(y_i - \mu_{Si} \leq x) = F_{\xi_i}(x)$. d'Haultfoeuille, Gaillac and Maurel (2021) and Crossley et al. (2021) show how one can relax this assumption with additional elicitations about higher order moments of the subjective belief distribution.

where ξ_i is orthogonal to $a + b\mu_{S_i}$. Equations (15) and (17) form a system of two linear equations with three latent variables. If b is known, then we can use a linear deconvolution to estimate the distributions of μ_{S_i}, 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 (not y_i) is the unbiased measure of beliefs. 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 again let w_i be the average salary in one's expected occupation. This exclusion restriction is now slightly weaker than the rational beliefs case because we can allow individuals to be optimistic both in their earnings elicitation and their expected occupation.[50] The key requirement is that this optimism reflects true beliefs. This IV strategy yields an estimate of b =3.13 (SE=0.22) (see Appendix Table A9). We again stress that our results are not very sensitive to estimates of b. In Section 5.3, we show 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 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, $E[\mu_i|\mu_{S_i}] = a + b\mu_{S_i}$.*

Beliefs about Binary Outcomes Appendix F provides details on belief estimation for binary outcomes (degree completion, employment, and non-default on student loans), which is similar to the method described above. 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.[51] Allowing $\gamma \neq 1$ in equation (14) is crucial in these settings because elicitations do not directly correspond to binary outcomes. We therefore focus our attention to the rational-beliefs case for these outcomes, though we also estimate the distribution of potentially biased beliefs about college completion using the

[50] See Conlon and Patel (2023), who note that students' often overestimate their odds of landing a job in their expected occupation, which suggests validity for the use of occupation-specific earnings as an instrument for beliefs.

[51] Because we do not have direct measures of one's 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.

(strong) assumption that normalizing 0–10 completion likelihoods to [0,1]-scale yields an unbiased measure of true beliefs about completion. We provide these results in the appendix.

Estimation Results Estimated belief densities for each outcome are plotted in Appendix Figure A3. Our findings suggest there is significant private information but also considerable uncertainty. For example, 40% of the residual variance of log earnings is known at the time of enrollment, while 60% is uncertain. As we discuss below, this residual uncertainty suggests considerable scope for insuring income risk, as risk-averse college-goers should be willing to accept a discounted valuation for equity contracts.

5.2 Estimating AV and WTA Curves

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

Average Value We begin by imposing our benchmark assumption of unidimensional heterogeneity, which means that those with higher beliefs will have a higher WTA. We can therefore without loss of generality index beliefs by their quantiles, $\theta \in [0,1]$. The marginal value curve, $MV(\theta)$, is then given by the $\theta-$quantile of the distribution of $E[Y|\theta]$. The average value curve, $AV(\theta)$, is the average of marginal values among all those with lower 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

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

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. 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. For the unemployed state ($Y = 0$), we assume individuals consume $1 - \delta_C$ times the amount they expect to consume in employment, $c(0) = (1 - \delta_C)\, E_S[c(Y)|Y > 0,\theta]$, where the consumption response to unemployment is calibrated to $\delta_C = .09$.[52] 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.[53] We then use the perceived distribution of Y given θ to construct both $E_S[Y|\theta]$ and the covariance term in equation (19) for both the case of rational and potentially biased beliefs.

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 F.

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 represents the marginal value curve, $MV(\theta)$, and the solid green line represents the average value curve, $AV(\theta)$. These estimated curves suggest that college-goers would have to accept valuations that are significantly lower than actuarially fair for a market to exist. The median individual expects to earn \$20,397 $= MV(0.5)$ in 2017. The 50% of individuals who expect to earn \$20,397 or less have salaries of \$12,471 $= AV(0.5)$ on average.[54] 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. The willingness-to-accept curve, $WTA(\theta)$, plotted in red, suggests they would reject any such contract. We estimate the median individual is willing to accept a valuation no lower than \$17,024 $= WTA(0.5)$, an implied 17% discount below future earnings. In other words, they would pay \$1.20 $= \frac{MV(0.5)}{WTA(0.5)}$ in present value for each dollar of equity financing, which falls short of the \$1.64 $= \frac{MV(0.5)}{AV(0.5)}$ required for the financier to profit from the contract. Beyond the median, we find that the WTA curve lies above the AV curve more generally—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.[55]

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

[52]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%.

[53]Empirical estimates of relative risk aversion often fall in the range of 0.5 to 4 (Chetty, 2006; Gandelman, Hernandez-Murillo 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).

[54]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 $14{,}049 = E[m(\theta)]$. As expected, this point estimate exceeds the lower bound of \$4,319 reported in Table 4. Appendix Table A10 reports point estimates of the mean magnitude alongside lower bound estimates for each of the four outcomes.

[55]Comparing $WTA(\theta)$ and $AV(\theta)$ for all $\theta \in (0,1)$ suffers an extreme quantile estimation problem discussed in Hendren (2013). We follow the proposed solution in Hendren (2013) and report p-values from tests of $WTA(\theta) > AV(\theta)$ for all θ above the 20th percentile of the $WTA(\theta)$ distribution.

of true beliefs, market existence is even less likely than under rational expectations. We estimate the median college-goer expects to earn \$30,313 $= E_S[Y|\theta = 0.5]$, but the true value of a stake in their earnings is \$21,165 $= MV(0.5)$. The average salary among those with below-median expected earnings is just \$13,197 $= AV(0.5)$, so this individual would have to accept a perceived discount of 56% for the financier to profit from their contract. But the individual is unwilling to accept any valuation below \$25,220 $= WTA(0.5)$. As in the case of rational expectations, we find that the WTA curve among college-goers with potentially biased beliefs lies everywhere above their AV curve, so that the market unravels. The p-value for the test that there exists a θ such that $AV(\theta) \geq WTA(\theta)$ is 0.09.

Biased beliefs and adverse selection both contribute to market unraveling. But the results in Figure 4B suggest that biased beliefs alone is unlikely to explain the absence of equity markets. To see why, note that if there were no asymmetric information, financiers could offer type-specific contracts at $\lambda(\theta) = MV(\theta)$. But in this scenario, our estimates suggest that 22% of college-goers—those with $WTA(\theta) < MV(\theta)$—would accept equity contracts at these actuarially fair valuations.[56]

The results so far consider financiers offering contracts to all college-goers (using valuations conditional on observables, X). But in the presence of biased beliefs, financiers may find it profitable to 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 earnings potential, this strategy could create a profitable market segment for the financier. To test this theory, Appendix Figure A4B plots the WTA and AV curves using potentially biased beliefs for those in the top quartile of predicted earnings based on observables, $E[Y|X]$. 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, 65% 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. Our estimates suggest that all three of these markets have unraveled. Figure 5A shows that for the completion-contingent loan market, the median individual has a 63% $= MV(0.5)$ chance of completing college. Among those who believe their chances of completion are worse than 63%, the average completion rate is just 38% $= AV(0.5)$.

[56] This fraction would be even larger if some of the elicitations reflect beliefs about later-career earnings as opposed to earnings after college.

A profitable contract would therefore provide the median individual with just \$0.38 in present-discounted financing for each dollar owed in the event they graduate. But we estimate this individual is willing to accept no less than $\$0.56 = WTA\,(0.5)$ for each completion-contingent dollar they pledge. In other words, they are willing to pay \$1.11 in present value for each dollar of completion-contingent financing, but this falls short of the \$1.67 required for the financier to profit from the contract. Beyond the median, we find 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.[57]

Figure 5B presents the results for the employment-contingent loan market that requires repayment only if employed after graduation. The median individual has a $72\% = MV\,(0.5)$ chance of being employed, but the average probability of employment among those with worse employment prospects is just $60\% = AV\,(0.5)$. We estimate that the median individual is willing to accept $\$0.69 = WTA\,(0.5)$ in present-discounted financing for each dollar owed if employed after college, which is more than the $\$0.60 = AV\,(0.5)$ 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-default on traditional student loans.[58] The median individual has a $85\% = MV\,(0.5)$ chance of avoiding default; but the average repayment rate of those who expect higher default likelihood is $61\% = AV\,(0.5)$. The median individual is willing to accept no less than $\$0.83 = WTA\,(0.5)$ in financing for each dollar owed in non-default, which is higher than $\$0.61 = AV\,(0.5)$. 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 0.001. This unraveling of dischargeable debt suggests that the existing market for private student debt might depend on the inability to discharge these loans in bankruptcy.[59]

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.

[57] 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 ($p < 0.001$).

[58] Appendix Figure A6 presents results for alternative discharge criteria: loans that are discharged in the event of delinquency and loans that are discharged in the event of delinquency or forbearance.

[59] 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).

5.3 Robustness

We discuss how variations on the assumptions made in our baseline estimation affect our core conclusions.[60]

Risk Aversion Our baseline case assumes a coefficient of relative risk aversion of $\sigma = 2$. Appendix Figure A7 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 above the AV curve.

Preference Heterogeneity The baseline specification assumes unidimensional heterogeneity so that those with a higher expected income, $E_S[y|\theta]$, always have a a higher $WTA(\theta)$. In Appendix Figure A8, we allow risk preferences by drawing σ from a distribution conditional on each type θ.[61] We present two cases: $\sigma \sim Unif[1,3]$ and $\sigma \sim Unif[0,4]$. Heterogeneity in risk aversion leads to slightly flatter AV curves (as expected), but the broad pattern is virtually unchanged; we find that the market would continue to unravel.

Exclusion Restriction Our approach relies on an exclusion restriction to identify γ in the case of rational beliefs and b in the case of potentially biased beliefs. Appendix Tables A11 and A12 shows we find similar values of γ and b using alternative instruments, and Appendix Figure A9 replicates our baseline Figure 4 but calibrates the values of γ and b to a range of plausible values between 0.5 and 1. We find very similar patterns of market unraveling, suggesting that the results are not that sensitive to reasonable values of γ and b.

Survey Question Interpretation The BPS survey asks about salary expectations in a questionnaire sequence that first asks respondents report their expected occupation. This means individuals could report beliefs about expected salary conditional on a particular career rather than beliefs about salary after college more broadly. We explore how this could potentially affect our results in two ways. First, we isolate a 10% subsample of BPS respondents who received an "abbreviated interview," with more general question wording and no occupation elicitation.[62] In Appendix Figure A10, we find a similar elicitation-outcome relationship from the remaining 90% of respondents

[60]For brevity, we only report robustness results for rational-beliefs specifications; robustness patterns also hold for the case of potentially biased beliefs.

[61]Our simulation assumes that preference heterogeneity is not correlated with the level of the expected outcome. We view this as a natural benchmark. 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.

[62]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 D.

who received 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 elicited probability 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 A11).

Subgroups Finally, our baseline results focus on the residual distribution of beliefs about the outcome Y after conditioning on observables, X. While we condition the contract valuations on X, we imagine contracts are offered to all subgroups. One concern with this 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 A12–A17, we report the WTA and AV curves separately for subgroups based on gender, school type, and STEM versus non-STEM major field of study.[63] 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

Our baseline model assumes individuals can borrow at the same rate as private financiers. In theory, credit constraints would make individuals more willing to accept financing like equity contracts. 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 10% higher than the risk-free rate, R. Appendix Figure A7 shows that all four markets would still unravel. In the earnings-equity market with rational beliefs, the median individual is willing to accept \$15,477, which is \$1,548 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.[64] In this case, however, our results suggest financiers would sooner offer non-dischargeable debt contracts at a liquidity premium than offer less profitable equity contracts.[65] In this sense, our results continue to explain why markets for

[63] In Appendix Figure A18, we also expand the sample to include extreme-valued elicitations we had omitted from our main biased-belief specification (see Footnote 48).

[64] Our estimates suggest R_θ would have to exceed R by at least 25% (4.4% per year from 2012 to 2017) to prevent equity markets from unraveling.

[65] Our results suggest such contracts would rely on the status of student debt as non-dischargeable in bankruptcy. If such privileges were removed, our results suggest that borrowers' private information about their likelihood of

state-contingent financing unravel.

While credit constraints make unraveling less likely, an abundance of available credit has 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 still wish to insure their post-college outcomes. In the absence of asymmetric information, we would expect borrowers to form a market for state-contingent insurance contracts with no intertemporal component.[66] So while generous public subsidies could perhaps explain why government-backed loans dominate most private lending, they struggle to explain the general absence of state-contingent contracts. They also cannot explain why those without access to government-subsidized loans face so few private financing options, as discussed in the next subsection.

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.[67] The entry strategy of these ISA providers is broadly consistent with many features of our model in a world where some financial 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 subset

future financial distress would lead to adverse selection in debt markets as well.

[66]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.

[67]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.

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 these market segments, ISAs have struggled to make profits. Of the thirty-five ISA providers listed in Table 5, only ten are still in operation.[68] 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.[69] These providers may fold once they observe the full outcomes of their initial cohorts.

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 G, we show that Mumford's findings are consistent with our estimates of AV and WTA curves, suggesting the Purdue ISA is likely not profitable. This might explain why the program has indefinitely suspended new contracts as of June 2022 (Moody, 2021).

While the experiences of existing ISA providers speak to the plausibility of our unraveling hypothesis, they can also shed light on alternative theories behind the scarcity of ISAs. For example, the existence of the ISAs we investigate, however short-lived and unprofitable, suggests that start-up costs are not likely to explain their rareness. Similarly, legal constraints[70] and issues of income verification[71] do not appear to create barriers to entry. Nonetheless, it is important to note that ISA providers have alluded to other factors beyond adverse selection as obstacles to profitability. For example, *Placement.com* and Purdue discuss regulatory uncertainty and borrower confusion as having played a role the failures of their ISAs (Linehan, 2022; Moody, 2021). While our analyses cannot rule out these alternative explanations, we note that many financial products manage to thrive in settings with confused customers or regulatory risks. Moreover, if one were to remove these barriers, our findings suggest that adverse selection would still quell the profitability of ISAs and related contracts.

[68] Note that many of these existing ISAs 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.

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

[70] Existing consumer finance law does not prohibit ISA contracts. A recent consent order from the Consumer Financial Protection Bureau (CFPB) classifies ISAs as "private education loans" (CFPB, 2022).

[71] ISA providers (and a variety of other companies) verify incomes with the IRS 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).

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 available alternatives to federal student loans?[72] In this section, we measure the welfare impact of such subsidies by constructing their marginal values of public funds (MVPFs). The MVPF measures the value of the subsidy to beneficiaries per dollar of net cost of the subsidy to the government.[73] Table 6 reports the components of these benefits and costs along with the resulting MVPF. Appendix H provides a detailed derivation of the MVPF in each market setting, and we discuss the key lessons in the main text.

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, $\lambda = E[Y] = \$24{,}032$. We assume for simplicity that this valuation is offered to all college-goers and does not vary with observables, X.[74] The WTA curves imply that 71% 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 \$0.46 per person who takes up the contract—the sum of \$0.35 in average net transfers from the government and a \$0.11 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; we use the latter to construct the MVPF for the biased beliefs case.

The net government costs of earnings-equity subsidies come from the net transfer to individuals (\$0.35 under rational beliefs), plus additional costs that might arise from individuals' behavioral responses to equity financing. Most notably, 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, pre-existing tax rates means that the government has a first-order stake in college-goers' incomes. Appendix H shows that the magnitude of this moral-hazard response can be calibrated using existing estimates of the taxable income elasticity with respect to the net-of-tax rate, which we set to 0.3 (Saez, Slemrod and Giertz,

[72] 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).

[73] 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.

[74] We therefore use estimates of WTA and AV curves that are constructed unconditional on observables to measure the take up and (negative) profits associated with these subsidies.

2012). The implied moral-hazard response to the equity contract costs the government an additional \$0.05 per dollar of mechanical government spending, or \$0.04 per dollar if take-up is determined by potentially biased beliefs.[75] This distortionary cost is less than half the magnitude of the welfare gain from risk reduction offered by the equity financing.

In contrast to earnings-equity subsidies, we find that subsidies for state-contingent debt contracts come with distortionary costs that exceed their value of risk reduction, leading to MVPF estimates below 1. For example, the risk premium offered by the employment-contingent loan of \$0.05 falls below the \$0.10 cost from the moral hazard response to the contract that we calibrate using estimates of the behavioral response to unemployment insurance in the review piece by Schmieder and Von Wachter (2016).[76] Another point of comparison is the untargeted grant. This policy amounts to direct transfer to college students with complete take up, resulting in an MVPF of 1. The earnings-equity MVPFs exceed one because the consumption-smoothing benefits of equity financing exceed the distortionary cost from the higher tax rate.

Including Effects on Future Earnings / Credit Constraints The preceding calculations assume that opting into risk-mitigating financing would have no effect on an individuals' human capital accumulation. However, there is a large literature documenting positive effects of grants and loans on future earnings. By translating these estimates into their respective welfare components, Hendren and Sprung-Keyser (2020) show how such earnings effects can often increase future tax revenue by enough to offset any initial expenditure. While it is difficult to know if subsidies for risk-mitigating financing would yield similar patterns, we can draw upon existing estimates of earnings effects of grants and loans to explore their potential impacts on the MVPF. For example, Gervais and Ziebarth (2019) find that \$1,000 in student-loan financing increases earnings by 1.6-2.8 percent ten years after graduation. Suppose that these effects would arise if individuals were given \$1000 in equity financing instead of loans. To calculate the impact on government revenue, we assume that (a) a 1.6 percent increase in earnings persists for 10 years (as shown in Gervais and Ziebarth (2019)), (b) the tax rate on earnings is 20%, and (c) that college-goers growth rate of earning is equal to the discount rate. These assumptions imply that the equity contract would increase long-term government revenue by \$0.44 per dollar of mechanical government spending. Since this increase in revenue is more than enough to offset upfront costs, it implies an infinite MVPF. If we make these same assumptions for state-contingent debt contracts, we find that the fiscal impact of subsidizing the employment-contingent loan is similarly large, resulting in an infinite MVPF. We find an MVPF of 5.09 for completion-contingent loan subsidies and 38.41 for a dischargeable-debt

[75] 0.3 is roughly equal to the median estimate of taxable income elasticity found in the literature (Saez, Slemrod and Giertz, 2012). Appendix H shows how we derive the fiscal cost of implicit tax increases from taxable income elasticity.

[76] For the other binary contracts, we are not aware of existing literature documenting the distortionary effects of these contracts. We therefore calibrate the fiscal externality assuming the behavioral response to the transfer is similar to the response to unemployment insurance distortions. See Appendix H for details.

subsidies. For the untargeted grant, we find an MVPF of 3.12, suggesting its welfare benefit falls short of those for all forms of state-contingent financing except the dischargeable-debt contract. However, we caution that these MVPF estimates assume that each method of financing yields the same earnings effect as student loans did in Gervais and Ziebarth (2019). The extensive literature on financial aid, loans, and post-college earnings suggests a range of effects could be plausible (Dynarski, 2002; Hoxby, 2018; Scott-Clayton and Zafar, 2019; Denning, Marx and Turner, 2019; Angrist, Autor and Pallais, 2022). There could also be no effect, especially if alternative forms of financing simply crowd out existing student debt. In this case, MVPFs would correspond to those in Column (8) of Table 6.

In summary, our welfare analysis suggests the risk-reduction benefits of equity contracts likely exceed the distortionary costs from their higher implicit tax on future earnings. But the ultimate welfare implications of subsidizing these contracts will depend on their causal effects on human capital accumulation. The estimation of these effects presents an important challenge for future research.

7 Conclusion

This paper explores the hypothesis that private information has unraveled risk-mitigating financial contracts for higher education. We do so by using information contained in subjective elicitations about future outcomes to quantify the frictions imposed by private information in several hypothetical markets for financing human capital investment. Our results suggest that the threat of adverse selection is a significant barrier to the existence of risk-mitigating contracts like the earnings-equity product envisioned by Friedman (1955). This unraveling phenomenon also explains why government-backed student debt is the dominant financing option for most college students. Our results suggest that government subsidies for state-contingent alternatives to traditional student loans might provide significant welfare gains by insuring borrowers against poor post-college outcomes.

Our results add to a growing body of evidence suggesting that information asymmetries prevent private markets from mitigating risk, such as health-related insurance Hendren (2013) or unemployment insurance Hendren (2017). Our analysis moves beyond insurance settings to investigate the role of private information in college financing. Because our framework can be applied to any state-contingent contract, insights from this study might extend beyond the higher-education setting to other financial markets. For example, testing for private knowledge of default risk among liquidity-constrained populations could help determine the role of adverse selection in consumer-credit markets. Similarly, our framework could be applied to capital markets to identify underinvestment in constrained firms and quantify the welfare impacts of Small Business Administration loans or investment subsidies. Our methods could also be used to investigate private information in labor contracts. 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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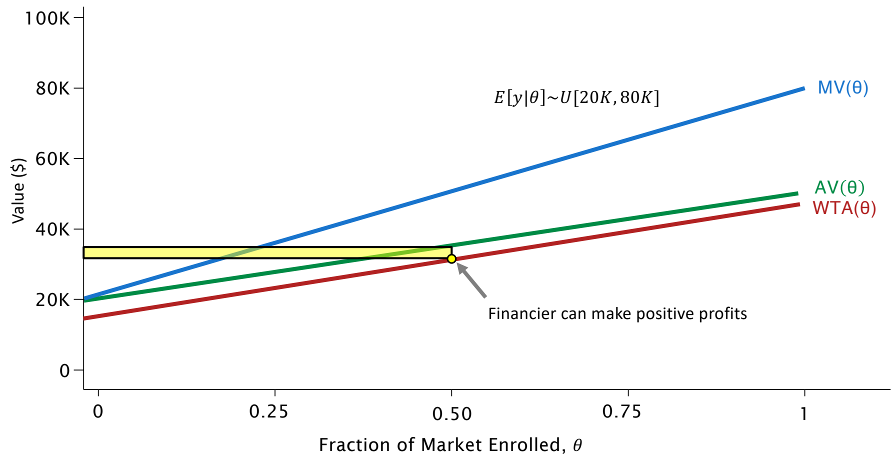
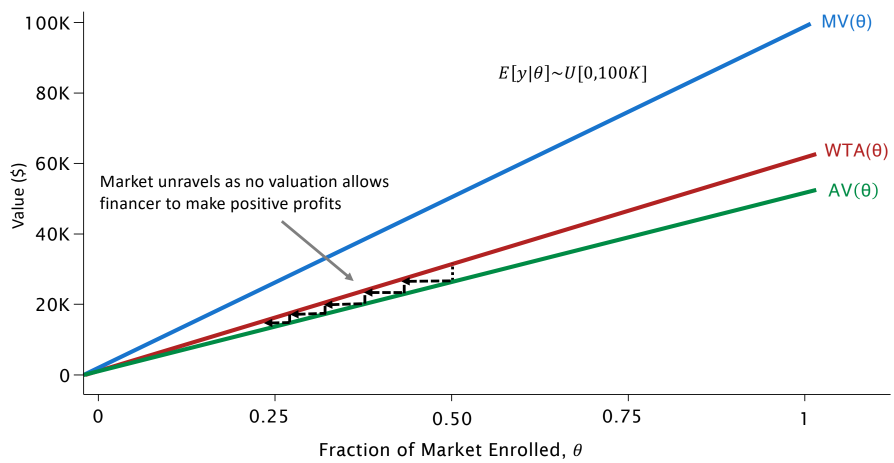
Figures and Tables

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



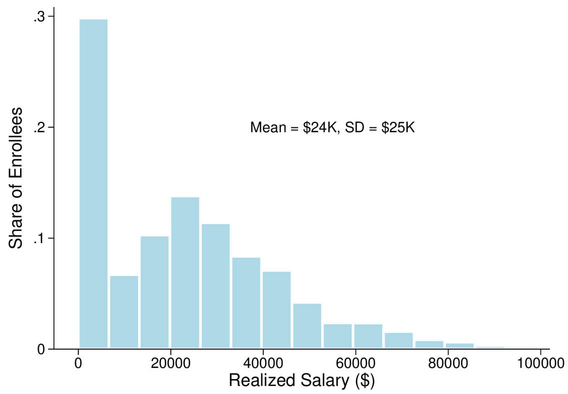
(A) Firms Can Make Profits, $WTA(\theta) < AV(\theta)$ **For Some** θ



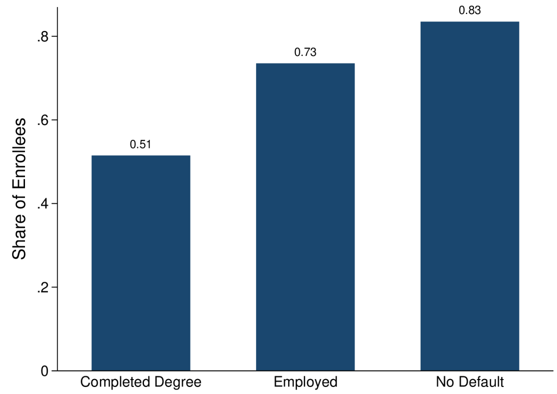
(B) Market Fully Unravels, $AV(\theta) < WTA(\theta)$ **For All** θ

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 quantiles 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.

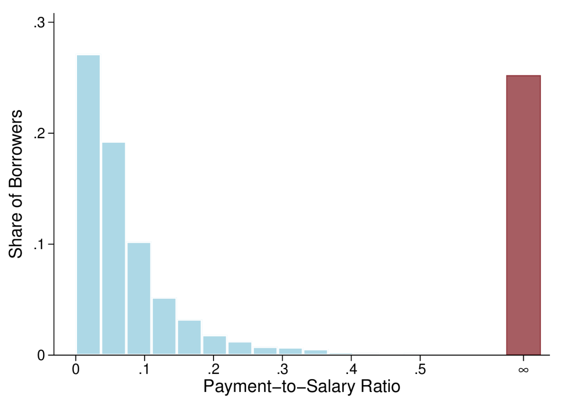
Figure 2: Summary Statistics for Selected Outcomes



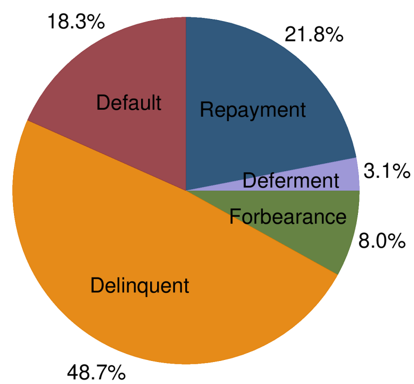
(A) Histogram of Realized Salary



(B) Mean Binary Outcomes



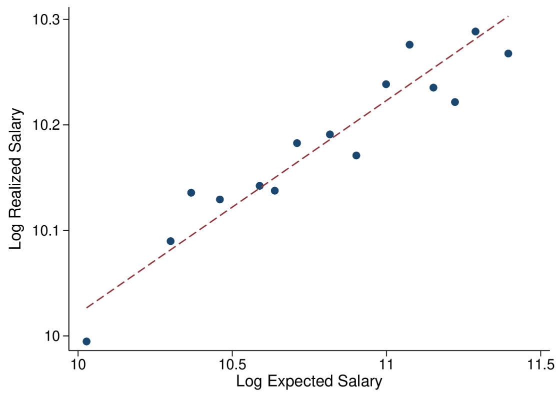
(C) Debt-Payment-to-Salary Ratio



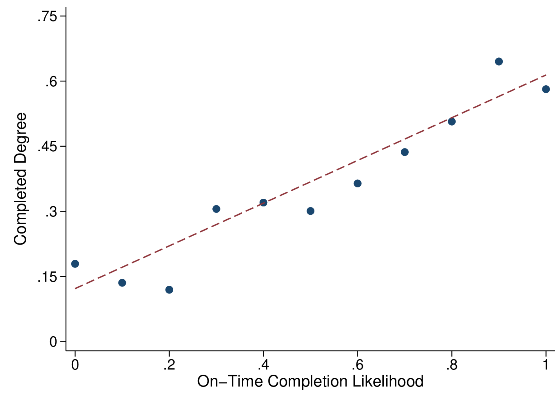
(D) Loan Repayment Status

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.

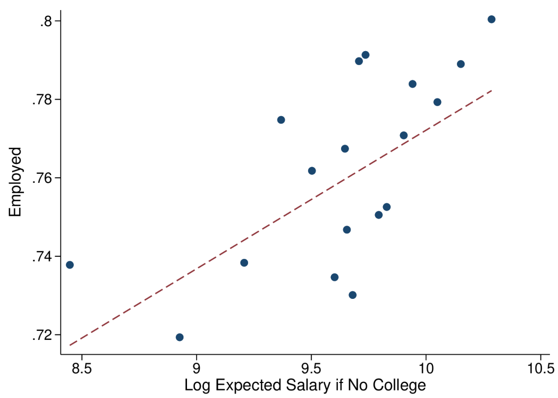
Figure 3: Realizations Versus Elicitations



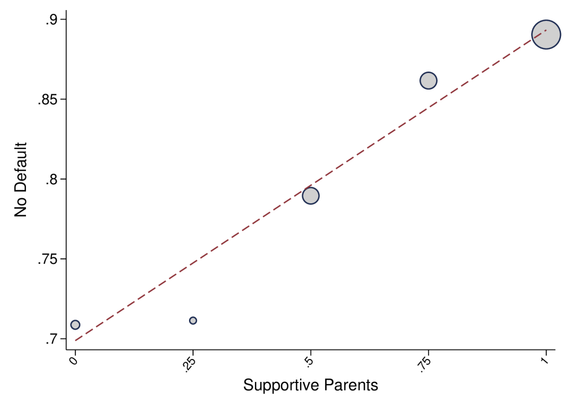
(A) Salary



(B) Completion



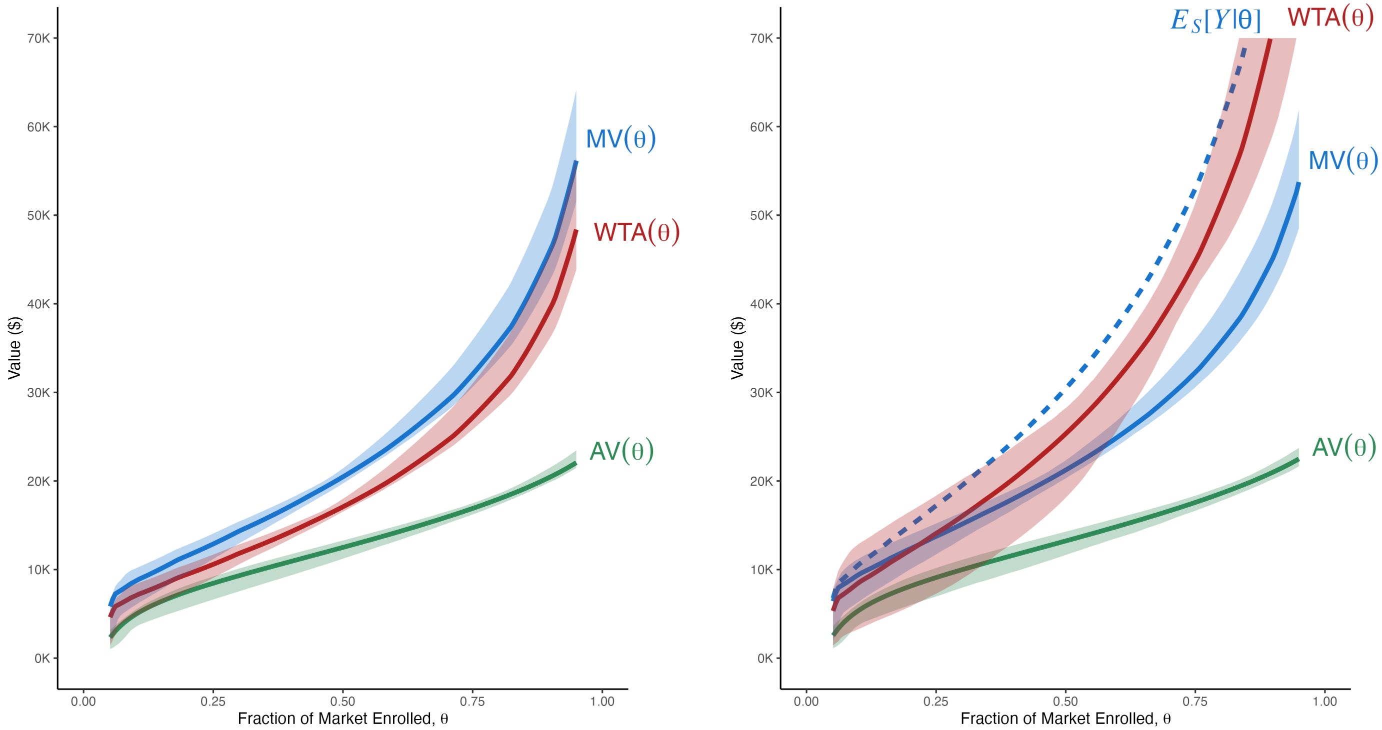
(C) Employment



(D) No Default

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 log salary in 2017 against and the log of expected salary, excluding responses in the bottom 2% and top 5%. Panel B reports reports the likelihood of completing college against the elicited 0–10 likelihood of on-time completion, which we divide by 10. 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." Raw responses are coded as (1) "Strongly disagree," (2) "Somewhat disagree," (3) "Neither disagree nor agree," (4) "Somewhat agree," and (5)"Strongly agree," which are normalized to a [0,1] scale. In panel D, grey bubbles reflect relative number of individuals reporting each response. Observations are weighted using cross-sectional BPS survey weights to reflect the national population of first-time college enrollees in 2012. 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.

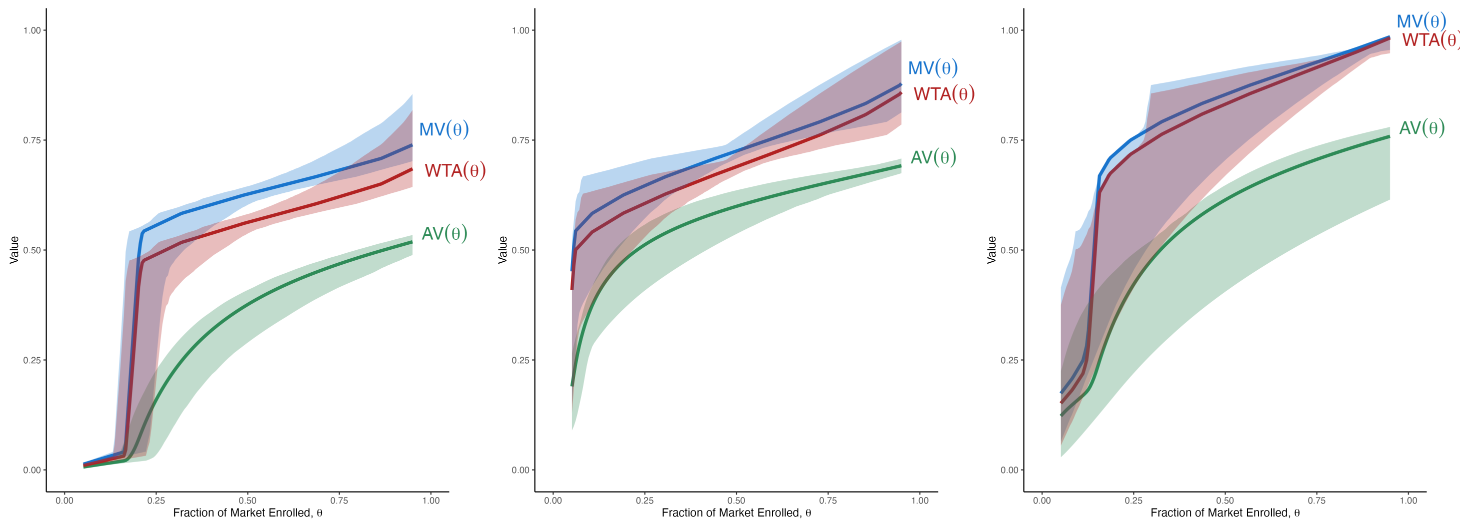
Figure 4: Estimates of Average Value and Willingness-to-Accept Curves for Earnings Equity Market



(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 taking up the contract, 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 quantiles of subjective salary expectations, $E_S[Y|\theta]$, are 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. The p-value for the test that there exists a θ such that $WTA(\theta) > AV(\theta)$ is $p < .001$ under rational beliefs and p =0.09 under biased beliefs. Following Hendren (2013), we restrict this test to the region $\theta > 0.2$ to prevent bias from extreme quantile estimation issues near $\theta = 0$. Note that this test of unraveling condition (7) 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.

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 defaulted on traditional student loans. Results are conditional on academic and institutional characteristics, as defined in Appendix Table A1. The shaded region presents 95% confidence intervals constructed via bootstrap resampling. The p-value for the test that there exists a θ such that $WTA(\theta) > AV(\theta)$ is $p < .001$ for all three markets. Following Hendren (2013), we restrict this test to the region $\theta > 0.2$ to prevent bias from extreme quantile estimation issues near $\theta = 0$. Note that this test of unraveling condition (7) accounts for correlated sampling error between the $WTA(\theta)$ and $AV(\theta)$ curves. 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.

Table 1: Summary Statistics: Elicitations and Realizations

Category	Variable	Mean	SD
Panel A: Ex-Ante Elicitations	Ever Completion Likelihood	0.931	0.184
	On-Time Completion Likelihood	0.841	0.210
	Expected Completion Year	2014.3	1.091
	Likelihood of Employment in Expected Occ.	0.815	0.173
	Exp. Occ. Employed	0.847	0.0937
	Expected Salary	56669.2	23350.2
	Highest Expected Salary	117110.8	142762.8
	Lowest Expected Salary	43923.5	26926.0
	Expected Salary	64064.2	44800.8
	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	0.843	0.243
	Supportive Classmates	0.807	0.268
	Supportive Parents	0.807	0.268
	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
	Ever Delinquent	0.620	0.485
	Ever Defaulted	0.165	0.371
	Employed	0.735	0.441
	Unemployed	0.158	0.365
	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. Statistics for "Delinquency" and "Default" are calculated only for student borrowers and indicate, respectively, whether the respondent fell delinquent or defaulted on a federal student loan at least once since beginning repayment. "Employed" indicates whether the respondent reported holding a job at some point between February and June of 2017, excluding those still enrolled during that period. "Unemployed" indicates whether the respondent was not employed and looking for work for one or more months since leaving college, as of June 2017. "Realized Salary" is the respondent's reported salary for their most recently held job between February and June of 2017, excluding not employed during that period. "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 D. Note that elicited likelihoods and subjective measures of supportiveness are normalized to a [0,1] scale. We remove expected-salary elicitations that fall below $12,000 or above $130,000 (bottom 2% and top 5% of responses, respectively). 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.

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 selected summary statistics for public-information and demographic variables used in our analysis. 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). "STEM" is a dummy variable for majoring in any of the following fields: science, technology, engineering, mathematics, business, or health care. Note that the "SAT Score" variable includes ACT scores transformed to an SAT scale (Dorans, 1999). Observations are weighted using 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 Beginning Postsecondary Students (BPS) study, authors' calculations.

Table 3: Presence of Private Information

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Log Salary	β Log Expected Salary	0.176***	0.101***	0.0794***	0.0764***	0.0751***	0.0726***	0.0844***	0.0857***	0.0714**
		(0.0233)	(0.0241)	(0.0244)	(0.0242)	(0.0241)	(0.0240)	(0.0219)	(0.0282)	(0.0279)
	N	11610	11610	11610	11610	11610	11610	11520	8580	8580
Panel B: Degree Completion	β On-Time Completion	0.492***	0.436***	0.359***	0.336***	0.339***	0.328***	0.320***	0.341***	0.341***
	Likelihood	(0.0223)	(0.0226)	(0.0221)	(0.0221)	(0.0221)	(0.0219)	(0.0217)	(0.0250)	(0.0251)
	N	18870	18870	18870	18870	18870	18870	18820	15610	15610
Panel C: Employment	β Log Expected Salary	0.0313***	0.0239**	0.0220**	0.0207*	0.0192*	0.0185*	0.0155	0.00731	0.00709
	if No College	(0.0107)	(0.0106)	(0.0107)	(0.0106)	(0.0106)	(0.0105)	(0.0102)	(0.0123)	(0.0122)
	N	13640	13640	13640	13640	13640	13640	13580	10530	10530
Panel D: No Default	β Supportive Parents	0.194***	0.136***	0.115***	0.108***	0.106***	0.0967***	0.0855***	0.0697***	0.0701***
		(0.0208)	(0.0212)	(0.0211)	(0.0207)	(0.0206)	(0.0204)	(0.0187)	(0.0237)	(0.0237)
	N	13490	13490	13490	13490	13490	13490	13410	10550	10550
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 $\times$ Major FE								X	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)–(9) include an increasing set of controls for observable information that are classified in Appendix Table A1. Columns (1)–(8) 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 characteristics, Column (4) adds controls for high school performance, Column (5) adds controls for demographic information, Column (6) adds controls for parental information, Column (7) adds institution fixed effects, and Column (8) adds institution-by-major fixed effects. Column (9) removes institution-by-major fixed effects but adds race and gender dummies. Panels A and C exclude students still enrolled as of February 2017. Panel A also drops the bottom 2% and top 5% of salary elicitation responses. Panel D excludes non-borrowers. Observations are weighted using cross-sectional BPS survey weights to reflect the national population of first-time college enrollees in 2012. Number of observations are 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.

Table 4: Lower Bound on Average Magnitude of Private Information

		(1)	(2)	(3)	(4)	(5)
Panel A: Log Salary	$E[m^Z]$	5256	4319	3247	2691	2413
	p-value	2.9e-47	2.5e-08	5.8e-08	6.2e-08	5.8e-05
	N	4490	4490	4490	4490	2440
Panel B: Degree Completion	$E[m^Z]$	.2175	.1496	.1245	.1101	.1113
	p-value	9.e-146	2.1e-47	1.8e-55	1.1e-42	1.2e-09
	N	7380	7380	7380	7380	4810
Panel C: Employment	$E[m^Z]$	.1162	.0961	.0643	.0502	.0466
	p-value	5.0e-87	1.0e-10	3.1e-11	6.2e-08	.2106
	N	5850	5850	5850	5850	3480
Panel D: No Default	$E[m^Z]$	.1213	.0754	.0597	.0492	.0481
	p-value	1.8e-15	1.6e-05	5.3e-05	4.1e-04	.0409
	N	4880	4880	4880	4880	2920
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 estimates of the average magnitude of information in elicitations, $E\left[m^Z\right]$, along with p-values for tests that $E[Y|X,Z] = E[Y|X]$, where Y is the outcome listed in each panel, Z is the set of all elicitations, and X includes publicly known observables corresponding to each column label. Estimates of $E\left[m^Z\right]$, reported in the top row of each panel, are calculated from equation (28) using out-of-sample random-forest predictions $E\left[Y|X,Z\right]$ and $E\left[Y|X\right]$. These estimates form a lower bound on the on the average magnitude of private information, $E[m(\theta)] \equiv E[MV(\theta) - AV(\theta)]$. Rows labeled "p-value" report p-values from F-tests on the joint significance Z in OLS regressions of Y against Z and X. Column (1) includes no controls for observable variables. Column (2) adds controls for academic and institutional 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 includes all private elicitations in Table 1. Categories of public information are defined in Table 2. Observations are weighted using BPS survey weights to reflect the national population of first-time college enrollees in 2012. Sample sizes reflect counts on the out-of-sample predictions. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations.

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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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, 2023).
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" (Robert Morris 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. Our sincerest thanks to Melanie Zaber for her help in completing this list.

Table 6: MVPF Components

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
								No Human Capital Effects		*Human Capital Effects*	
Selection On...		Take-up	Transfer	Consumption Smoothing	WTP	FE Moral Hazard	FE Human Capital	Cost to Govt	MVPF	Cost to Govt	MVPF
Rational Beliefs	Earnings Equity	0.72	0.34	0.12	0.47	-0.05	0.45	0.39	1.19	-0.05	∞
		(0.01)	(0.03)	(0.01)	(0.03)	(0.00)	(0.01)	(0.03)	(0.04)	(0.03)	–
	Completion-Contingent Loan	0.52	0.27	0.10	0.37	-0.13	0.35	0.40	0.92	0.05	7.14
		(0.02)	(0.03)	(0.00)	(0.03)	(0.00)	(0.01)	(0.04)	(0.01)	(0.04)	–
	Employment-Contingent Loan	0.55	0.11	0.05	0.17	-0.10	0.36	0.21	0.78	-0.15	∞
		(0.03)	(0.05)	(0.00)	(0.05)	(0.00)	(0.01)	(0.05)	(0.04)	(0.06)	–
	Dischargeable Loan	0.44	0.60	0.03	0.63	-0.29	0.31	0.90	0.70	0.58	1.08
		(0.03)	(0.12)	(0.01)	(0.11)	(0.01)	(0.01)	(0.13)	(0.03)	(0.14)	(0.07)
	Grant	1.00	1.00	0.00	1.00	0.00	0.68	1.00	1.00	0.32	3.12
		–	–	–	–	–	–	–	–	–	–
Biased Beliefs	Earnings Equity	0.52	0.45	0.13	0.58	-0.04	0.35	0.49	1.17	0.14	4.11
		(0.04)	(0.05)	(0.05)	(0.10)	(0.00)	(0.02)	(0.04)	(0.09)	(0.06)	–

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 default (row 4). For each contract, the MVPF is calculated at valuation $\lambda = E[Y]$ and contract size $\eta = \frac{1}{E[Y]}$, 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 fiscal externality from the distortion associated with the implicit tax on earnings associated with the risk-mitigating contracts, "FE Moral Hazard." Column (6) reports the size of the fiscal externality resulting from the provision of the education finance, "FE Human Capital." Column (7) measures total cost excluding the human capital externality, which equals the size of the transfer minus the moral hazard externality. Column (8) reports the MVPF excluding the human capital externality, which is the ratio of WTP in Column (4) to net government cost in Column (7). Columns (9) and (10) repeat the calculations of net government cost (7) and MVPF (8), but includes the human capital externality (6) into the cost calculation. Source: U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students (BPS) study, authors' calculations.