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

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We examine whether adverse selection has unraveled private markets for equity and state-contingent debt contracts for financing higher education. Using survey data on beliefs, we show a typical college-goer would have to repay $1.64 in present value for every $1 of financing to overcome adverse selection in an equity market. We find that risk-averse college-goers are not willing to accept these terms, so markets unravel. We discuss why moral hazard, biased beliefs, and outside credit options are less likely to explain the absence of these markets. We quantify the welfare gains for subsidizing equity-like contracts that mitigate college-going risks. (*JEL* D82, D83, G51, I22, I23, I26, J24)

Investing in college delivers persistently high returns to both individuals and society but also comes with significant risk. Nearly half of all college enrollees in the United States fail to complete their degrees. Conditional on completion, only 85 percent find work after graduation. Even by age 40, 15 percent 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 percent of student borrowers default on their debt within 5 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, p. 138) 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

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[1] Employment and completion statistics are calculated six years from enrollment using the 2012 Beginning Postsecondary Students (BPS) study, a representative sample of first-time college enrollees in 2012 (National Center for Education Statistics 2020a). Household income among 40-year-old college graduates is calculated using the 2012 American Community Survey (Ruggles et al. 2023). Five-year default rates are taken from the 2009 repayment cohort in Table 8 of Looney and Yannelis (2015).

> 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 postsecondary 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 United States.

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 overoptimistic 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) 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 an individual's earnings prospects" (Friedman 1955, p. 138), 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 2012/2017 Beginning Postsecondary Students study (BPS). The BPS data include subjective expectations, postcollege 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

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

on a comprehensive set of observable characteristics, we find that elicitations are predictive of postcollege 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, overoptimistic beliefs, or both.

In the second part of our analysis, we estimate a structural model of beliefs and survey elicitations, allowing us to test for market unraveling in each setting. Motivated by likely measurement error in elicitations and the potential for biased beliefs, we estimate distributions for two types of beliefs: the rational beliefs that individuals would hold if they knew the mapping between their private information and future outcomes, and 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 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 equity markets for postcollege earnings. Under rational beliefs, the median individual expects to earn \$20,414, but the average earnings of those willing to accept lower valuations are just $\$12{,}480 = AV(0.5)$. 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 $\$17{,}029 = WTA(0.5)$. 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' overoptimism interacts with adverse selection to make market existence even less likely. In the absence of private information, however, a sizable fraction of college-goers would still accept actuarially fair equity contracts, suggesting that biased beliefs can amplify unraveling forces but cannot explain missing markets independently of adverse selection.

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

[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 postgraduate earnings but not for all outcomes we study.

each of these state-contingent debt markets, the WTA curve lies everywhere above the AV curve. These patterns explain why nondischargeable 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 preexisting taxes on earnings. Nonetheless, we show that for plausible elasticities of taxable income (ETI of 0.3; see 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 earnings-equity contract has an MVPF in excess of 1, even if it does nothing to improve enrollment, persistence, or performance in college.[5] If instead we assume 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 postcollege earnings would likely unravel, we cannot 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, and it could be that adverse selection coexists with other forces that prevent market existence. 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, our results show that adverse selection hinders financial markets' ability to insure the risks faced by college-goers, and policies to reduce those risks 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

[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.

[5]By contrast, subsidizing the three state-contingent debt contracts we consider comes with distortionary costs that exceed the value of risk reduction, although 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.

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 United Kingdom 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).

Methodologically, our paper complements a large literature using subjective information to measure expectations and uncertainty (Manski 2004; Jappelli and Pistaferri 2010; d'Haultfœuille, 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.

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

[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.

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

I. 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 financing under adverse selection, moral hazard, and biased beliefs. We also discuss a simple extension that captures credit constraints.[9] We use the model to clarify the role of these forces in determining market existence and to provide guidance on the welfare impact of government subsidies that would help open up these markets.

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

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

[9] In online 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.

"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:

$$(1) \qquad u(c_1, c_2, a) \equiv u(c_1; \theta) + \beta u(c_2; \theta) + \psi(a; \theta),$$

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 $E_S[Y|\theta]$ denote type θ's subjective (mean) beliefs about their realization of Y, and let $E[Y|\theta]$ 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 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

$$(2) \qquad \lambda u_1(\theta) - \beta E_S[Y u_2 | \theta] \geq 0,$$

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 postcollege 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,

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

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 noncontingent loan. In our baseline model, we assume $R_\theta = R$, which would be true if financiers could offer borrowers noncontingent 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 IVD.

[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 online Appendix C.

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

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

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 bias. A more positive bias term (overoptimism) increases borrower's $WTA(\theta)$. 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

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

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

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

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

$$AV(\theta) < WTA(\theta) \ \forall\theta. \quad (7)$$

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]

[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, $\{(\eta_\theta, \lambda_\theta)\}_\theta$.

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 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 noncontingent financial contracts. We explore credit constraints and outside lending options in Section IVD.

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:

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

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 postcollege 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 $MV(\theta)$

[15] Online 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 V.

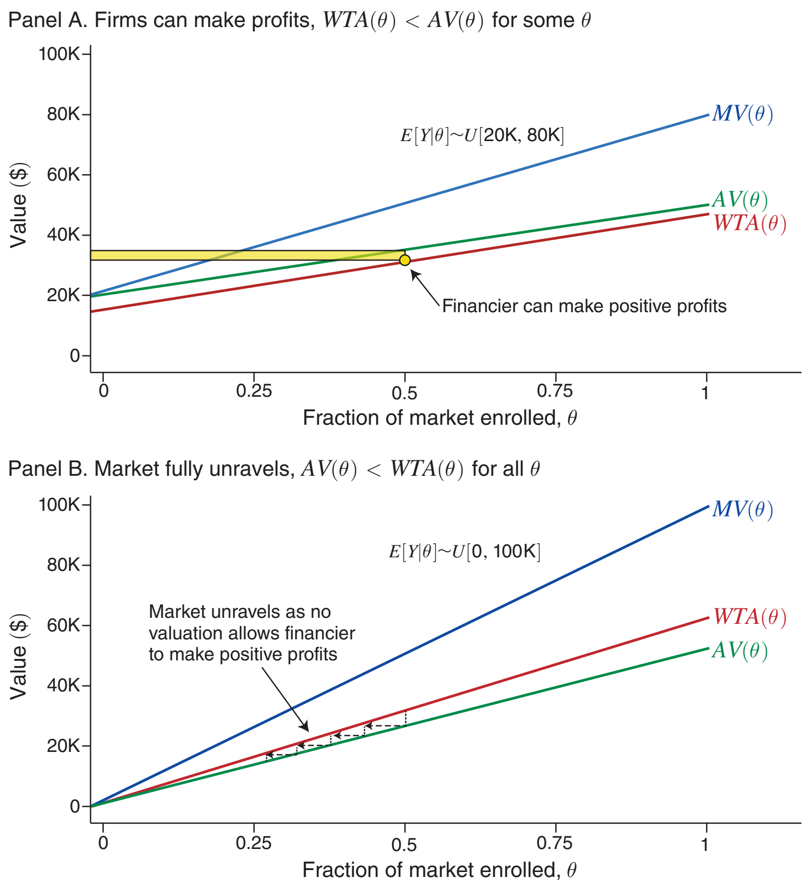

FIGURE 1. MODEL OF MARKET UNRAVELING: $AV(\theta)$ AND $WTA(\theta)$ CURVES

Notes: 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 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 between \$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.

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.

Panel A of Figure 1 depicts a scenario in which individuals' privately expected postcollege salaries, $E[Y|\theta]$, are uniformly distributed between \$20,000 and \$80,000. In this scenario the median individual ($\theta = 0.5$) expects to earn $MV(0.5) = \$50{,}000$ but is willing to accept a valuation of $WTA(0.5) = \$30{,}000$. Because this reservation price is \$5,000 lower than the average value of worse risks ($AV(0.5) = \$35{,}000$), the firm can set $\lambda = \$30{,}000$ and earn positive profits, depicted by the yellow rectangle.

Panel B of Figure 1 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 ($WTA(\theta) < \$30{,}000$) 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 $WTA(\theta) > \$25{,}000$ 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 IIIB). 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 overoptimistic 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 IV.

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

[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 IV for a more detailed discussion.

II. Data and Summary Statistics

Quantifying adverse selection for contracts that do not exist is not straightforward because we cannot observe data on individuals' contract decisions. Our empirical strategy, therefore, uses imperfect measures of 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 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 survey includes ex post realized outcomes corresponding to our hypothetical contracts—earnings, degree completion, employment status, and loan-repayment status. Second, the administrative data include a wide array of observable information that hypothetical financiers could potentially use to set contract terms. Finally, the 2012 survey includes private elicitations concerning expected earnings, degree-completion likelihood, and other information unlikely to be observable by financiers. 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 postcollege earnings in 2017, $Y = Salary$. Panel A of Figure 2 reports the distribution of postcollege 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 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 $(Y = \mathbf{1}\{Complete\})$, an employment-contingent loan that only requires repayment if borrowers find employment $(Y = \mathbf{1}\{Employed\})$, and a dischargeable loan that only requires repayment if borrowers avoid default on their existing student loans, $(Y = \mathbf{1}\{No\ Default\})$. 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 percent of 2012 enrollees had completed their degree, and

[18] We provide more details on BPS survey questions and data collection procedures in online 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.

Table 1—Summary Statistics: Elicitations and Realizations

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	55,881.4	23,085.0
Highest Expected Salary	117,110.8	142,762.8
Lowest Expected Salary	43,923.5	26,926.0
Expected Salary	64,064.2	44,800.8
Expected Salary if No College	17,332.5	7,823.6
Exp. Occ. Salary	30,073.1	8,503.5
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	6,463.8	9,512.1
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	32,701.5	24,345.6
Number of Credit Cards	1.051	0.816
Credit Card Balance	1,234.9	3,171.3
Paid Credit Card Balance	0.604	0.489

Notes: This table provides summary statistics for the complete set of outcomes and elicitations used in our nonparametric deconvolution and maximum-likelihood exercises. Data are taken from the 2012/17 Beginning Postsecondary Students 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" provide 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 online 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 \$9,000 or above \$120,000 (bottom 2 percent and top 5 percent 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.

Sources: NCES (2020a); authors' calculations

only 73 percent were employed. Of those who borrowed, 17 percent have already defaulted on their debt.[21]

[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.

TABLE 2—SUMMARY STATISTICS: PUBLIC INFORMATION

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	18,218.3	34,962.9
Tuition	9,620.2	10,939.2
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	1,102.2	137.5
Md. Parent Income	32,140.1	20,578.2
Md. 6-Yr Earnings	29,529.6	8,105.7
Performance		
High School GPA	3.058	0.613
SAT Score	1,008.7	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	77,816.3	73,684.7
EFC	10,245.3	16,865.8
Protected classes		
Black	0.176	0.381
Female	0.565	0.496

Notes: 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.

Sources: NCES (2020a); authors' calculations

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 include linked FAFSA records, administrative high school and college records, administrative loan data, and a battery of survey data on family backgrounds. Online 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: (i) academic characteristics, which include the

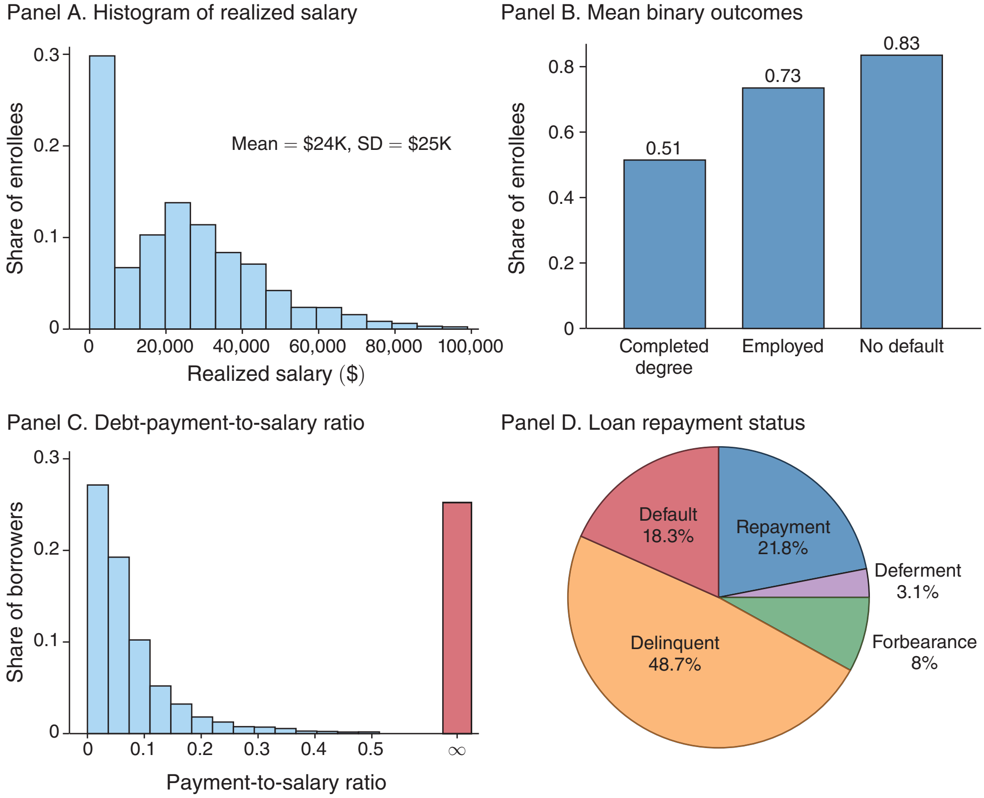

Figure 2. Summary Statistics for Selected Outcomes

Notes: 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 defaults. 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 nonrepayment 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: NCES (2020a); authors' calculations

college-goer's degree type, major field of study (14 categories), and age at enrollment; (ii) institution characteristics, such as the enrollment size of the institution, admission rate, tuition, degree offerings, and urban versus rural location;[22] (iii) high school performance measures, which include high school GPA and SAT/ACT scores;[23] (iv) demographic information, which includes citizenship status, marital

[22] We supplement these institution-level variables with information from the College Scorecard database, which includes median parent income, entering test scores, and demographic compositions as of 2011 (Department of Education 2023). Scorecard information is linked using 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).

status, number of children, state of residence prior to enrollment; and (v) 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.

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 responses to a battery of BPS survey questions eliciting individuals' beliefs about uncertain outcomes, including their likelihood of degree completion, their expected occupation, their expected salary after college, and the salary they would expect to earn if they had not attended college. We supplement these elicitations with several variables that are difficult to publicly verify, detailed in online Appendix D, including the level of financial support they expect to receive from their parents. Panel B of Table 1 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.

III. Exploring the Relationship between Elicitations and Outcomes

In this section we explore the relationship between elicitations and outcomes. In the subsections below, 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.

A. *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, $E[Y|X,\theta,Z] = E[Y|X,\theta]$.[25] This assumption means any predictive information found in Z must reflect predictive information in θ.[26] 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 $H_0: \beta = 0$.

[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 III we show their inclusion does not significantly affect our results.

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

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

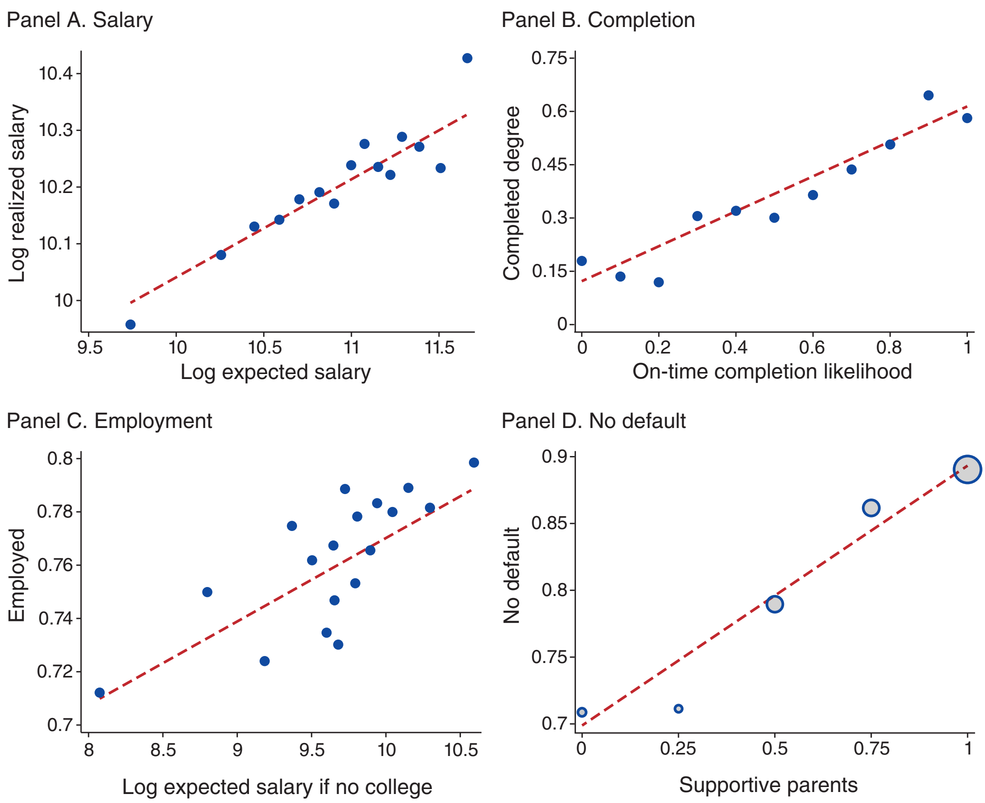

Figure 3. Realizations versus Elicitations

Notes: This figure plots realized outcomes against subjective elicitations asked in the 2012 survey. Panels A through C report binned scatterplots. Panel A reports log salary in 2017 against the log of expected salary, excluding responses in the bottom 2 percent and top 5 percent. Panel B reports the likelihood of completing college against the elicited 0–10 likelihood of on-time completion, which we divide by ten. 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 (i) "Strongly disagree," (ii) "Somewhat disagree," (iii) "Neither disagree nor agree," (iv) "Somewhat agree," and (v) "Strongly agree," which are normalized to a $[0,1]$ scale. In panel D, gray 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.

Sources: NCES (2020a); authors' calculations

Figure 3 presents binned scatterplots of each outcome against a single elicitation without any controls. In Table 3, we report the corresponding OLS estimates of β, both unconditionally (column 1) and conditional on a variety of observable characteristics financiers might use to price contracts (columns 2 through 7). For all four outcomes, we find significant predictive power in the elicitations, Z.

In panel A of Figure 3, we plot employed individuals' log salary in 2017 against the log of the "expected future salary" they reported in 2012.[27] Those who report higher

[27] 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 the 6.6 percent of salary elicitations that fall below \$9,000 or above \$120,000. These cutoffs correspond to the bottom 1 percent and top 1 percent of realized

Table 3—Presence of Private Information

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. log salary							
β log expected salary	0.173	0.103	0.0806	0.0766	0.0740	0.0812	0.0711
	(0.0224)	(0.0230)	(0.0232)	(0.0229)	(0.0228)	(0.0211)	(0.0261)
Observations	11,640	11,640	11,640	11,640	11,640	11,550	8,610
Panel B. Degree completion							
β on-time completion likelihood	0.492	0.436	0.358	0.338	0.328	0.317	0.339
	(0.0223)	(0.0226)	(0.0221)	(0.0221)	(0.0219)	(0.0218)	(0.0252)
Observations	18,870	18,870	18,870	18,870	18,870	18,820	15,610
Panel C. Employment							
β log expected salary if no college	0.0313	0.0239	0.0220	0.0192	0.0186	0.0154	0.00719
	(0.0107)	(0.0106)	(0.0107)	(0.0106)	(0.0105)	(0.0102)	(0.0122)
Observations	13,640	13,640	13,640	13,640	13,640	13,580	10,520
Panel D. No default							
β supportive parents	0.194	0.136	0.115	0.106	0.0967	0.0857	0.0701
	(0.0208)	(0.0212)	(0.0211)	(0.0206)	(0.0204)	(0.0187)	(0.0237)
Observations	13,490	13,490	13,490	13,490	13,490	13,410	10,550
Control categories							
Academic		X	X	X	X	X	X
Institution			X	X	X	X	X
Performance				X	X	X	X
Demographics				X	X	X	X
Parental					X	X	X
Institution FE						X	X
Institution × Major FE							X
Protected							X

Notes: This table reports estimated coefficients on elicitation variables with associated standard errors from OLS regressions of outcomes against elicitations and public information. Panels A through D correspond to regressions of log salary, degree completion, employment, and on-time repayment in 2017 against log elicited salary, elicited on-time completion likelihood, elicited log expected salary if no college, and elicited assessment of parental support in 2012, respectively. Columns 1–7 include an increasing set of controls for observable information that are classified in online 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 and demographic information, column 5 adds controls for parental information, column 6 adds institution fixed effects, and column 7 adds institution-by-major fixed effects as well as race and gender dummies. Panels A and C exclude students still enrolled as of February 2017. Panel A also drops the bottom 2 percent and top 5 percent of salary elicitation responses. Panel D excludes nonborrowers. 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.

Sources: NCES (2020a); authors' calculations

expected salaries in 2012 earn higher average salaries in 2017. Panel A of Table 3 shows that without controls, we find a slope of $\hat{\beta} = 0.173$ (SE $= 0.022$).[28] Much of this relationship is explained by observable characteristics—adding academic and institutional controls reduces this point estimate to 0.081 (SE $= 0.023$) in

2017 salaries for full-time workers in our sample. Online Appendix Table A2 reports the coefficients on the full sample, and online 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 IIID.

[28] 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 IIID.

column 3. Conditional on these academic and institutional characteristics, however, adding more covariates in columns 4 through 7 has a comparatively small impact on estimates of β. We find a slope of 0.077 (SE $=$ 0.023) after adding controls for student performance and demographics, and a slope of 0.081 (SE $=$ 0.021) when further adding parental characteristics and institutional fixed effects. Even including institution-by-major fixed effects and protected classes—a particularly demanding specification given the small samples within schools—retains a slope of $\hat{\beta} = 0.071$ (SE $= 0.026, p = 0.006$).

Turning to our next market setting, panel B of Figure 3 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 $= 0.022$). Panel B of Table 3 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 in column 3 ($\hat{\beta} = 0.358$, SE $= 0.022$), but it remains relatively stable when adding further controls in columns 4 through 7.

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 the outcome, Y, as long its relationship with Y only reflects information that is known to the individual, (i.e., $E[Y|X,\theta,Z] = E[Y|X,\theta]$). For employment, we let Z be the log of the salary respondents say they would expect to earn if they were not attending college. In panel C of Figure 3, 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 column 3 of panel C of Table 3, 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 in columns 4 through 7 yields less precise coefficients that are statistically indistinguishable from both the academic controls specification and from zero.

Finally, we test for private information concerning federal student loan repayment. As with the employment outcome, individuals are not directly asked about their likelihood of default, but they are asked how much their parents support their education, which potentially relates to their ability to repay student debts. Panel D of Figure 3 shows that student borrowers who report greater parental encouragement for college are more likely to avoid defaulting on their federal student loans through 2017. Conditional on academic and institution characteristics, panel D of Table 3 shows the slope of this relationship to be $\hat{\beta} = 0.116$ (SE $= 0.0211$), which remains statistically significant even after including our full set of control variables.[29]

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

[29] In online Appendix Table A3, we present regression coefficients for alternative loan repayment outcomes ($Y =$ *No Delinquencies* and $Y =$ *No Delinquencies or Forbearances*).

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.[30] 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.

B. *Magnitude of Private Information*

Table 3 establishes the existence of private information but 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.[31] Here, we leverage the predictive power of the full set of elicitations to infer something about the magnitude of the threat of adverse selection.

Borrowing from Hendren (2013), we define the *magnitude of information in Z* as

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

where $r_i \equiv E[Y \mid X = X_i, Z = Z_i] - E[Y \mid X = X_i]$. The magnitude, m_i^Z, measures the difference between an individual's expected outcome given Z and those of observationally identical peers with lower elicitation-predicted outcomes. While point estimation of our model's unraveling condition relies on a more structural approach in Section IV, this reduced-form magnitude measure has a useful theoretical meaning without imposing parametric assumptions. Under our benchmark assumptions of rational beliefs and unidimensional heterogeneity, Hendren (2013) shows that the average magnitude, $E_i[m_i^Z]$, is no larger than the average difference between MV and AV curves:

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

In other words, $E_i[m_i^Z]$ provides a lower bound on the average "discount" below actuarially fair valuation an individual would need to accept to prevent market unraveling.

In Table 4, we estimate these lower bound magnitudes for each outcome. The first row of each panel reports estimates of $E[m_i^Z]$ using machine learning predictions of

[30] 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 online 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 of those predictions still imply a considerable amount of residual uncertainty. 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. We discuss these concerns and our strategy for addressing them in Section IIID.

[31] 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. Online Appendix Table A5 regresses realized salaries against two elicitations—expected future salary and expected degree completion—and finds significant coefficients on both.

Table 4—Lower Bound on Average Magnitude of Private Information

	(1)	(2)	(3)	(4)	(5)
Panel A. log salary					
$E[m^Z]$	5,291	3,952	3,455	2,664	2,389
p-value	7.8e-53	8.6e-09	2.6e-08	3.4e-08	1.3e-04
Observations	4,490	4,490	4,490	4,490	2,430
Panel B. Degree completion					
$E[m^Z]$	0.2171	0.1427	0.1203	0.1098	0.1045
p-value	1.0e-143	1.2e-45	5.1e-45	4.2e-38	1.4e-09
Observations	7,380	7,380	7,380	7,380	4,820
Panel C. Employment					
$E[m^Z]$	0.1167	0.0953	0.0639	0.0497	0.0472
p-value	5.8e-95	4.0e-11	8.9e-12	3.2e-08	0.167
Observations	5,840	5,840	5,840	5,840	3,470
Panel D. No default					
$E[m^Z]$	0.127	0.0753	0.0596	0.0486	0.0467
p-value	1.2e-15	5.0e-06	1.4e-05	1.1e-04	0.0189
Observations	4,880	4,880	4,880	4,880	2,930
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

Notes: This table reports estimates of the average magnitude of information in elicitations, $E[m^Z]$, 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 $E[m^Z]$, reported in the top row of each panel, are calculated from equation (8) using out-of-sample random-forest predictions of $E[Y|X,Z]$ and $E[Y|X]$. These estimates form a lower bound 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 of 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.

Sources: NCES (2020a); authors' calculations

$E[Y|X,Z]$ and $E[Y|X]$. Details of this procedure are provided in online Appendix E. The second row of each panel reports p-values for tests of joint significance of elicitations, Z, conditional on public information, X, in a linear regression. In each specification, Z_i includes all elicitations, and X includes observable variables from the control categories specified in the bottom panel.[32]

Panel A considers the earnings-equity market case when Y is salary.[33] Without conditioning on observable characteristics, the average college-goer's elicitations predict

[32] To be conservative, we include only elicitations, Z, and the firm's observables, X, in individuals' information sets. In online 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.

[33] 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 online Appendix E.

\$5,291 higher earnings than their peers with lower predicted salaries. Conditioning on institutional and academic characteristics, this difference is reduced to \$3,952; it remains \$2,664 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 percent to 22 percent 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 the private information found in elicitations. Panel B of Table 4 shows that the average college-goer has a completion probability that is at least 10.5pp to 21.7pp 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 by rational beliefs, college-goers would have to be willing to accept financing that is at least 20 percent to 43 percent below their actuarially fair valuations for a completion-contingent loan market to exist. Panels C–D of Table 4 show that the average college-goer is 4.7pp to 11.7pp more likely to find employment and 4.7pp to 12.7pp 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 at least 6–16 percent and 27–75 percent 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 concern, online 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 (two- versus four-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 amount of private information contained in elicitations is enough for adverse selection to threaten the profitability of these hypothetical contracts.

C. *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 planned 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' postgraduate 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 online Appendix B, we investigate the relationship between elicitations, realized salaries, and planned 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 (NCES 2020b). 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. They are also less likely to actually enroll in IDR when they begin loan repayment.[34] These patterns suggest the elicitations contain information individuals would use in deciding whether to take up our hypothetical contracts.[35]

D. *Biased Beliefs versus Elicitation Error*

Evidence from IDR suggests borrowers use their beliefs to make strategic financial decisions, but those beliefs could potentially reflect biased expectations of the future. In our sample, college-goers report expected salaries of $55,912 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 percent of respondents complete on time, and only 51 percent 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 upward bias in college-goers' beliefs (i.e., $E_S[Y|\theta] > E[Y|\theta]$). Unless this overoptimism were 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 of less than one in panel A of Figure 3 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 IV will allow for this heterogeneity in the degree of bias.

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

[34] These patterns are broadly consistent with findings in previous literature. Mumford (2022) finds that participants in an income-share agreement reported higher self-reported salary expectations than those who applied but did not participate. Abraham et al. (2020) find 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.

[35] In online 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.

question framing.[36] 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 misrepresentations 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.[37] 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 \$55,912 average expected salary reported in the BPS.[38] 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 27, our main sample drops these outlier responses, and including them attenuates our estimates considerably (see online 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.

IV. 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: (i) the rational beliefs implied by the empirical mapping of private information onto future earnings, and (ii) 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 potentially biased beliefs. However, as we noted above, elicited beliefs likely suffer from biased responses and nonclassical measurement error.[39] Estimating these two distributions allows us to test for unraveling under two scenarios: one in which individuals hold

[36] In Fischhoff et al. (2000), more than 12 percent of survey respondents report a higher likelihood of dying in the next year than dying in the next 3 years. Hurd and McGarry (2002) show that bunched responses to mortality questions are best interpreted as coarse measures of subjective probabilities, where responses like "50 percent" correspond to anything in the 30 percent to 70 percent 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 trade-offs.

[37] See online Appendix D for the complete text of survey questions. The prompt for earnings expectations mentions salary "once you begin working" in your expected occupation. In Section IVC, we isolate a 10 percent 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 panel A of Figure 3.

[38] This relationship persists if we condition on respondents' expected occupation. In online 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.

[39] 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

rational beliefs when deciding whether to accept a contract and another in which they hold potentially biased beliefs but are assumed to report those beliefs with mean-zero error in the BPS survey.

A. *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.[40] In online 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 $y_i = \log(Y_i)$ denote the log of their realized salary and θ_i denote their type, which corresponds to the information they have about their future earnings. A log specification allows us to model uncertainty in the earnings process as a proportional shock, as is common in previous literature (Guvenen 2007).[41] We assume the realization y_i is the sum of rational beliefs about y_i, which we denote by $\mu_i \equiv E[y_i | \theta_i]$, and a mean-zero homoskedastic error term, $\epsilon_i \sim f_\epsilon(\epsilon_i)$, which captures i's uncertainty around y:

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

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

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

where $\nu_i \sim f_\nu(\nu_i)$ 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.

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

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

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.

[40] 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.

[41] Later, we transform beliefs aboutsalary conditional on employment, $F(Y|Y > 0, \theta)$, and beliefs about employment, $\Pr(Y > 0 | \theta)$, into beliefs about level earnings, $E[Y | \theta]$. See online Appendix F.

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

To identify γ, we use a canonical instrumental variables technique for measurement error correction (Fuller 1987). Equation (12) lets us treat y_i as an unbiased measurement of μ_i in equation (14). We can therefore estimate γ with an IV regression of z_i on y_i, where we instrument for y_i using a second elicitation, w_i. Identification of γ requires $cov(w_i, \nu_i') = 0$.[42] 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_i, 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.[43] 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.[44] 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 IVC 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 restriction 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 $\gamma = 0.69$ (SE $= 0.16$) in equation (14).[45] 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.[46] The deconvolution yields nonparametric estimates of distributions for the latent variables in our model—$f_\mu(\mu_i)$, $f_\epsilon(\epsilon_i)$, and $f_{\nu'}(\nu_i')$. We summarize this identification result in Remark 1.

REMARK 1 (Rational Beliefs): *Suppose that ϵ_i in equation* (12) *is distributed with pdf $f_\epsilon(\epsilon_i)$ that is independent of μ_i. Suppose that elicitations, z_i, can be expressed as in equation* (14)*, with ν_i' distributed according to pdf $f_{\nu'}(\nu_i')$ that is independent of μ_i. Suppose that γ is either known or there exists a second elicitation, w_i, which*

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

[43] Postgraduate salaries are taken from the 2008 Baccalaureate and Beyond (B&B08) study (NCES 2018), which we match to BPS occupation elicitations (occ_i) using three-digit occupation codes. Note that postgraduate 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 are in online Appendix D.

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

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

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

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, $\mu_{S_i} \equiv E_S[y_i | \theta_i]$.

Potentially Biased Beliefs, μ_S.—To identify the distribution of potentially biased beliefs, $f_{\mu_S}(\mu_{S_i})$, we can no longer use realized y_i as an unbiased measure of beliefs $(E[y | \mu_{S_i} = \mu_S] \neq \mu_S)$. 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, $E[Z_i | \theta_i] = E_S[Y_i | \theta_i, Y_i > 0]$.[47] This assumption implies $z_i = \log(Z_i)$ in equation (13) can be written as

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

where $\bar{\alpha} \equiv \log(E_S[e^{\epsilon_i} | \theta_i]) - \log(E[e^{\nu_i}])$ 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_{S_i} and a homoskedastic error term:

$$y_i = E[y_i | \mu_{S_i}] + \xi_i = E[\mu_i | \mu_{S_i}] + \xi_i, \tag{16}$$

where the second equality follows from taking expectations in equation (12). We assume a linear approximation to this conditional expectation function, $E[\mu_i | \mu_{S_i}] = a + b\mu_{S_i}$, 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.[48] We then write (16) as

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

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.

[47] 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 percent (below \$9,000) and top 5 percent (above \$120,000) of salary elicitations when estimating the biased-belief distribution.

[48] 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 $\Pr_S(y_i - \mu_{S_i} \leq x) = F_{\xi_i}(x)$. d'Haultfœuille, 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.

Our approach to identifying 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 be 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.[49] The key requirement is that this optimism reflects true beliefs. This IV strategy yields an estimate of $b = 0.70$ (SE $= 0.17$) (see online Appendix Table A9). We again stress that our results are not very sensitive to estimates of b. In Section IVC, 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 distributions 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, $E[\mu_i \mid \mu_{S_i}] = a + b\mu_{S_i}$.*

Beliefs about Binary Outcomes.—Online Appendix F provides details on belief estimation for binary outcomes (degree completion, employment, and nondefault 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.[50] 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 (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 online Appendix.

Estimation Results.—Estimated belief densities for each outcome are plotted in online Appendix Figure A3. Our findings suggest there is significant private

[49] 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.

[50] 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, overoptimism about employment prospects would amplify our market unraveling results below.

information but also considerable uncertainty. For example, 40 percent of the residual variance of log earnings is known at the time of enrollment, while 60 percent 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.

B. *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 θ-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:

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

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

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

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 percent earnings shock corresponds to a 0.23 percent 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 $\delta_C = 0.09$.[51] We calibrate our baseline value of relative risk aversion to be $\sigma = 2$ but assess robustness to $\sigma = 1$ and $\sigma = 3$ in Section IVC.[52] We then use the perceived distribution of Y given θ to

[51] Hendren (2017) estimates a causal effect of unemployment on consumption ranging from 7 percent to 11 percent, while Ganong and Noel (2019) estimate values between 6 percent and 12 percent.

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

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 online Appendix F.

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 \$20,414 $= MV(0.5)$ in 2017. The 50 percent of individuals who expect to earn \$20,414 or less have salaries of \$12,480 $= AV(0.5)$ on average.[53] So, the median individual would have to accept a 39 percent 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 \$17,029 $= WTA(0.5)$, an implied 17 percent 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.[54]

Panel B of Figure 4 reports the results for the case of potentially biased beliefs. As noted in Section IIID, college-goers appear to be overly optimistic. If these elicitations reflect unbiased measures of true beliefs, market existence is even less likely than under rational expectations. We estimate the median college-goer expects to earn \$30,468 $= E_S[Y|\theta = 0.5]$, but the true value of a stake in their earnings is \$21,220 $= MV(0.5)$. The average salary among those with below-median expected earnings is just \$13,243 $= AV(0.5)$, so this individual would have to accept a perceived discount of 57 percent for the financier to profit from their contract. But the individual is unwilling to accept any valuation below \$25,340 $= WTA(0.5)$. 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 0.07.

[53] 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, $E[m^Z]$, from Section III. For the earnings-equity market, we estimate a mean magnitude equal to 14,064 $= E[m(\theta)]$. As expected, this point estimate exceeds the lower bound of \$3,952 reported in Table 4. Online Appendix Table A10 reports point estimates of the mean magnitude alongside lower bound estimates for each of the four outcomes.

[54] 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 twentieth percentile of the $WTA(\theta)$ distribution.

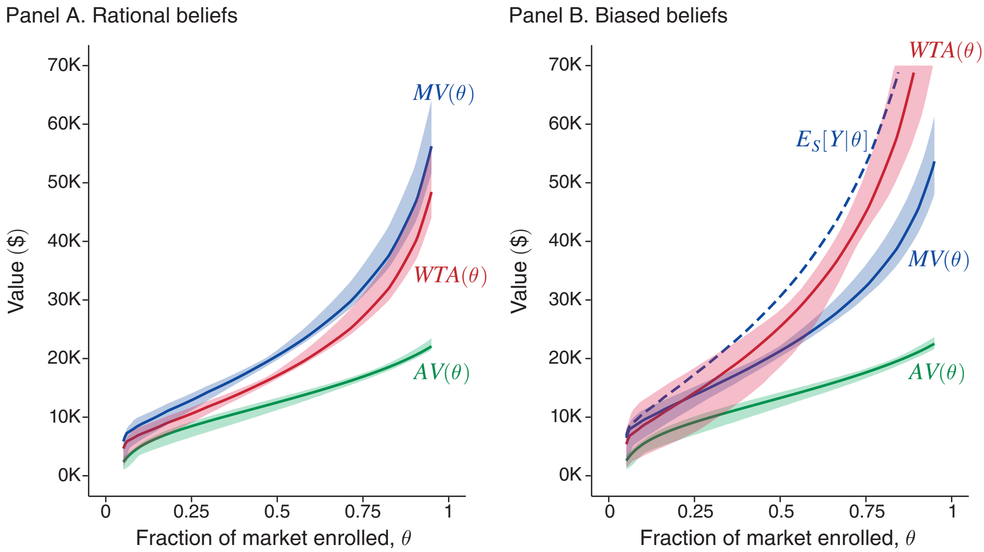

Figure 4. Estimates of Average Value and Willingness-to-Accept Curves for Earnings-Equity Market

Notes: 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 online Appendix Table A1. The shaded region presents 95 percent confidence intervals constructed via bootstrap resampling. The p-value for the test that there exists a θ such that $WTA(\theta) > AV(\theta)$ is $p < 0.001$ under rational beliefs and $p = 0.07$ 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.

Sources: NCES (2020a); authors' calculations

Biased beliefs and adverse selection both contribute to market unraveling. But the results in panel B of Figure 4 suggest that biased beliefs alone are 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 percent of college-goers—those with $WTA(\theta) < MV(\theta)$—would accept equity contracts at these actuarially fair valuations.[55]

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 prescreened 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

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

potential, this strategy could create a profitable market segment for the financier. To test this theory, panel B of online Appendix Figure A4 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, 61 percent 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.

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. Panel A of Figure 5 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 percent, the average completion rate is just $37\% = AV(0.5)$. A profitable contract would therefore provide the median individual with just \$0.37 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 \$1.70 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.[56]

Panel B of Figure 5 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, panel C of Figure 5 presents the results for the dischargeable debt contract that only requires repayment in the event of nondefault on the borrower's existing

[56] Online 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 provide an unbiased measurement of subjective beliefs, $E[Z_i/10|\theta] = \Pr_S(Complete)$. Under these assumptions, we find considerable overoptimism, with median beliefs exceeding true completion likelihood by 37pp. This overoptimism amplifies market nonexistence, so that the AV curve once again lies everywhere below the WTA curve ($p < 0.001$).

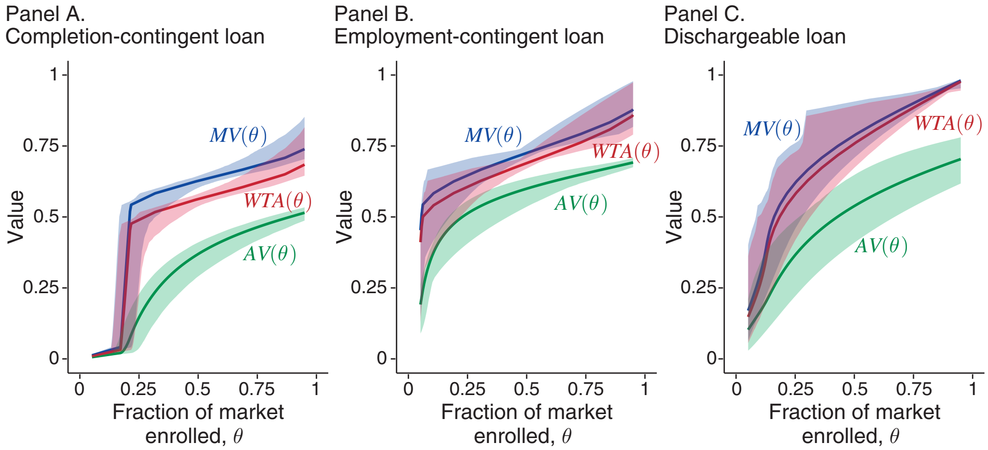

Figure 5. Estimates of Average Value and Willingness-to-Accept Curves for State-Contingent Loan Markets

Notes: 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 online Appendix Table A1. The shaded region presents 95 percent confidence intervals constructed via bootstrap resampling. The p-value for the test that there exists a θ such that $WTA(\theta) > AV(\theta)$ is $p < 0.001$ 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.

Sources: NCES (2020a); authors' calculations

federal student loans.[57] The median individual has a $79\% = MV(0.5)$ chance of avoiding default, but the average repayment rate of those who expect higher default likelihood is $54\% = AV(0.5)$. The median individual is willing to accept no less than $\$0.76 = WTA(0.5)$ in financing for each dollar owed in nondefault, which is higher than $\$0.54 = AV(0.5)$. 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.[58]

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] Online Appendix Figure A6 presents results for alternative discharge criteria: debt that is discharged in the event of delinquency on existing student loans and debt that is discharged in the event of delinquency or forbearance on existing student loans.

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

C. *Robustness*

We discuss how variations on the assumptions made in our baseline estimation affect our core conclusions.[59]

Risk Aversion.—Our baseline case assumes a coefficient of relative risk aversion of $\sigma = 2$. Online 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 higher $WTA(\theta)$. In online Appendix Figure A8, we allow risk preferences to vary by drawing σ from a distribution conditional on each type θ.[60] 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. Online Appendix Tables A11 and A12 show we find similar values of γ and b using alternative instruments, and online 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 to 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 percent subsample of BPS respondents who received an "abbreviated interview," with more general question wording and no occupation elicitation.[61] In online Appendix Figure A10, we find a similar elicitation-outcome relationship from the remaining 90 percent of respondents who received the full-text question referencing their expected occupation. Second,

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

[60] 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.

[61] 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 online Appendix D.

we reestimate the belief distribution replacing the salary elicitation Z_{sal} with a composite elicitation constructed as follows:

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

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 online 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 online 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.[62] 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.

D. *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 percent higher than the risk-free rate, R. Online 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 \$15,481, which is \$1,548 lower than what they would accept without credit constraints but still higher than the \$12,480 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.[63] In this case, however, our results suggest financiers would sooner offer nondischargeable debt contracts at a liquidity premium than offer less profitable equity contracts.[64] In this sense, our results continue to explain why markets for state-contingent financing unravel.

[62] In online Appendix Figure A18, we also expand the sample to include extreme-valued elicitations we had omitted from our main biased-belief specification (see footnote 47).

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

[64] Our results suggest that without this nondischargeability, private student-debt contracts would also be vulnerable to adverse selection because borrowers possess private information about their likelihood of future financial distress.

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 postcollege outcomes. In the absence of asymmetric information, we would expect borrowers to form a market for state-contingent insurance contracts with no intertemporal component.[65] 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.

E. *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.[66] 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 boot camps, 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 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.

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

[66] We are grateful to Melanie Zaber for her help in completing this list. For details on the structure of many of these ISAs, see Zaber, Steiner, and Arana (2023); Zaber et al. (2023); and Zaber and Steiner (2021).

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	Nonprofit organization	2003–2006	Defunct	Undergraduate students	No website currently functions. The most recent page from internet archives is copyrighted 2005–2006 (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	Nonprofit 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 2022).
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. Brenau's servicer, Vemo, collapsed in 2022 (Yoder 2022).

(*continued*)

Table 5 (*continued*)

Provider	Type	Years	Status	Target group	Notes
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).
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	Nonprofit 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).

(*continued*)

Table 5 (*continued*)

Provider	Type	Years	Status	Target group	Notes
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" (William J. 2023).
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	Nonprofit 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–	Prelaunch	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).

Notes: This table reports a list of current and former income-share agreement 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 nonprofit 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. "Target 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.

Despite targeting these market segments, ISAs have struggled to make profits. Of the 35 ISA providers listed in Table 5, only 10 are still in operation.[67] The "Tuition Postponement Option" at Yale University folded after providing just 3,300 contracts over 7 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 have been in operation longer than

[67] 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.

six years, which is shorter than most ISA contract periods.[68] 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 postcollege incomes of ISA participants are roughly $5,000 lower than those of students who applied for the ISA but did not enroll. In online 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 2022).

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[69] and issues of income verification[70] 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 in the failures of their ISAs (Linehan 2022; Moody 2022). 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, the potential presence of these forces does not mean markets would not unravel in their absence. On the contrary, our findings suggest that if one were to remove any such barriers, adverse selection would still quell the profitability of ISAs and related contracts.

V. 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?[71] 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.[72] Table 6 reports the components of these benefits and costs

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

[69] 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 2021).

[70] ISA providers (and a variety of other companies) verify incomes with the IRS by requiring participants to sign form 4506-T, which provides transcripts of tax returns to third parties. Income verification details for the Purdue ISA can be found in a sample ISA contract (https://web.archive.org/web/20221229155549/https://www.purdue.edu/backaboiler/disclosure/contract.html)(Purdue University 2022).

[71] 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).

[72] 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.

along with the resulting MVPF. Online 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.[73] The WTA curves imply that 72 percent of the population would accept an earnings-equity contract if they held rational beliefs, and 52 percent 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 \$0.12 risk premium for the contract's insurance value. For our biased beliefs specification, the individuals taking up the contract perceive a benefit of \$0.45 on average, but in reality, they experience an ex post welfare gain of \$0.58; 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, preexisting tax rates means that the government has a first-order stake in college-goers' incomes. Online 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 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.[74] 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).[75] Another point of comparison is the untargeted grant.

[73] 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.

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

[75] 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 online Appendix H for details.

Table 6—MVPF Components

	Take-up (1)	Transfer (2)	Consumption smoothing (3)	WTP (4)	FE moral hazard (5)	FE human capital (6)	Cost to govt (7)	MVPF (8)
Panel A. Rational beliefs								
Earnings equity	0.71	0.35	0.12	0.46	−0.05	0.44	0.40	1.17
	(0.01)	(0.03)	(0.01)	(0.03)	(0.00)	(0.01)	(0.03)	(0.03)
w/ human capital effects							*−0.04*	∞
							(0.03)	–
Completion-contingent loan	0.50	0.29	0.09	0.38	−0.13	0.34	0.42	0.90
	(0.02)	(0.04)	(0.00)	(0.03)	(0.00)	(0.01)	(0.04)	(0.00)
w/ human capital effects							*0.08*	*4.75*
							(0.04)	–
Employment-contingent loan	0.57	0.11	0.05	0.16	−0.10	0.37	0.21	0.78
	(0.03)	(0.05)	(0.00)	(0.05)	(0.00)	(0.01)	(0.05)	(0.04)
w/ human capital effects							*−0.16*	∞
							(0.06)	–
Default discharge	0.41	0.22	0.04	0.26	−0.09	0.30	0.31	0.84
	(0.05)	(0.06)	(0.00)	(0.06)	(0.00)	(0.02)	(0.06)	(0.02)
w/ human capital effects							*0.01*	*36.01*
							(0.07)	–
Grant	1.00	1.00	0.00	1.00	0.00	0.67	1.00	1.00
	–	–	–	–	–	–	–	–
w/ human capital effects							*0.33*	*3.07*
							–	–
Panel B. Biased beliefs								
Earnings equity	0.52	0.45	0.12	0.58	−0.04	0.35	0.50	1.17
	(0.04)	(0.05)	(0.05)	(0.10)	(0.00)	(0.02)	(0.04)	(0.09)
							0.15	*3.89*
w/ human capital effects							*(0.06)*	–

Notes: This table reports components of the marginal value of public funds (MVPF), defined in Section V. Components are reported for each of four hypothetical contracts: salary-based equity contracts (row 1), state-contingent debt contracts that are dischargeable in the event of dropout (row 2), nonemployment (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 were 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. Numbers in italic repeat the calculations of net government cost (column 7) and MVPF (column 8) but include the human capital externality (column 6) into the cost calculation. Bootstrapped standard errors are provided in parentheses. Standard errors are missing ("–") when point estimates were entirely calibrated or bootstrapping generated one or more infinite values.

Sources: NCES (2020a); authors' calculations

This policy amounts to a direct transfer to college students with complete take-up, resulting in an MVPF of 1. The earnings-equity MVPFs exceed 1 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 individual's 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 10 years after graduation. Suppose that these effects would arise if individuals were given \$1,000 in equity financing instead of loans. To calculate the impact on government revenue, we assume that (i) a 1.6 percent increase in earnings persists for 10 years (as shown in Gervais and Ziebarth 2019), (ii) the tax rate on earnings is 20 percent, and (iii) 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 up-front 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 4.75 for completion-contingent loan subsidies and 36.01 for dischargeable-debt subsidies. For the untargeted grant, we find an MVPF of 3.07, 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 postcollege 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 the upper-row estimates of each contract 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.

VI. 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 postcollege outcomes.

Our results add to a growing body of evidence suggesting that information asymmetries prevent private markets from mitigating risk, such as those for 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 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.

REFERENCES

Abbott, Brant, Giovanni Gallipoli, Costas Meghir, and Giovanni L. Violante. 2019. "Education Policy and Intergenerational Transfers in Equilibrium." *Journal of Political Economy* 127 (6): 2569–2624.

Abraham, Katharine G., Emel Filiz-Ozbay, Erkut Y. Ozbay, and Lesley J. Turner. 2020. "Framing Effects, Earnings Expectations, and the Design of Student Loan Repayment Schemes." *Journal of Public Economics* 183: 104067.

Adams, William, Liran Einav, and Jonathan Levin. 2009. "Liquidity Constraints and Imperfect Information in Subprime Lending." *American Economic Review* 99 (1): 49–84.

Agarwal, Sumit, Souphala Chomsisengphet, and Chunlin Liu. 2010. "The Importance of Adverse Selection in the Credit Card Market: Evidence from Randomized Trials of Credit Card Solicitations." *Journal of Money, Credit and Banking* 42 (4): 743–54.

Akerlof, George A. 1970. "The Market for Lemons: Quality Uncertainty and the Market Mechanism." *Quarterly Journal of Economics* 84 (3): 488–500.

Angrist, Joshua, David Autor, and Amanda Pallais. 2022. "Marginal Effects of Merit Aid for Low-income Students." *Quarterly Journal of Economics* 137 (2): 1039–90.

Arcidiacono, Peter, V. Joseph Hotz, and Songman Kang. 2012. "Modeling College Major Choices using Elicited Measures of Expectations and Counterfactuals." *Journal of Econometrics* 166 (1): 3–16.

Arcidiacono, Peter, V. Joseph Hotz, Arnaud Maurel, and Teresa Romano. 2020. "Ex Ante Returns and Occupational Choice." *Journal of Political Economy* 128 (12): 4475–4522.

Armantier, Olivier, Wändi Bruine de Bruin, Simon Potter, Giorgio Topa, Wilbert Van Der Klaauw, and Basit Zafar. 2013. "Measuring Inflation Expectations." *Annual Review of Economics* 5 (1): 273–301.

Attanasio, Orazio, and Katja Kaufmann. 2009. "Educational Choices, Subjective Expectations, and Credit Constraints." NBER Working Paper 15087.

Ausubel, Lawrence M. 1999. "Adverse Selection in the Credit Card Market." Unpublished.

Bachmann, Ruediger, Giorgio Topa, and Wilbert van der Klaauw, eds. 2022. *Handbook of Economic Expectations.* New York, NY: Elsevier.

Baker, Rachel, Eric Bettinger, Brian Jacob, and Ioana Marinescu. 2018. "The Effect of Labor Market Information on Community College Students' Major Choice." *Economics of Education Review* 65: 18–30.
Bareham, Hanneh. 2023. "Stride Income-Share Agreements: 2023 Review." https://www.bankrate.com/loans/student-loans/reviews/stride/ (accessed April 16, 2023).
Barr, Nicholas, Bruce Chapman, Lorraine Dearden, and Susan Dynarski. 2017. "Getting Student Financing Right in the US: Lessons from Australia and England." Unpublished.
Base Human Capital. 2019. "StudentSmart Loans." https://web.archive.org/web/20190118131857/https://www.base-hc.com/ (accessed November 14, 2022).
Berman, Jillian. 2017. "Students Get Tuition Aid for a Piece of Their Future." *Wall Street Journal*, September 10. https://www.wsj.com/articles/students-get-tuition-aid-for-a-piece-of-their-future-1505096100.
Berman, Jillian. 2021. "These Students Thought They Were Paying for Their Education with an Innovative Alternative to Loans — but the True Cost Was Hidden, Lawsuit Alleges." *Market Watch*. https://www.marketwatch.com/story/these-students-thought-they-were-paying-for-their-education-with-an-innovative-alternative-to-loans-but-the-true-cost-was-hidden-lawsuit-alleges-11625173226.
Better Future Forward (BFF). 2022. https://www.betterfutureforward.org/apply (accessed November 14, 2022).
Bettinger, Eric P., Bridget Terry Long, Philip Oreopoulos, and Lisa Sanbonmatsu. 2012. "The Role of Application Assistance and Information in College Decisions: Results from the H&R Block FAFSA Experiment." *Quarterly Journal of Economics* 127 (3): 1205–42.
Bonhomme, Stéphane, and Jean-Marc Robin. 2010. "Generalized Non-parametric Deconvolution with an Application to Earnings Dynamics." *Review of Economic Studies* 77 (2): 491–533.
Britton, Jack W., and Jonathan Gruber. 2019. "Do Income Contingent Student Loan Programs Distort Earnings? Evidence from the UK." NBER Working Paper 25822.
Busta, Hallie. 2019. "Should Your College Offer an Income-share Agreement?" Higher Ed Dive. https://www.highereddive.com/news/5-questions-for-colleges-considering-income-share-agreements/558054/.
Chapman, Bruce. 2006. "Income Contingent Loans for Higher Education: International Reforms." In *Handbook of the Economics of Education,* Vol. 2, edited by Eric A. Hanushek and Finis Welch, 1435–1503. Amsterdam: Elsevier.
Charness, Gary, Uri Gneezy, and Vlastimil Rasocha. 2021. "Experimental Methods: Eliciting Beliefs." *Journal of Economic Behavior & Organization* 189: 234–56.
Chetty, Raj. 2006. "A New Method of Estimating Risk Aversion." *American Economic Review* 96 (5): 1821–34.
Conlon, John J., and Dev Patel. 2023. "What Jobs Come to Mind? Stereotypes about Fields of Study." Unpublished.
Conlon, John J., Laura Pilossoph, Matthew Wiswall, and Basit Zafar. 2018. "Labor Market Search with Imperfect Information and Learning." NBER Working Paper 24988.
Consumer Financial Protection Bureau (CFPB). 2021. *2021-CFPB-0005*. Washington, DC: Consumer Financial Protection Bureau.
Cowen, Tyler. 2019. "How Much Is Your Education Worth? Depends How Much You Make." *Bloomberg News*. https://www.bnnbloomberg.ca/how-much-is-your-education-worth-depends-how-much-you-make-1.1239687.
Crossley, Thomas, Yifan Gong, Todd R. Stinebrickner, and Ralph Stinebrickner. 2021. "Examining Income Expectations in the College and Early Post-college Periods: New Distributional Tests of Rational Expectations." NBER Working Paper 28353.
Del Rey, Elena, and Bertrand Verheyden. 2011. "Loans, Insurance and Failures in the Credit Market for Students." Unpublished.
Denning, Jeffrey T., Benjamin M. Marx, and Lesley J. Turner. 2019. "ProPelled: The Effects of Grants on Graduation, Earnings, and Welfare." *American Economic Journal: Applied Economics* 11 (3): 193–224.
Department of Education. 2023. "College Scorecard Database." Department of Education. https://collegescorecard.ed.gov/data/ (accessed February 10, 2024).
de Silva, Tim. 2023. "Insurance Versus Moral Hazard in Income-contingent Student Loan Repayment." Unpublished.
d'Haultfœuille, Xavier, Christophe Gaillac, and Arnaud Maurel. 2021. "Rationalizing Rational Expectations: Characterizations and Tests." *Quantitative Economics* 12 (3): 817–42.
Dobbie, Will, and Paige Marta Skiba. 2013. "Information Asymmetries in Consumer Credit Markets: Evidence from Payday Lending." *American Economic Journal: Applied Economics* 5 (4): 256–82.
Dominitz, Jeff. 1998. "Earnings Expectations, Revisions, and Realizations." *Review of Economics and Statistics* 80 (3): 374–88.

Dorans, Neil J. 1999. *Correspondences between ACT and SAT I scores*. New York, NY: College Entrance Examination Board.

Douglas-Gabriel, Danielle. 2017. "A New Way Emerges to Cover College Tuition. But Is It a Better Way?" *Washington Post*. https://www.washingtonpost.com/local/education/a-new-way-emerges-to-cover-college-tuition-but-is-it-a-better-way/2017/12/31/6519d100-d9c9-11e7-b859-fb0995360725_story.html?noredirect=on&utm_term=.630f90bd105d.

Dynarski, Susan. 2002. "The Behavioral and Distributional Implications of Aid for College." *American Economic Review* 92 (2): 279–85.

Dynarski, Susan, C. J. Libassi, Katherine Michelmore, and Stephanie Owen. 2021. "Closing the Gap: The Effect of Reducing Complexity and Uncertainty in College Pricing on the Choices of Low-income Students." *American Economic Review* 111 (6): 1721–56.

Eastern Kentucky University (EKU). 2022. "Income Share Agreement (ISA) Funding." https://web.archive.org/web/20220302034004/https://advantage.eku.edu/income-share-agreement-isa-funding (accessed January 23, 2023).

Einav, Liran, Amy Finkelstein, and Mark R. Cullen. 2010. "Estimating Welfare in Insurance Markets Using Variation in Prices." *Quarterly Journal of Economics* 125 (3): 877–921.

Einav, Liran, Mark Jenkins, and Jonathan Levin. 2012. "Contract Pricing in Consumer Credit Markets." *Econometrica* 80 (4): 1387–1432.

Evans, Brent J., Angela Boatman, and Adela Soliz. 2019. "Framing and Labeling Effects in Preferences for Borrowing for College: An Experimental Analysis." *Research in Higher Education* 60 (4): 438–57.

Findeisen, Sebastian, and Dominik Sachs. 2016. "Education and Optimal Dynamic Taxation: The Role of Income-contingent Student Loans." *Journal of Public Economics* 138: 1–21.

Finkelstein, Amy, and Nathaniel Hendren. 2020. "Welfare Analysis Meets Causal Inference." *Journal of Economic Perspectives* 34 (4): 146–67.

Fischhoff, Baruch, Aandrew M. Parker, Wändi Bruine de Bruin, Julie Downs, Claire Palmgren, Robyn Dawes, and Charles F. Manski. 2000. "Teen Expectations for Significant Life Events." *Public Opinion Quarterly* 64 (2): 189–205.

Friedman, Milton. 1955. "The Role of Government in Education." In *Economics and the Public Interest*, edited by Robert Solo, 123-44. New Brunswick, NJ: Rutgers University Press.

Fuller, Wayne A. 1987. *Measurement Error Models.* New York, NY: John Wiley & Sons.

Fuster, Andreas, and Basit Zafar. 2023. "Survey Experiments on Economic Expectations." In *Handbook of Economic Expectations,* edited by Rüdiger Bachmann, Giorgio Topa, and Wilbert van der Klaauw, 107–30. London: Academic Press.

Gallinelli, Nicholas. 2019. "Flatiron School No Longer Offers an Income Share Agreement or ISA." *Flatiron School Blog*. https://flatironschool.com/blog/things-to-know-flatiron-school-income-share-agreement/.

Gandelman, Nestor, and Ruben Hernandez-Murillo. 2015. "Risk Aversion at the Country Level." *Federal Reserve Bank of St. Louis Review* 97 (1): 53–66.

Ganong, Peter, Damon Jones, Pascal Noel, Fiona Greig, Diana Farrell, and Chris Wheat. 2020. "Wealth, Race, and Consumption Smoothing of Typical Income Shocks." NBER Working Paper 27552.

Ganong, Peter, and Pascal Noel. 2019. "Consumer Spending During Unemployment: Positive and Normative Implications." *American Economic Review* 109 (7): 2383–2424.

Gary-Bobo, Robert J., and Alain Trannoy. 2015. "Optimal Student Loans and Graduate Tax Under Moral Hazard and Adverse Selection." *RAND Journal of Economics* 46 (3): 546–76.

Gervais, Martin, and Nicolas L. Ziebarth. 2019. "Life after Debt: Postgraduation Consequences of Federal Student Loans." *Economic Inquiry* 57 (3): 1342–66.

Giustinelli, Pamela. 2023. "Expectations in Education." In *Handbook of Economic Expectations*, edited by Ruediger Bachmann, Giorgio Topa, and Wilbert van der Klaauw, 193–224. Cambridge, MA: Academic Press.

Gong, Yifan, Todd Stinebrickner, and Ralph Stinebrickner. 2019. "Uncertainty About Future Income: Initial Beliefs and Resolution During College." *Quantitative Economics* 10 (2): 607–41.

Gourinchas, Pierre-Olivier, and Jonathan A. Parker. 2002. "Consumption over the Life Cycle." *Econometrica* 70 (1): 47–89.

Gupta, Arpit, and Christopher Hansman. 2019. "Selection, Leverage, and Default in the Mortgage Market." Unpublished.

Guvenen, Fatih. 2007. "Learning Your Earning: Are Labor Income Shocks Really Very Persistent?" *American Economic Review* 97 (3): 687–712.

Handel, Benjamin R. 2013. "Adverse Selection and Inertia in Health Insurance Markets: When Nudging Hurts." *American Economic Review* 103 (7): 2643–82.

Harrison, David. 2021. "Schumer Again Calls on Biden to Cancel $50,000 per Borrower in Federal Student Debt." *Wall Street Journal*, June 28. https://www.wsj.com/articles/schumer-again-calls-on-biden-to-cancel-50-000-per-borrower-in-federal-student-debt-11624911980.

Hartley, Jon. 2016. "Purdue's Income Sharing Agreement Solution to The Student Debt Crisis." *Forbes Magazine*, August 30. https://www.forbes.com/sites/jonhartley/2016/08/30/purdues-income-sharing-agreement-solution-to-the-student-debt-crisis/?sh=5966c11a3eea.

Hendren, Nathaniel. 2013. "Private Information and Insurance Rejections." *Econometrica* 81 (5): 1713–62.

Hendren, Nathaniel. 2017. "Knowledge of Future Job Loss and Implications for Unemployment Insurance." *American Economic Review* 107 (7): 1778–1823.

Hendren, Nathaniel, and Ben Sprung-Keyser. 2020. "A Unified Welfare Analysis of Government Policies." *Quarterly Journal of Economics* 135 (3): 1209–1318.

Herbst, Daniel. 2023. "The Impact of Income-driven Repayment on Student Borrower Outcomes." *American Economic Journal: Applied Economics* 15 (1): 1–25.

Herbst, Daniel, and Nathaniel Hendren. 2024. "Replication data for: Opportunity Unraveled: Private Information and the Missing Markets for Financing Human Capital." American Economic Association [publisher], Inter-university Consortium for Political and Social Research [distributor]. https://doi.org/10.3886/E198510V1.

Hoxby, Caroline M. 2018. "The Productivity of US Postsecondary Institutions." In *Productivity in Higher Education*, edited by Caroline M. Hoxby and Kevin Stange, 31–66. Chicago, IL: University of Chicago Press.

Hoxby, Caroline M., and Sarah Turner. 2015. "What High-achieving Low-income Students Know About College." *American Economic Review* 105 (5): 514–17.

Hurd, Michael D., and Kathleen McGarry. 2002. "The Predictive Validity of Subjective Probabilities of Survival." *Economic Journal* 112 (482): 966–85.

Jacobs, Bas, and Sweder J. G. van Wijnbergen. 2007. "Capital-market Failure, Adverse Selection, and Equity Financing of Higher Education." *FinanzArchiv* 63 (1): 1–32.

Jacobs, Joshua A. 2021. "Income-Share Agreements on the Job Market: Debt Versus Equity." Unpublished.

Jappelli, Tullio, and Luigi Pistaferri. 2010. "The Consumption Response to Income Changes." *Annual Review of Economics* 2 (1): 479–506.

Jeanne, Olivier, and Romain G. Rancière. 2006. "The Optimal Level of International Reserves for Emerging Market Countries: Formulas and Applications." Unpublished.

Johnson, Sydney. 2019. "So You Want to Offer an Income-Share Agreement? Here's How 5 Colleges Are Doing It." EdSurge. https://www.edsurge.com/news/2019-02-15-so-you-want-to-offer-an-income-share-agreement-here-s-how-5-colleges-are-doing-it.

Karamcheva, Nadia, Jeffrey Perry, and Constantine Yannelis. 2020. "Income-Driven Repayment Plans for Student Loans." Unpublished.

Karlan, Dean, and Jonathan Zinman. 2009. "Observing Unobservables: Identifying Information Asymmetries with a Consumer Credit Field Experiment." *Econometrica* 77 (6): 1993–2008.

Kenzie Academy. 2020. "What is an Income Share Agreement?" https://kenzie.snhu.edu/blog/what-to-look-for-in-an-income-share-agreement/ (accessed November 14, 2022).

Kerr, Emma. 2021. "Income Share Agreements: What to Know." *US News and World Report*. https://www.usnews.com/education/best-colleges/paying-for-college/articles/income-share-agreements-what-students-should-know.

Ladine, Bret. 2001. "'70s Debt Program Finally Ending." *Yale Daily News*, March 27. https://yaledailynews.com/blog/2001/03/27/70s-debt-program-finally-ending/.

Leif. 2021. "Leif's Impact 2021: 22,000 Students Educated." https://www.leif.org/blog/leifs-impact-2021-22-000-students-educated (accessed November 14, 2022).

Linehan, Sean (**@seanlinehan**). 2022. "I launched an Income Share Agreement (ISA) company in 2019. Our company survived, but our use of ISAs did not." Twitter, March 21, 2022, https://twitter.com/seanlinehan/status/1505923007096700939?s=20&t=HjvtQ788YIUAaON7iMrOgA.

Lochner, Lance, and Alexander Monge-Naranjo. 2016. "Student Loans and Repayment: Theory, Evidence, and Policy." In *Handbook of the Economics of Education*, Vol. 5, edited by Eric A. Hanushek, Stephen Machin, and Ludger Woessman, 397–478. New York, NY: Elsevier.

Lochner, Lance J., and Alexander Monge-Naranjo. 2011. "The Nature of Credit Constraints and Human Capital." *American Economic Review* 101 (6): 2487–2529.

Looney, Adam, and Constantine Yannelis. 2015. "A Crisis in Student Loans?: How Changes in the Characteristics of Borrowers and in the Institutions They Attended Contributed to Rising Loan Defaults." *Brookings Papers on Economic Activity* 45 (2): 1–68.

Lumni. 2022. https://usa.lumniportal.net (accessed November 14, 2022).

Madonia, Greg, and Austin C. Smith. 2019. "All-In or Checked-Out? Disincentives and Selection in Income Share Agreements." *Journal of Economic Behavior and Organization* 161: 52–67.

Manski, Charles F. 2004. "Measuring Expectations." *Econometrica* 72 (5): 1329–76.

Manski, Charles F., and John D. Straub. 2000. "Worker Perceptions of Job Insecurity in the Mid-1990s: Evidence from the Survey of Economic Expectations." *Journal of Human Resources* 35 (3): 447–79.

Marx, Benjamin M., and Lesley J. Turner. 2019. "Student Loan Nudges: Experimental Evidence on Borrowing and Educational Attainment." *American Economic Journal: Economic Policy* 11 (2): 108–41.

MentorWorks. 2023. "About Us." https://mentorworks.com/about/ (accessed January 23, 2023).

Milgrom, Paul, and Ilya Segal. 2002. "Envelope Theorems for Arbitrary Choice Sets." *Econometrica* 70 (2): 583–601.

Moody, Josh. 2022. "Purdue Backs Off Income-Share Agreements." *Inside Higher Ed*, June 22. https://www.insidehighered.com/news/2022/06/23/purdue-pauses-new-income-share-agreement-enrollments.

Mueller, Andreas I., and Johannes Spinnewijn. 2023. "Expectations Data, Labor Market, and Job Search." In *Handbook of Economic Expectations*, edited by Ruediger Bachmann, Giorgio Topa, and Wilbert van der Klaauw, 677–713. Cambridge, MA: Academic Press.

Mueller, Andreas I., Johannes Spinnewijn, and Giorgio Topa. 2021. "Job Seekers' Perceptions and Employment Prospects: Heterogeneity, Duration Dependence, and Bias." *American Economic Review* 111 (1): 324–63.

Mumford, Kevin J. 2022. "Student Selection into an Income Share Agreement." Unpublished.

National Center for Education Statistics (NCES). 2018. "2008/12 Baccalaureate and Beyond (B&B) study data." National Center for Education Statistics (accessed June 5, 2023).

National Center for Education Statistics (NCES). 2020a. "2012/17 Beginning Postsecondary Students (BPS) study with PETS data." National Center for Education Statistics (accessed June 5, 2023).

National Center for Education Statistics (NCES). 2020b. "2016/17 Baccalaureate and Beyond (B&B) study data." National Center for Education Statistics (accessed June 5, 2023).

National Center for Education Statistics (NCES). 2023. "Datalab Codebooks." National Center for Education Statistics. https://nces.ed.gov/datalab/ (accessed November 7, 2023).

Nerlove, Marc. 1975. "Some Problems in the Use of Income-contingent Loans for the Finance of Higher Education." *Journal of Political Economy* 83 (1): 157–83.

Northeastern University. 2022. "Billing and Payments: Financing Options." https://studentfinance.northeastern.edu/billing-payments/financing-options/ (accessed November 14, 2022).

Norwich University. 2021. "Invest in U." https://www.norwich.edu/shoulder-to-shoulder/2734-scholarships (accessed November 14, 2022).

Pacific Lutheran University (PLU). 2023. "Income Share Agreements." https://web.archive.org/web/20220120232531/https://www.plu.edu/student-financial-services/plu-persistence-graduation-programs/ (accessed January 23, 2023).

Palacios, Miguel. 2004. *Investing in Human Capital: A Capital Markets Approach to Student Funding.* Cambridge, UK: Cambridge University Press.

Pålsson, Anne-Marie. 1996. "Does the Degree of Relative Risk Aversion Vary with Household Characteristics?" *Journal of Economic Psychology* 17 (6): 771–87.

Purdue University. 2022. "Back-a-Boiler." Purdue.edu. https://www.purdue.edu/backaboiler (accessed November 14, 2022).

Robert Morris University. 2020. "RMU to Make College More Affordable Through Income Share Agreements." https://www.rmu.edu/about/news/rmu-make-college-more-affordable-through-income-share-agreements (accessed November 14, 2022).

Robertson Education Empowerment Foundation (REEF). 2006. "Student Securities: Overview." https://web.archive.org/web/20080629221734/http://www.studentsecurities.com/company/ (accessed November 14, 2022).

Rockhurst University. 2021. "FAQs." https://web.archive.org/web/20211203160748/https://rockhurst.vemoeducation.com/ (accessed November 14, 2022).

Rudegeair, Peter. 2016. "Online Lender's Secret to Success: Past Failure." *Wall Street Journal*. https://www.wsj.com/articles/online-lenders-secret-to-success-past-failure-1465723802.

Ruggles, Steven, Sarah Flood, Matthew Sobek, Daniel Backman, Annie Chen, Grace Cooper, Stephanie Richards, Renae Rogers, and Megan Schouweiler. 2023. "IPUMS USA: Version 14.0 [dataset]. Minneapolis, MN: IPUMS." IPUMS. https://doi.org/10.18128/D010.V14.0 (accessed February 10, 2024).

Saez, Emmanuel, Joel Slemrod, and Seth H. Giertz. 2012. "The Elasticity of Taxable Income with Respect to Marginal Tax Rates: A Critical Review." *Journal of Economic Literature* 50 (1): 3–50.

Schmieder, Johannes F., and Till Von Wachter. 2016. "The Effects of Unemployment Insurance Benefits: New Evidence and Interpretation." *Annual Review of Economics* 8: 547–81.

Scott-Clayton, Judith, and Basit Zafar. 2019. "Financial Aid, Debt Management, and Socioeconomic Outcomes: Post-college Effects of Merit-based Aid." *Journal of Public Economics* 170: 68–82.

Shavell, Steven. 1979. "On Moral Hazard and Insurance." *Quarterly Journal of Economics* 93 (4): 541–62.

Siegel, Robert. 2007. "2005 Law Made Student Loans More Lucrative." *National Public Radio*, April 24. https://www.npr.org/2007/04/24/9803213/2005-law-made-student-loans-more-lucrative.

Sloan, Karen. 2022. "Stanford Law to Offer 'Income Share' Financing as Law School Costs Soar." *Reuters.* https://www.reuters.com/legal/legalindustry/stanford-law-offer-income-share-financing-law-school-costs-soar-2022-09-15/.

Spinnewijn, Johannes. 2015. "Unemployed but Optimistic: Optimal Insurance Design with Biased Beliefs." *Journal of the European Economic Association* 13 (1): 130–67.

Stantcheva, Stefanie. 2017. "Optimal Taxation and Human Capital Policies over the Life Cycle." *Journal of Political Economy* 125 (6): 1931–90.

Stephens-Davidowitz, Seth. 2013. "The Cost of Racial Animus on a Black Presidential Candidate: Using Google Search Data to Find What Surveys Miss." Unpublished.

Stinebrickner, Ralph, and Todd Stinebrickner. 2008. "The Effect of Credit Constraints on the College Drop-out Decision: A Direct Approach Using a New Panel Study." *American Economic Review* 98 (5): 2163–84.

Stroebel, Johannes. 2016. "Asymmetric Information About Collateral Values." *Journal of Finance* 71 (3): 1071–1112.

Student Freedom Initiative. 2023. "Anchor Donors." https://studentfreedominitiative.org/anchor-donors/ (accessed January 23, 2023).

Tourangeau, Roger, and Ting Yan. 2007. "Sensitive Questions in Surveys." *Psychological Bulletin* 133 (5): 859–83.

University of Colorado at Boulder. 2022. "A New Way to Pay For Your University of Colorado Boulder Education." https://web.archive.org/web/20220625020650/https://cuengineering.vemoeducation.com/ (accessed January 23, 2023).

Van der Klaauw, Wilbert. 2012. "On the Use of Expectations Data in Estimating Structural Dynamic Choice Models." *Journal of Labor Economics* 30 (3): 521–54.

Warren, Elizabeth. 2020. "My Plan to Cancel Student Loan Debt on Day One of my Presidency." Elizabethwarren.com, https://elizabethwarren.com/plans/student-loan-debt-day-one (accessed July 14, 2021).

William Jessup University. 2023. "Income Share Agreements." https://jessup.edu/admissions/financial-aid/undergrad/#1611277265088-547ff640-a6d3 (accessed January 23, 2023).

Wiswall, Matthew, and Basit Zafar. 2015. "Determinants of College Major Choice: Identification Using an Information Experiment." *Review of Economic Studies* 82 (2): 791–824.

Wiswall, Matthew, and Basit Zafar. 2021. "Human Capital Investments and Expectations About Career and Family." *Journal of Political Economy* 129 (5): 1361–1424.

Yoder, Steven. 2022. "Colleges Are Already Ditching Income-Share Agreements." *WIRED*. https://www.wired.com/story/income-share-agreements-hechinger-report/.

Zaber, Melanie A., and Elizabeth D. Steiner. 2021. *Are Income Share Agreements Fair? A Close Look at the Potential Risks and Benefits of an Emerging Financial Aid Option.* Santa Monica, CA: RAND Corporation.

Zaber, Melanie A., Elizabeth D. Steiner, and Jessica Arana. 2023. *Decoding Income Share Agreements: A Resource for Learners and Financial Aid Professionals.* Santa Monica, CA: RAND Corporation.

Zaber, Melanie A., Elizabeth D. Steiner, Hana Gebremariam, Asya Spears, Zohan Hasan Tariq, and Katherine Grace Carman. 2023. *Income Share Agreements: Market Structure, Communication, and Equity Implications of a Student Loan Alternative.* Santa Monica, CA: RAND Corporation.

Zingales, Luigi. 2012. "The College Graduate as Collateral." *New York Times*, June 13. https://www.nytimes.com/2012/06/14/opinion/the-college-graduate-as-collateral.html.

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