Accounting for Tuition Increases across U.S. Colleges*

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Abstract

This paper sheds light on the persistent rise in college tuition between the late 1980s and the Great Recession using a combination of detailed micro data and a newly developed dynamic equilibrium model of the higher education, student loan, and labor markets. The model features equilibrium sorting between heterogeneous students and imperfectly competitive colleges that gives rise to rich tuition pricing patterns within and across institutions. The integration of this framework into a full life cycle model with income risk, student loan borrowing, and default makes it possible to disentangle the contribution of several different economic forces to increasing college prices. The quantitative analysis successfully accounts for the entire growth in net tuition during this period and identifies demand-side factors—particularly expansions in federal student aid and rising parental transfers—as the primary culprits, followed by more modest supply-side contributions from lagging public funding and Baumol's cost disease.

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1 Introduction

Over the past few decades, the stubborn upward march of college tuition across all major segments of higher education has led to growing concerns about access, affordability, and mounting student loan debt. Among selective, frequently wealthy private research institutions, net tuition—that is, sticker price minus institutional aid coming in the form of need-based and merit-based scholarships—increased by 50% between 1987 and 2010 in real terms (from $15,500 to $23,700 in constant 2010 dollars) and by an astonishing 140% (from $2,700 to $6,400) for non-selective public teaching colleges that tend to be more resource constrained.[1] Several explanations have emerged to explain these and other higher education trends pertaining to enrollment, graduation, and post-graduation outcomes, but little consensus has emerged regarding their quantitative salience. While some explanations highlight the importance of broad macroeconomic forces, such as rising labor market skill premia that increase the value of a college degree, others focus on college-specific factors such as cuts in state appropriations or the unintended consequences of federal student aid.

This paper quantitatively evaluates several prominent theories of tuition inflation using detailed micro-data and a rich equilibrium macroeconomic model that incorporates several key features of the higher education landscape. To organize thinking, we separate the theories which involve factors that directly affect college supply from those that revolve around forces that shift demand. On the supply side, Baumol's cost disease emphasizes the commonality between higher education and other service sectors, where the stipulated combination of stagnant productivity growth and rising labor costs creates persistent inflationary pressures. Another common supply-side explanation focuses on the role of declining state appropriations for public institutions. We analyze this theory both independently and within the broader context of changes to other sources of non-tuition revenue. On the demand side, we examine the frequently-mentioned Bennett hypothesis, which attributes higher tuition to the same federal student aid programs that are meant to help with college affordability. Specifically, we assess the contribution of pre-Great Recession reforms to the Federal Student Loan Program (such as the addition of unsubsidized loans in 1993) as well as the evolution of loan limits, interest rates, and Pell Grants. Lastly, we also quantify the role of rising labor market skill premia and higher parental income through their impact on college demand.

With the presence of extensive public subsidies, complicated financial aid rules, market power, and widespread price discrimination, higher education functions quite differently from most other markets. Furthermore, non-profit institutions—which are the focus of this paper—face different objectives and incentives than profit-maximizing firms. To capture these features, we assume that colleges maximize quality, which is a function of per-student investment and average student ability, just as in the static models of Epple, Romano, and Sieg (2006) and Epple, Romano, Sarpca, and Sieg (2017). By operating with market power, colleges engage in price discrimination to balance student recruitment against the need to raise revenue for quality-enhancing investment. Students,

[1] This time period omits the most recent wave of significant policy changes implemented since the Great Recession.

in turn, weigh cost and quality when choosing from among the set of colleges to which they receive an offer of admission. In equilibrium, the endogenous sorting of students across colleges affects both dimensions of the college quality distribution, which creates a computationally challenging fixed point problem. Our quantitative framework does well at capturing this sorting.

We find that the aforementioned theories in conjunction can explain the entire increase in average college net tuition since 1987. Another bottom line is that no single force is entirely responsible for the multi-decade upward march in net college prices. Instead, more expensive college is the result of a confluence of forces. Even so, some clear messages emerge. First, the expansion in Federal aid has the largest quantitative effect on tuition inflation across all college types. Although in an absolute sense financial aid has affected net tuition at public colleges the most, it accounts for a larger share of tuition inflation at private colleges. Next up in importance are the demand-inducing effects of higher parental income, college earnings premia, and graduation rates. At public colleges—particularly teaching-focused, non-selective institutions—relative cutbacks in government appropriations as a share of institutional revenue have also led to significantly higher net tuition charges for students and their families. By contrast, we find that Baumol's cost disease plays little role in driving up net tuition, instead primarily reducing enrollment and quality-enhancing spending.

1.1 Related Literature

A growing literature employs general equilibrium models to analyze higher education while taking the behavior of colleges and tuition as given. For example, Abbott, Gallipoli, Meghir, and Violante (2019) develop an equilibrium model to analyze financial aid policies intended to promote college attendance. Their framework features a rich intergenerational setting, intervivos transfers, and college attendance financed partly by grants and loans. In other work, Athreya and Eberly (2016) study the impact of a rising college wage premium on college attainment in the presence of heterogeneous drop-out risk and post-graduation earnings risk. Hendricks and Leukhina (2016) and Chatterjee and Ionescu (2012) also investigate the importance of drop-out risk for college attainment. Garriga and Keightley (2010), Lochner and Monge-Naranjo (2011), Belley and Lochner (2007), and Keane and Wolpin (2001) also develop equilibrium models to answer various important questions that lie at the intersection of macroeconomics and higher education.

This paper endogenizes tuition and the response of colleges to evolving market conditions and policies. In this vein, recent work by Jones and Yang (2016) closely mirrors the objectives here. They explore the role of skill-biased technical change in explaining the rise in college costs from 1961 to 2009. However, their study differs from this paper in several ways. First, this paper takes a unified look at both supply-side and demand-side factors that influence tuition, whereas they focus on the role of cost disease. Second, the object of interest in Jones and Yang (2016) is college costs, which increased by 35% in real terms between 1987 and 2010, whereas this paper addresses the much larger 92% increase in net tuition. Also, whereas they use a competitive, representative college framework, this paper employs a model with heterogeneous, imperfectly competitive colleges, peer effects, and student loan borrowing with default. Fillmore (2016) and Fu (2014) develop rich frameworks with heterogeneous colleges, but in both cases, students have static, reduced-form utility functions. Furthermore, peer effects are exogenous in Fillmore (2016), and Fu (2014) does not allow price discrimination based on ability and income. More recently, Cai and Heathcote (2020) develop a tractable static framework with competitive, profit-maximizing colleges and heterogeneous students to evaluate the impact of rising income inequality on college tuition. Although the colleges lack monopoly pricing power, the perfect segmentation of the market by student type and presence of peer effects gives rise to student-specific tuition schedules. The authors are able to characterize the equilibrium in closed-form for a simplified version of the model, and in a richer model they are able to show quantitatively that a general increase in income dispersion and fattening of the right tail are significant driving forces for higher net tuition. These results mirror our findings on the importance of parental income for college tuition.

Methodologically, the most closely related papers to ours are Epple et al. (2006), Epple et al. (2017), and our earlier paper, Gordon and Hedlund (2019). The former two papers develop a static model of heterogeneous, quality-maximizing colleges that operate in an environment of imperfect competition and engage in price discrimination. Gordon and Hedlund (2019) embed this framework in a broader macroeconomic model but consider only the case of a single, monopolistic college. Such a case greatly simplifies computation but implies exaggerated market power with colleges facing no competitive pressure besides that provided by the outside option of skipping college entirely. This paper takes the important step of adding heterogeneous colleges, which allows for rich competition and sorting.

This paper also relates to a large empirical literature that estimates the effects of macroeconomic factors and policy interventions on tuition and enrollment. The origins of cost disease emerge from seminal works by Baumol and Bowen (1966) and Baumol (1967). They lay out a clear mechanism: productivity increases in the economy at large drive up wages everywhere, which service sectors that lack productivity growth pass along by increasing their relative prices. Recently, Archibald and Feldman (2008) use cross-sectional industry data to forcefully advance the idea that cost and price increases in higher education closely mirror trends for other service industries that utilize highly educated labor. In short, they "reject the hypothesis that higher education costs follow an idiosyncratic path."

The empirical literature has conflicting findings on the impact of state higher education appropriations on college tuition. For example, Heller (1999) suggests a negative relationship between state appropriations and tuition, asserting that "the higher the support provided by the state, the lower generally is the tuition paid by all students." Recent empirical work by Chakrabarty, Mabutas, and Zafar (2012), Koshal and Koshal (2000), and Titus, Simone, and Gupta (2010) support this hypothesis, but notably, Titus et al. (2010) show that this relationship only holds up in the short run. Lastly, in a large study commissioned by Congress in the 1998 re-authorization of the Higher Education Act of 1965, Cunningham, Wellman, Clinedinst, Merisotis, and Carroll (2001a) conclude that "decreasing revenue from government appropriations was the most important factor associated with tuition increases at public 4-year institutions."

Shifting to demand-side factors, the empirical literature is split on the impact of financial aid on tuition. For example, McPherson and Shapiro (1991), Singell and Stone (2007), Rizzo and Ehrenberg (2004), Turner (2012), Turner (2017), Long (2004a), and Long (2004b) find at least some evidence in support of the Bennett hypothesis, though they disagree on the magnitude of the pass-through of aid into higher tuition and whether public or private institutions are more responsive. Most recently, Lucca, Nadauld, and Shen (2019) find a 65% pass-through effect for changes in federal subsidized loans and positive but smaller pass-through effects for changes in Pell Grants and unsubsidized loans. Similarly, Cellini and Goldin (2014) show that tuition is 78% higher at for-profit colleges that participate in federal student aid compared to those that do not. By contrast, in their commissioned report for the 1998 re-authorization of the Higher Education Act, Cunningham et al. (2001a); Cunningham, Wellman, Clinedinst, Merisotis, and Carroll (2001b) conclude that "the models found no associations between most of the aid variables and changes in tuition in either the public or private not-for-profit sectors." Long (2006) and Frederick, Schmidt, and Davis (2012) echo these sentiments.

We also analyze how labor market trends over the past few decades have impacted tuition. Empirically, Autor, Katz, and Kearney (2008) report that the college earnings premium increased from 58% in the mid-1980s to 93% in 2005, which Autor et al. (2008), Katz and Murphy (1992), Goldin and Katz (2007), and Card and Lemieux (2001) ascribe to skill-biased technological change and a fall in the relative supply of college graduates. In recent work, Andrews, Li, and Lovenheim (2012) and Hoekstra (2009) study the *distribution* of college earnings premia and find substantial heterogeneity attributable to variation in college quality.

2 The Model

The model consists of an imperfectly competitive higher education sector embedded in an open economy environment populated by a continuum of heterogeneous households and a government which administers a student loan program and operates a social security system for retired workers.

2.1 Colleges

The higher education sector consists of $\#K$ college types with each $k \in K$ containing a positive measure $g(k)$ of identical non-profit colleges. In light of this non-profit status, colleges are not profit-maximizers but instead seek to maximize quality, which is a function of the average academic ability

X_k of the student body, investment per student I_k, and enrollment N_k.[2] Higher academic ability and investment per student improve quality, whereas schools may differ on whether they prefer to have larger or smaller enrollment. Thus, quality $q_k(X_k, I_k, N_k)$ also depends directly on k.

Besides differing in the weights they place on each of the components of quality, colleges are ex-ante heterogeneous with respect to their sources of non-tuition funding, their operating costs, and expected student outcomes. Beginning with the revenues side of the balance sheet, colleges receive type-specific government appropriations $G_k(N_k)$ and private endowment funding $E_k(N_k)$, which may depend on enrollment. On the spending side, colleges face operating costs $pC_k(N_k)$ that are distinct from the cost of investment pI_kN_k—where p is the relative price of college inputs—and do not enter the college's quality function. Turning to student outcomes, colleges offer different student-specific dropout probabilities and labor market prospects. Specifically, a student of type $s = (x, y)$ that consists of academic ability x (an amalgum of innate ability and human capital at age 18) and parental income y drops out with probability $\delta_k(s)$ or else, upon graduation after J_Y years, receives earnings premium $\lambda_k(s)$. Besides these sources of ex-ante heterogeneity, colleges differ as a result of equilibrium sorting and endogenous investment.

College admissions and enrollment take place through competitive search. Specifically, colleges post vacancies in submarkets $m \equiv (k, T, s)$ indexed by college type k, net tuition T, and student characteristics s. By assumption, colleges commit to charging fixed net tuition $T(m)$ to students who match in submarket m until they either drop out with probability $\delta(m) \equiv \delta_{k(m)}(s(m))$ or graduate. Each vacancy costs κ_k to post and is filled with probability $\rho(\theta(m))$, which depends on the market tightness $\theta(m)$ between vacancies and student applications. Colleges can post vacancies in multiple submarkets simultaneously, which gives rise to within-school tuition dispersion and a heterogeneous student body, consistent with the data.

To avoid complications from strategic investment and dynamic market power, the model adopts some assumptions from Gordon and Hedlund (2019)—including additive separability of q across cohorts and a cohort-by-cohort balanced budget rule—that render the college's decision problem independent across cohorts. To simplify matters further, cohort-specific operating costs, non-tuition revenue, and college quality are functions of each cohort's total dropout-adjusted enrollment over time, and colleges have access to perfect capital markets where they can borrow interest-free against the future tuition payments *of that same cohort only*, i.e. there is no cross-cohort subsidization. Thus, upon matriculation, colleges immediately value the cohort-specific sequence of tuition payments $T(m)$, $(1-\delta(m))T(m)$, $(1-\delta(m))^2T(m)$, etc. at $T(m)\omega(m)$, where $\omega(m) = \sum_{j=1}^{J_Y}(1-\delta(m))^{j-1}$.[3]

[2] This formulation of the college's objective function follows Epple et al. (2006, 2017) and was also used in Gordon and Hedlund (2019). The appendix also provides several pieces of supporting evidence.

[3] The counterparty is an unmodeled deep-pocketed lender, and the 0% is just to simplify the algebra.

The within-cohort optimization problem for college type k is

$$\begin{aligned} &\max_{\substack{v(m)\geq 0,\\ X_k, I_k, N_k}} q_k(X_k, I_k, N_k) \\ \text{s.t. } pI_kN_k + pC_k(N_k) + \kappa_k \int v(m)dm &= \int T(m)\omega(m)v(m)\rho(\theta(m))dm + G_k(N_k) + E_k(N_k) \\ X_k &= \int x(m)\omega(m)v(m)\rho(\theta(m))dm/N_k \\ N_k &= \int \omega(m)v(m)\rho(\theta(m))dm \end{aligned} \tag{1}$$

In active submarkets, $\theta(m) > 0$, the first order conditions imply that net tuition satisfies

$$T(m) = \underbrace{\frac{\kappa_k}{\omega(m)\rho(\theta(m))}}_{\text{Markup}} + \overbrace{\underbrace{pI_k + pC_k'(N_k) - [G_k'(N_k) + E_k'(N_k)]}_{\text{Marginal resource cost}} - \underbrace{p\frac{q_N}{q_I}N_k}_{\text{Size discount}} - \underbrace{p\frac{q_X}{q_I}(x(m) - X_k)}_{\text{Ability discount}}}^{EMC_k(s(m))} \tag{2}$$

where EMC stands for effective marginal cost.

Intuitively, for each unit mass of vacancies in submarket m, the college pays cost κ_k, successfully enrolls a measure $\rho(\theta(m))$ of type-$s(m)$ students, and receives net payoff $T(m) - EMC_k(s(m))$ equal to the difference between net tuition T and what Epple et al. (2006) have coined the effective marginal cost $EMC_k(s)$ of a type-s student. As is standard with marginal costs, $EMC_k(s)$ takes into account the marginal resources expended by the college to educate a student, which equals the difference between the sum of marginal investment and operating costs, $pI_k + pC_k'(N_k)$, and the sum of marginal government appropriations and private endowment funding, $G_k'(N_k) + E_k'(N_k)$.

Unlike with canonical production firms, $EMC_k(s)$ also adjusts for the marginal contribution of type-s students to each component of the college's quality function. For example, colleges provide greater tuition discounts to students who create positive peer effects by virtue of having high academic ability relative to the institution average, $x > X$. Returning to equation 2, the first term reflects a price markup that arises because of search frictions but which will represent market power more generally when taking the model to the data. If equation 2 were not satisfied, the college would either set vacancies to zero—in the case where the right side exceeds the left side—or else to infinity in the opposite case. Thus, equation 2 must hold with equality in active submarkets.

To arrive at the average net tuition per student at each college, take the expectation of equation 2 over the enrollment distribution (i.e. integrate with respect to $\omega(m)v(m)\rho(\theta(m))/N_k$), which yields

$$T_k = \kappa_k\frac{V_k}{N_k} + pI_k + pC_k'(N_k) - [G_k'(N_k) + E_k'(N_k)] - p\frac{q_N}{q_I}N_k, \tag{3}$$

where V_k is total vacancy costs, and κ_kV_k/N_k is the average markup. This equation states that average net tuition equals marginal resource costs minus the size discount plus the average markup.

2.2 Households

Households go through three phases of life: youth, working age, and retirement. The opportunities and risks they encounter, the public policies they face, and the resulting decisions they make depend on their stage in the life cycle.

2.2.1 Youth and College Students

Each period, a fixed mass of heterogeneous youth with characteristics $s = (x, y)$ drawn from the distribution $\Gamma(s)$ enter the economy at high school graduation age $j = 1$ and receive a vector of taste shocks $\{\epsilon_k\}$ that impact the utility they receive from deciding whether and where to attend college. After receiving these taste shocks, youth either enter the workforce, $k = 0$, or they choose how many college applications e to fill out and where to submit them, $m = (k, T, s)$. Completing e applications causes disutility $\psi(e-1)^2$ and results in a successful offer of admission (i.e. a match) from a type-$k(m)$ college charging net tuition $T(m)$ with probability $e\eta(\theta(m))$. Given a choice of college type k, a tradeoff emerges whereby a student seeking an offer of admission at cheaper net tuition T must exert greater effort e, resulting in higher search disutility. To simplify the discrete choice over college types k, students can only send applications to a single submarket.

Youth who opt to pursue higher education receive two distinct benefits. First, they enjoy additive flow utility $v_k(I_k)$ while in college, which is increasing in college investment. Second, they earn higher future labor income. Students who avoid the annual dropout probability $\delta_k(s)$ for all J_Y years and successfully graduate receive log earnings premium $\lambda_k(s)$. Students who drop out after j years receive a premium of $\lambda_k(s)j/(J_Y + 1)$, which implies a sheepskin effect from diploma receipt (relatively to dropping out after J_Y) equal to $J_Y/(J_Y + 1)$.

Students face total cost of attendance $COA(T) = T+\phi$, where ϕ represents non-tuition expenses. Need-based government grants $\zeta(COA(T), EFC(s))$ defray some of this cost, with eligibility based on $COA(T)$ and the expected family contribution $EFC(s)$, which is set by policymakers. Students must then decide how to finance the remaining net cost of attendance, $NCOA(T, s) = COA(T) - \zeta(COA(T), EFC(s))$, between out-of-pocket family resources and borrowing using student loans.

The Federal Student Loan Program (FSLP) offers students two complementary loan options. For those with financial need—that is, a net cost of attendance that exceeds their expected family contribution, i.e. $NCOA(T, s) > EFC(s)$—subsidized loans represent the first line of borrowing because they do not accrue interest while students are enrolled in college. However, in addition to the eligibility requirement, students are subject to an annual subsidized borrowing limit of $\bar{b}_j^{sub}$ in year $j = 1, \ldots, J_Y$ of college and an aggregate subsidized limit of $\bar{l}^{sub}$. Together, the statutory ceilings and need-based eligibility yield an annual subsidized limit for students with net cost of attendance $NCOA$ and expected financial contribution EFC of $\min\{\bar{b}_j^{sub}, \max\{0, NCOA - EFC\}\}$.

Analogously, define the maximum subsidized loan balance that a student can accumulate by college year j as $\widetilde{l}_j^{sub}(NCOA, EFC) \equiv \min\{\bar{l}^{sub}, \sum_{i=1}^{j} \min\{\bar{b}_i^{sub}, (NCOA - EFC)^+\}\}$. Since their advent in 1993, unsubsidized loans—which accrue interest at the rate i—have allowed students regardless of need to finance the remaining net cost of attendance, although the FSLP also imposes an annual combined borrowing limit of $\bar{b}_j$ and an aggregate combined limit of $\bar{l}$. To capture this change in loan regime, we introduce an annual *unsubsidized* loan limit $\bar{b}_j^{unsub}$ for notational convenience which equals 0 before 1993 and $\bar{b}_j$ after 1993. The post-1993 unsubsidized limit is non-binding after taking into account the constraint on annual combined borrowing of $b_{sub} + b_{unsub} \leq \min\{\bar{b}_j, NCOA\}$. Analogously, we define $\bar{l}^{unsub}$ to be 0 before 1993 and $\bar{l}$ after 1993. Just as before, this constraint is non-binding after taking into account the cumulative combined borrowing limit of $l'_{sub} + \frac{l'_{unsub}}{1+i} \leq \bar{l}$.[4]

Under the maintained assumption that students first exhaust subsidized borrowing before taking out any unsubsidized loans, the total balance l acts as a sufficient statistic for the student debt portfolio (l_{sub}, l_{unsub}). Specifically, l can be decomposed as

$$(l_{sub}, l_{unsub}) = \begin{cases} (l, 0) & \text{if } l \leq \widetilde{l}_{j-1}^{sub}(NCOA, EFC) \\ (\widetilde{l}_{j-1}^{sub}(NCOA, EFC), l - \widetilde{l}_{j-1}^{sub}(NCOA, EFC)) & \text{otherwise.} \end{cases} \tag{4}$$

where the $j-1$ refers to the constraint faced last period. A corresponding decomposition exists for any new l' chosen in year j of college, where $(l'_{sub}, l'_{unsub}) \equiv (l_{sub} + b_{sub}, (1+i)(l_{unsub} + b_{unsub}))$. To summarize, the annual and aggregate *subsidized* borrowing limits are encoded into the definition of $\widetilde{l}_j^{sub}(NCOA, EFC)$ and the decomposition of total debt. What remain are the annual and aggregate combined borrowing limits, $b_{sub} + b_{unsub} \leq \min\{\bar{b}_j, NCOA\}$ and $l'_{sub} + \frac{l'_{unsub}}{1+i} \leq \bar{l}$, respectively.

Besides loans, students can finance their spending on consumption and college education using endowment income e_Y and parental transfers $\xi EFC(s)$, which they receive in proportion $\xi \in [0,1]$ to their expected family contribution. Thus, a type-s college student has budget constraint

$$c + NCOA(T, s) \leq e_Y + \xi EFC(s) + b_{sub} + b_{unsub}. \tag{5}$$

2.2.2 Workers and Retirees

Workers (retirees) receive labor income (retirement benefits) $\mu_j e^z$, where μ_j is a deterministic age-dependent profile and z follows a random walk with innovations $\varepsilon \sim \mathcal{N}(0, \mathbf{1}_{[j<J_{retire}]}\sigma_\varepsilon^2)$—implying that workers, but not retirees, face income risk. Workers draw their initial education-dependent z_0 upon entering the labor market, whether at $j=1$ as a high school graduate or upon leaving college. The government then taxes this income at rate τ. All households (including college students) value consumption according to the period utility function $u(c)$ and discount the future at rate β.

Workers and retirees can save using risk-free bonds a with interest rate r, but student loans represent the only source of borrowing in the model. Borrowers with outstanding loan balance l and

[4] Equivalently, current balances plus new borrowing must not exceed $\bar{l}$, i.e., $l_{sub} + b_{sub} + l_{unsub} + b_{unsub} \leq \bar{l}$.

remaining duration $t \leq t_{max}$ face repayment obligations of $p(l,t) = l\frac{i(1+i)^{t-1}}{(1+i)^t-1}$, where $p(l,t)$ is the standard amortization amount. The evolution of t and l follows $t' = t-1$ and $l' = (l-p(l,t))(1+i)$, respectively. Borrowers also have the option to default, but unlike with other forms of consumer debt, current law prohibits the discharge of student debt through bankruptcy except in extreme cases. Instead, default simply places borrowers in a state of delinquency where they skip making payments but also suffer proportional wage garnishment χ for earnings above a minimum threshold $\underline{e}$ and collections penalties which add a fraction ι to their outstanding balance. Borrowers rehabilitate their loan and leave delinquency by making a regular payment, which ends garnishment and resets the loan duration to t_{max}.

2.3 Household Decision Problems

This section discusses the household decision problems, moving backward from workers/retirees to college students and, lastly, to youth.

2.3.1 Consumption, Savings, and Student Loan Repayment

At the beginning of each period, workers in good standing, $f = 0$, choose whether to make a student loan payment or default, in which case they suffer the balance penalty ι. Their value function is

$$V_j(a,l,t,z,f=0) = \max\{V_j^R(a,l,t,z), V_j^D(a,l(1+\iota),z)\}. \tag{6}$$

where V^R is the value of repayment and V^D is the value of default.

Workers with delinquent debt, $f = 1$, make an analogous decision to either stay delinquent or rehabilitate the loan by making a payment, which resets the clock to t_{max}. Their value function is

$$V_j(a,l,z,f=1) = \max\{V_j^R(a,l,t_{\max},z), V_j^D(a,l,z)\} \tag{7}$$

Workers who make a payment choose how much to consume and save and have value function

$$\begin{gathered} V_j^R(a,l,t,z) = \max_{a' \geq 0} u(c) + \beta \mathbb{E}_{\varepsilon'} V_{j+1}(a',l',t',z+\varepsilon',f'=0) \\ \text{such that } c + a'/(1+r) + p(l,t) \leq (1-\tau)\mu_j e^z + a \\ l' = (l-p(l,t))(1+i) \\ t' = \max\{t-1,0\} \end{gathered} \tag{8}$$

The value function associated with choosing to remain in default is

$$
\begin{aligned}
V_j^D(a,l,z) &= \max_{a'\geq 0} u(c) + \beta \mathbb{E}_{\varepsilon'} V_{j+1}(a', l', z+\varepsilon', f'=1) \\
\text{such that } c + a'/(1+r) &\leq (1-\tau)\mu_j e^z - \chi \max\{0, (1-\tau)\mu_j e^z - \underline{e}\} + a \\
l' &= \max\{0, (l - \chi \max\{0, (1-\tau)\mu_j e^z - \underline{e}\}(1+i)\}
\end{aligned}
\tag{9}
$$

where $\chi \max\{0, (1-\tau)\mu_j e^z - \underline{e}\}$ is garnished earnings, which are applied to the loan balance.

2.3.2 Financing College

Students who matched in college submarket $m = (k, T, s)$ with current student debt l choose their consumption and how much additional student debt to borrow. Their value function is

$$
\begin{aligned}
Y_j(m,l) = \max_{c, b_{sub}, b_{unsub} \geq 0} u(c) + v_{k(m)}(I_{k(m)}) + \beta \Bigg\{ & \overbrace{[1-\delta(m)]\mathbf{1}_{[j<J_Y]} Y_{j+1}\left(m, l'\right)}^{\text{stay in college}} \\
& + \overbrace{[1-\delta(m)]\mathbf{1}_{[j=J_Y]} \mathbb{E}_{\varepsilon'} V_{j+1}\left(a'=0, l', t_{max}, z' = \lambda(m) + \sqrt{j+1}\varepsilon', f'=0\right)}^{\text{graduate}} \\
& + \overbrace{\delta(m) \mathbb{E}_{\varepsilon'} V_{j+1}\left(a'=0, l', t_{max}, z' = \lambda(m)\frac{j}{J_Y+1} + \sqrt{j+1}\varepsilon', f'=0\right)}^{\text{drop out}} \Bigg\}
\end{aligned}
\tag{10}
$$

$$
\begin{aligned}
&\text{such that } c + NCOA(T(m), s(m)) \leq e_Y + \xi EFC(s(m)) + b_{sub} + b_{unsub} \\
&l' = \overbrace{l_{sub} + b_{sub}}^{l'_{sub}} + \overbrace{(1+i)(l_{unsub} + b_{unsub})}^{l'_{unsub}} \\
&b_{sub} \leq \min\{\bar{b}_j^{sub}, (NCOA - EFC)^+\}, \quad b_{unsub} \leq \bar{b}_j^{unsub}, \quad l'_{sub} \leq \bar{l}^{sub}, \quad \frac{l'_{unsub}}{1+i} \leq \bar{l}^{unsub} \\
&b_{sub} + b_{unsub} \leq \min\{\bar{b}_j, NCOA\}, \quad l'_{sub} + \frac{l'_{unsub}}{1+i} \leq \bar{l}
\end{aligned}
$$

where $\delta(m)$ and $\lambda(m)$ denote dropout risk and the post-college earnings premium, respectively, and the decomposition of l into (l_{sub}, l_{unsub}) based on the optimality of exhausting subsidized borrowing before taking out any unsubsidized loans comes from equation 4.

2.3.3 College Choice

Conditional on applying to type-k colleges, youth choose search effort e and net tuition T—thus entering submarket $m = (k, T, s)$—to solve

$$\widehat{Y}(k; s) \equiv \max_{e \geq 1, T \geq 0} Y(\underbrace{k, T, s}_{m}) - \psi(e-1)^2 \tag{11}$$

Let $\widehat{Y}(0; s)$ denote the value function for youth who skip college, $k = 0$, which satisfies

$$\widehat{Y}(0; s) = \mathbb{E}_{\varepsilon'} V_1(a = 0, l = 0, t = 0, z = \varepsilon, f = 0) \tag{12}$$

and includes s merely for notational symmetry with equation 11.

After receiving their vector of taste shocks $\{\epsilon_k\}$—which are distributed according to a Type 1 extreme value distribution—youth choose whether and where to attend college by solving

$$\max_{k \in \{0\} \cup K} \widehat{Y}(k; s) + \frac{1}{\sigma_\epsilon} \epsilon_k. \tag{13}$$

The choice probabilities—and therefore attendance rates—for type-s students are then

$$A(k; s) = \frac{\exp(\sigma_\epsilon \widehat{Y}(k; s))}{\sum_{\widetilde{k}=0}^{K} \exp(\sigma_\epsilon \widehat{Y}(\widetilde{k}; s))}. \tag{14}$$

2.4 Government

The government operates the student loan and social security programs. Outlays include new loans and retirement benefits, while revenues come from the earnings tax, loan payments, and wage garnishment on delinquent borrowers. Because we are not evaluating welfare in the model, we do not impose budget balance. Instead, the earnings tax rate τ is estimated from the data, as discussed in section 3.2.4.

2.5 Equilibrium

An equilibrium consists of market tightnesses $\theta(m)$, vacancy postings $v(m)$, value functions $\widehat{Y}(k; s)$, $Y_j(m, l)$, and $V_j(a, l, t, z, f)$, application rates $A(k; s)$, and tax rate τ such that colleges optimally choose $v(m)$, households maximize utility, market tightnesses are consistent with the behavior of colleges and youth applicants, and the government sets τ to balance its budget.

3 Parametrization of the Model

This section describes the data sources and methodology used to parametrize the model. Some of the parameters are chosen based on external estimates, others are estimated directly from the data, and the remainder are jointly determined to minimize the distance between a set of moments in the model and data. The model is normalized such that one model unit for any financial variable is equivalent to \$1,000 in 2010 dollars, and the risk-free rate is set to 2%, i.e. $r = 0.02$.

3.1 Colleges

This section describes the parametrization of the college's objective function, quality $q_k(X_k, I_k, N_k)$; the custodial cost function $C_k(N_k)$ for non-quality-enhancing expenditures; the non-tuition revenue functions for government appropriations, $G_k(N_k)$, and endowment funding, $E_k(N_k)$; the matching function $M(u, v)$; dropout probabilities $\delta_k(s)$; earnings premia $\lambda_k(s)$; and the remaining college parameters.

3.1.1 College Data

We use National Center for Education Statistics (NCES) Integrated Postsecondary Education Data System (IPEDS) institution-level data curated and harmonized by the Delta Cost Project (DCP) to construct a mapping between colleges in the model and data. We focus on the period 1987–2010 given data limitations and to defer to future work modeling the complex ways in which changes to the economic and policy environment that took place in the aftermath of the Great Recession impacted the higher education market.[5]

Categorizing Colleges We classify schools into $K = 7$ types based on three dimensions: whether they are under public (G) or private (P) control, whether they are teaching-focused (T) or research-intensive (R) according to their Carnegie Classification, and whether they are selective (S) or non-selective (N) based on mean SAT scores of the student body. Sections C.1 and C.2 in the appendix provide additional details on the sample selection and classification procedures. The reason there are seven rather than $2^3 = 8$ college types is that none of the public teaching-focused colleges meet the criteria for being selective, implying that there are no GTS (public, teaching, selective) colleges.

[5] For example, the unemployment rate remained significantly elevated for several years, which had an impact both on the immediate opportunity cost of attending college and students' internal assessment of the likely rate of return. The prolonged collapse in house prices compounded the financial distress from unemployment by making it more difficult for people to tap into home equity to pay for college. In the aftermath of the crisis, the Federal government instituted a sequence of large increases in the maximum Pell grant amount. In addition, the Federal government implemented significant structural changes to income-based repayment. At the state level, the deterioration in state tax revenues eventually led to cuts in higher education appropriations per full-time equivalent (FTE) student. Data from the State Higher Education Executive Officers (SHEO) Association reveals that 2010 was the first year when appropriations fell below 2005 levels, as seen in Figure 2.1 found here: `https://shef.sheeo.org/data-downloads/`.

The number of schools within each type $g(k)$ is given by the number of schools in the data.[6] The number of PTN, GTN, and PRN colleges ranges between 120 and 640, while the number of selective schools ranges from 20 to 42.

College Balance Sheets Colleges are complex, multifaceted organizations, which manifests itself in their balance sheets. In line with the model, we distill college budgets into net tuition revenue T, government appropriations G, endowment funding E, custodial costs pC, recruiting costs $\kappa V \equiv \kappa \int v dm$, and quality-enhancing investment pI. Thus, the model's budget constraint can be written as

$$pC + pI + \kappa V = T + G + E. \tag{15}$$

Section C.3 in the appendix explains in detail the mapping between college revenue and expenditure categories in the model and the data, while section C.4 explains the mapping between full-time-equivalent (FTE) enrollments in the model and data. These mappings are relevant for the purposes of estimating non-tuition revenue and custodial cost functions in the model as well as ultimately for evaluating the predictions of the model for the variables of interest, especially net tuition. Summary statistics by school type and year—including the budgetary items discussed above—are given in table 20 in the appendix, but most of the values can be inferred from figures 4 and 6 and table 9.

3.1.2 College Quality

We assume that q is a constant elasticity of substitution (CES) quality function

$$q_k(X_k, I_k, N_k) = \left(\alpha_{X,k} X_k^{\frac{\epsilon-1}{\epsilon}} + \alpha_{I,k} I_k^{\frac{\epsilon-1}{\epsilon}} + \alpha_{N,k} N_k^{\frac{\epsilon-1}{\epsilon}}\right)^{\frac{\epsilon}{\epsilon-1}}. \tag{16}$$

Consistent with equation 16, we estimate type-specific values of α_X and α_N, while normalizing $\alpha_I = 1$ for each college. In addition, the elasticity parameter ϵ is the same across all colleges. Thus, the college-side of the model gives rise to $2 \times 7 + 1 = 15$ (recall $K = 7$) parameters to be identified. All of these parameters (plus some others discussed momentarily) are determined jointly using the model, which section 3.4 covers in detail.

3.1.3 Custodial Costs

We measure custodial costs in the data as the residual in equation 15 using the mapping between between model and data described in sections 3.1.1 and C.3. Thus, we require non-missing observations for each college's tuition, endowment revenue, etc. to calculate the residual. We assume that

[6] There is virtually no school entry or exit in the data over this time period. Thus, we focus on colleges in the sample for all years 1987–2010 and assume that $g(k)$ is time-invariant.

custodial costs take on the following form:

$$pC_k(N_{k,t};t) = \exp(\alpha_k + \beta_k t + \delta_k N_{k,t} + \zeta_k N_{k,t} t), \tag{17}$$

which has its "efficient scale" at $1/(\delta_k + \zeta_k t)$ at each t, i.e. the cost function can shift over time.[7]

Measuring custodial costs as residuals from the college balance sheet as described above, we determine the cost function coefficients by estimating separately for each k the following:

$$\log pC_{i,t} = \alpha_k + \beta_k t + \sum_{\tilde{i}} \gamma_{\tilde{i}} \mathbf{1}[\tilde{i} = i] + \delta_k N_{i,t} + \zeta_k N_{i,t} t + \epsilon_{i,t}, \tag{18}$$

where $\gamma_{\tilde{i}}$ are fixed effects, and $N_{i,t}$ is FTE enrollment at college i in year t in the college-level data.

Table 1 presents the estimates, and figure 1 plots the estimated curves for 1987 along with dots representing actual mean enrollment for each school type. As one can see, actual enrollments are all on the downward sloping portion of the average total cost (ATC) curve, implying that marginal cost (MC) is below ATC. Moreover, it is evident that the efficient scale has been growing over time for all schools except PTS. The implied average fixed cost in 1987 ranges from \$1,200 to \$5,300 in 2010 dollars, and the marginal cost is on the order of one to three thousand dollars.

	Total custodial costs in thousands of 2010 dollars, logged						
	GTN	GRN	PTN	PRN	GRS	PTS	PRS
FTEs	264.8	100.3	796.2	430.7	30.22	845.8	70.96
	(25.40)	(13.01)	(38.45)	(17.27)	(2.55)	(5.52)	(2.49)
FTEs×Years	-0.776	-0.844	-7.861	-2.123	-0.152	11.85	-0.0738
	(-5.82)	(-5.01)	(-10.57)	(-2.52)	(-1.00)	(4.40)	(-0.14)
Years	0.0158	0.0176	0.0213	0.0240	0.0140	0.0175	0.0293
	(45.24)	(21.90)	(59.24)	(16.67)	(10.61)	(15.03)	(17.82)
Constant	-6.301	-4.981	-6.965	-5.958	-3.896	-6.171	-4.277
	(-411.49)	(-159.61)	(-860.06)	(-169.95)	(-47.29)	(-74.84)	(-56.50)
Observations	7080	3120	16248	1224	480	864	1032
FTE mean	0.0015	0.0041	0.0004	0.0014	0.0070	0.0005	0.0026
FTE s.d.	0.0022	0.0024	0.0004	0.0009	0.0057	0.0004	0.0015
Avg. FC	1.24	1.68	2.34	1.84	2.92	4.21	5.27
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: "FTEs" are FTEs mapped to model units; "Years" are years since 1987; "Avg. FC" is the implied fixed cost in 1987 divided by the mean FTE; t-stats in parentheses.

Table 1: Custodial Cost Function Estimates by School Type

[7] The efficient scale solves $\frac{\partial pC_k(N_k;t)}{\partial N_k} = pC_k(N_k;t)/N_k$, which gives $(\delta_k + \zeta_k t)pC_k = pC_k/N_k$ or $N_k = (\delta_k + \zeta_k t)^{-1}$.

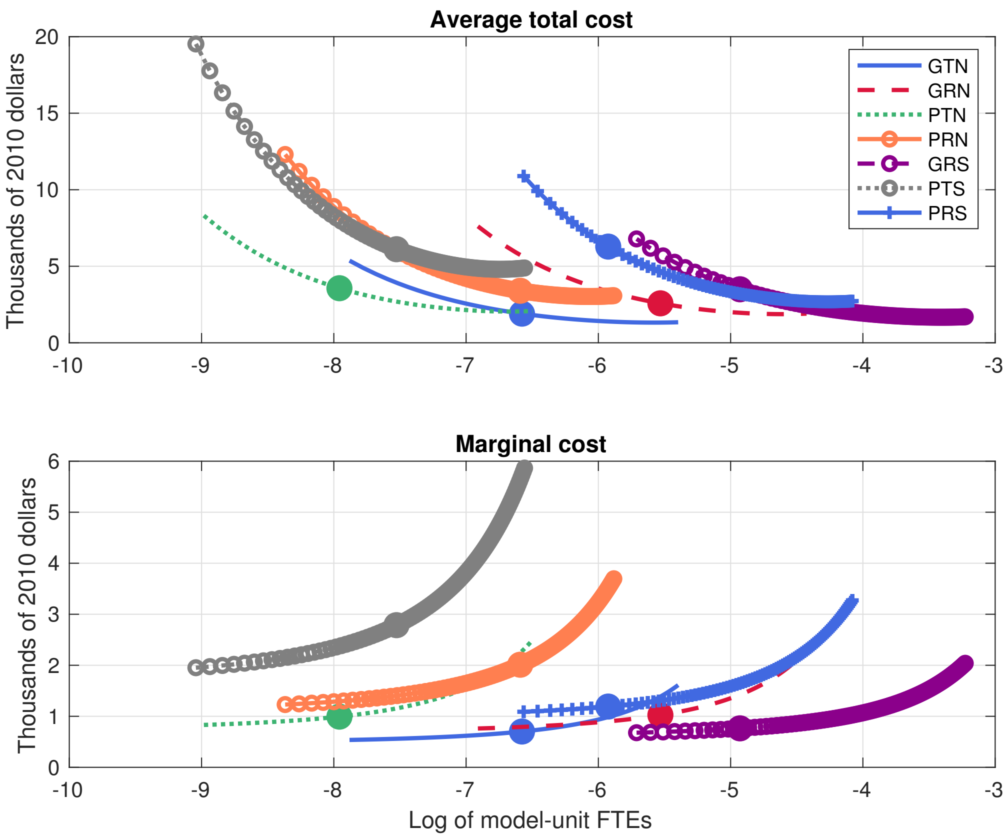


Figure 1: Estimated Cost Function (1987 Values) with Data Enrollments

3.1.4 Non-Tuition Revenue

We assume that the non-tuition revenue functions for government appropriations and endowment funding are of the form

$$G_k(N_k;t) = \frac{a_{G,t}N_{k,t}^{1-\gamma}}{1-\gamma} - a_{G,t}b_G(N_{k,t}^*)^{-\gamma}N_{k,t} \tag{19}$$

$$E_k(N_k;t) = \frac{a_{E,t}N_{k,t}^{1-\gamma}}{1-\gamma} - a_{E,t}b_E(N_{k,t}^*)^{-\gamma}N_{k,t} \tag{20}$$

where $N_{k,t}^*$ is year-t observed enrollment. The rationale behind this choice of functional form is that it ensures that the following properties hold: (1) $G_k(0;t) = E_k(0;t) = 0$, (2) the Inada condition holds, i.e. $\lim_{N_k \downarrow 0} G_k'(N_k;t) = \lim_{N_k \downarrow 0} E_k'(N_k;t) = \infty$, (3) non-tuition revenue is consistent with the data, i.e. $G_k(N_{k,t}^*;t) = G_{k,t}^*$ and $E_k(N_{k,t}^*;t) = E_{k,t}^*$, and (4) the elasticity of non-tuition revenue with respect to enrollments equals that observed from the data, i.e. $G_k'(N_{k,t}^*;t)N_{k,t}^*/G_{k,t}^* = \epsilon_G^*$ and $E_k'(N_{k,t}^*;t)N_{k,t}^*/E_{k,t}^* = \epsilon_E^*$. Given some $\gamma \in (0,1)$, b_G is identified from $\epsilon_G^* = \frac{1-b_G}{1/(1-\gamma)-b_G}$, and then $a_{G,t}$ is identified from $a_{G,t}(1/(1-\gamma) - b_G){N_{k,t}^*}^{1-\gamma} = G_{k,t}^*$. The same approach is used to identify

b_E and $a_{E,t}$. It turns out, as section C.5 explains in greater detail, that any value of $\gamma \in (0, 1)$ can be supported but that setting $\gamma = 0.75$ works well for computational stability.

We measure the elasticities with respect to enrollment of both types of non-tuition revenue—in addition to that for custodial costs, which will prove useful in the joint parametrization procedure of section 3.4—by estimating the following equation:

$$\Delta_5 \log Y_{it} = \beta_0 + \beta_g \mathbf{1}_{[i,public]} \Delta_5 \log N_{it} + \beta_p \mathbf{1}_{[i,private]} \Delta_5 \log N_{it} + \epsilon_{i,t}, \tag{21}$$

where Δ_5 denotes a 5-year difference operator, $Y_{i,t}$ is one of {private non-tuition revenue per FTE, public non-tuition revenue per FTE, custodial costs per FTE}, $\mathbf{1}_{i,public}$ and $\mathbf{1}_{i,private}$ are indicators for whether the college is public or private, respectively, and $N_{i,t}$ is FTEs in model units.[8] We take a 5 year difference to allow any regular adjustments in state or private support to have some effect. Table 2 presents the estimates. Note that while these estimates have the dependent variable in per person terms, one can get the value in levels via $\beta_g + 1$ or $\beta_p + 1$. For example, an elasticity of one is consistent with the total revenue or cost being fixed, a value below negative one indicates that revenues or costs fall in levels, and an elasticity above negative one indicates an increase in levels.

	Private non-tuition rev.	Public non-tuition rev.	Custodial costs
Public×FTEs	-0.881	-0.899	-0.767
	(-5.99)	(-16.69)	(-32.03)
Private×FTEs	-1.407	-0.631	-0.646
	(-30.12)	(-19.71)	(-49.36)
Constant	0.0402	0.0889	0.0216
	(1.81)	(6.36)	(3.56)
Observations	14110	21771	23214
Year effects	Yes	Yes	Yes
School fixed effects	Yes	Yes	Yes

Note: FTEs are mapped to model units; costs per FTE, revenues per FTE, and FTEs are in 5-year log differences; t-stats in parentheses.

Table 2: Elasticities with Respect to Enrollment of Non-tuition Revenues and Custodial Costs.

3.1.5 Dropout Probabilities and Earnings Premia

We let $J_Y = 5$ to reflect the fact that the median time to degree is 52 months.[9] This value implies a sheepskin effect—given by $1 - J_Y/(J_Y + 1)$ in the model—of 17%, which is in the range of

[8] We include local appropriations in public non-tuition revenue and remove it from private non-tuition revenue.

[9] The distribution of completion times can be found here: https://nces.ed.gov/fastfacts/display.asp?id=569.

estimates provided by Jaeger and Page (1996). Graduation rates and earnings premia depend both on school type and individual student ability. To best match the data while maintaining tractability of estimation, we assume that the dependence of $\delta_k(s)$ and $\lambda_k(s)$ on student characteristics $s = (x, y)$ is through ability alone and that the functions take the form

$$(1 - \delta_k(x))^{J_Y} = \min\left\{\left(1 - \overline{\delta}_k\right)^{J_Y}\left(\mu_\delta + (1 - \mu_\delta)\frac{x}{X_k}\right), 1\right\} \tag{22}$$

$$\lambda_k(x) = \overline{\lambda}_k\left(\mu_\lambda + (1 - \mu_\lambda)\frac{x}{X_k}\right) \tag{23}$$

where the term $(1 - \delta_k(x))^{J_Y}$ is the probability of *not* dropping out $J_Y = 5$ years in a row—in other words, the probability of successfully graduating. The parameters μ_δ and μ_γ represent the relative contribution of college type to the likelihood of graduation and to earnings premia, respectively.

We estimate μ_δ and μ_γ using NLSY97 individual-level data. For μ_δ, we re-write equation 22 as

$$grad_i/\overline{grad}_{k(i)} = x_i/X_{k(i)} + \mu_\delta\left(1 - x_i/X_{k(i)}\right), \tag{24}$$

where $grad_i$ is a dummy for whether individual i graduated college, and x_i is a uniformly distributed measure of individual ability from the AFQT that takes on values between 0 and 1.[10] We do not observe the identity of the college that individual i attended and thus cannot assign a college type k from the P/G, T/R, and S/N classifications. As a proxy, we group colleges into quintiles ordered by sticker price tuition from the NLSY97. Thus, $\overline{grad}_{k(i)}$ is the average graduation rate for the quintile $k(i)$ of the college that individual i attended. Similarly, $X_{k(i)}$ is average student ability in the school quintile. We then estimate μ_δ using ordinary least squares and follow an analogous procedure to estimate μ_λ corresponding to the earnings premium, where λ_i is an individual's real equivalized income from ages 27–33 divided by the average income (using the same metric) of those who never enrolled.[11] Based on the results reported in table 3, we take the college's relative contribution in both cases to be $\mu_\lambda = \mu_\delta = 0.66$.

3.1.6 Matching Function and Vacancy Posting Costs

We assume a matching function of the form $M(u, v) = \min\{u, u^{1-\gamma}v^\gamma\}$, which implies the following relationship between the probability ρ that a vacancy gets filled and the acceptance probability η for an aspiring college student:

$$\eta(\rho^{-1}(y)) = \min\{1, y^{-\gamma/(1-\gamma)}\}. \tag{25}$$

[10] In the college-level data, the measure of ability is SAT scores, which we assume are normally distributed. Taking the inverse of the cumulative density function for SAT scores gives a uniformly distributed relative ability measure.

[11] The NLSY results are unweighted, but the coefficients in the first row of table 3 are little changed at just over 0.28 and 0.29 going from left to right if weighted.

	Relative premium $\lambda^k(x)/\bar{\lambda}^k$	Relative graduation $(1-\delta^k(x))^5/(1-\bar{\delta}^k)^5$
Relative ability x/X^k	0.325	0.332
	(8.02)	(8.49)
Constant	0.682	0.664
	(15.83)	(15.95)
Observations	2113	2267
R^2	0.030	0.031

Note: t-statistics in parentheses; sample is youths who enrolled.

Table 3: School vs. Individual Contributions to Earnings Premia and Dropout Probabilities

Rearranging equation 2 implies that

$$\rho(\theta(m)) = \frac{\kappa_k}{\omega(m)[T(m) - EMC_k(s(m))]}. \tag{26}$$

Assuming that ρ is invertible, the implied optimal market tightness $\theta^*(m)$ solves (26) and results in an equilibrium acceptance probability of

$$\eta(\theta^*(m)) = \eta\left(\rho^{-1}\left(\frac{\kappa_k}{\omega(m)[T(m) - EMC_k(s(m))]}\right)\right). \tag{27}$$

Using equation 25, we then have

$$\eta(\theta^*(m)) = \min\left\{1, \left(\frac{\omega(m)[T(m) - EMC_k(s(m))]}{\kappa_k}\right)^{\gamma/(1-\gamma)}\right\} \tag{28}$$

Note that this acceptance probability is strictly increasing in net tuition until $T = \frac{\kappa}{\omega} + EMC$ and constant at 1 beyond that. Consequently, it is never optimal for students to apply to a submarket with tuition above $\frac{\kappa}{\omega} + EMC$. Therefore, in equilibrium, any active submarket must satisfy

$$T(m) = \frac{\kappa_k}{\omega}\eta(\theta^*(m))^{(1-\gamma)/\gamma} + EMC_k(s(m)). \tag{29}$$

This expression will prove useful for parametrizing γ and values of κ_k for each college type.

Vacancy Posting Costs In the model, vacancy posting costs κ_k determines the degree of price dispersion conditional on a student's ability. In particular, if $\kappa_k = 0$, net tuition exactly equals $EFC_k(s_Y)$, which is a function of student ability but not parental income. Thus, κ_k controls the degree to which the model can generate parental income gradients in net tuition consistent with those observed in the data from colleges' practice of giving need-based institutional aid.

College Scorecard data—which provides information for five income bins on net tuition and fees along with enrollment—allows us to measure the parental income gradient for each of the seven school types. Denoting T_{ij} as the average net tuition in income bin j for college i and T_i^* as overall average net tuition for college i, we define the average net tuition deviation as $\hat{T}_{ij} = (T_{ij} - T_i^*)/T_i^*$. Analogously, we define the net parental income deviation as $\hat{Y}_{ij} = (Y_{ij} - Y_i^*)/Y_i^*$.[12]

Our parental income gradient measure is the school-type-specific coefficient β_k in the regression

$$\hat{T}_{ij} = \alpha_{k(i)} + \beta_{k(i)}\hat{Y}_{ij} + \epsilon_{ij} \tag{30}$$

where i is college, j is income bin, and $k(i)$ is the college type to which i belongs. The underlying data are illustrated in figure 2, and table 4 gives the estimates. All the school types display a strongly significant—both in an economic and statistical sense—parental income gradient measure.

	GTN	GRN	PTN	PRN	GRS	PTS	PRS
$\hat{Y}$	0.226	0.277	0.183	0.204	0.596	0.826	0.798
	(33.54)	(35.71)	(58.91)	(19.82)	(28.81)	(29.36)	(26.41)
Constant	-0.00269	-0.00649	-0.0149	-0.0170	0.00583	-0.0116	-0.00324
	(-0.38)	(-1.02)	(-6.29)	(-2.54)	(0.45)	(-0.75)	(-0.19)
Observations	1254	610	2518	220	100	180	210

Note: dependent variable is $\hat{T}$; t-stats are in parentheses.

Table 4: Parental Income Gradients by School Type

To use β_k to infer κ_k, recall from equation 29 that the maximum net tuition a type-s student would pay is $\kappa_k/\omega_k(s) + EMC_k(s)$, and the lowest net tuition is $EMC_k(s)$.[13] From the optimization problem in equation 11, it is evident that students with high-income parents will opt for submarkets with higher T and higher η to economize on search effort, whereas students with less financial means will take the opposite approach, paying less but searching more. To identify κ_k, we assume there is a parental income cutoff above which students pay the full sticker price tuition. Specifically, let that cutoff be $y \geq Y^* + \overline{n}\sigma_{Y,k}$ for some $\overline{n}$, where $\sigma_{Y,k}$ is the standard deviation of parental income. Similarly, we assume that students with parental income $y \leq Y^* + \underline{n}\sigma_{Y,k}$ pay the lowest possible net tuition. Substituting these two endpoints into equation 30, differencing, and rearranging yields

$$\kappa_k = T_k^* \omega_k \beta_k \frac{(\overline{n} + \underline{n})\sigma_{Y,k}}{Y_k^*} \tag{31}$$

[12] For the top income bin, the bin is \$110,000+, within which we assumed average parental income was \$140,000. The overall averages are computed using the enrollment weights. Unfortunately, for public schools, only in-state students are included in the sample. Thus, the mean net tuition from the College Scorecard data does not perfectly align with the IPEDS net tuition measure.

[13] The notation $\omega_k(s)$ is shorthand for $\omega(m) = \sum_{j=1}^{J_Y}(1-\delta(m))^{j-1}$ where $\delta(m) = \delta_k(s)$ because $m = (k, T, s)$.

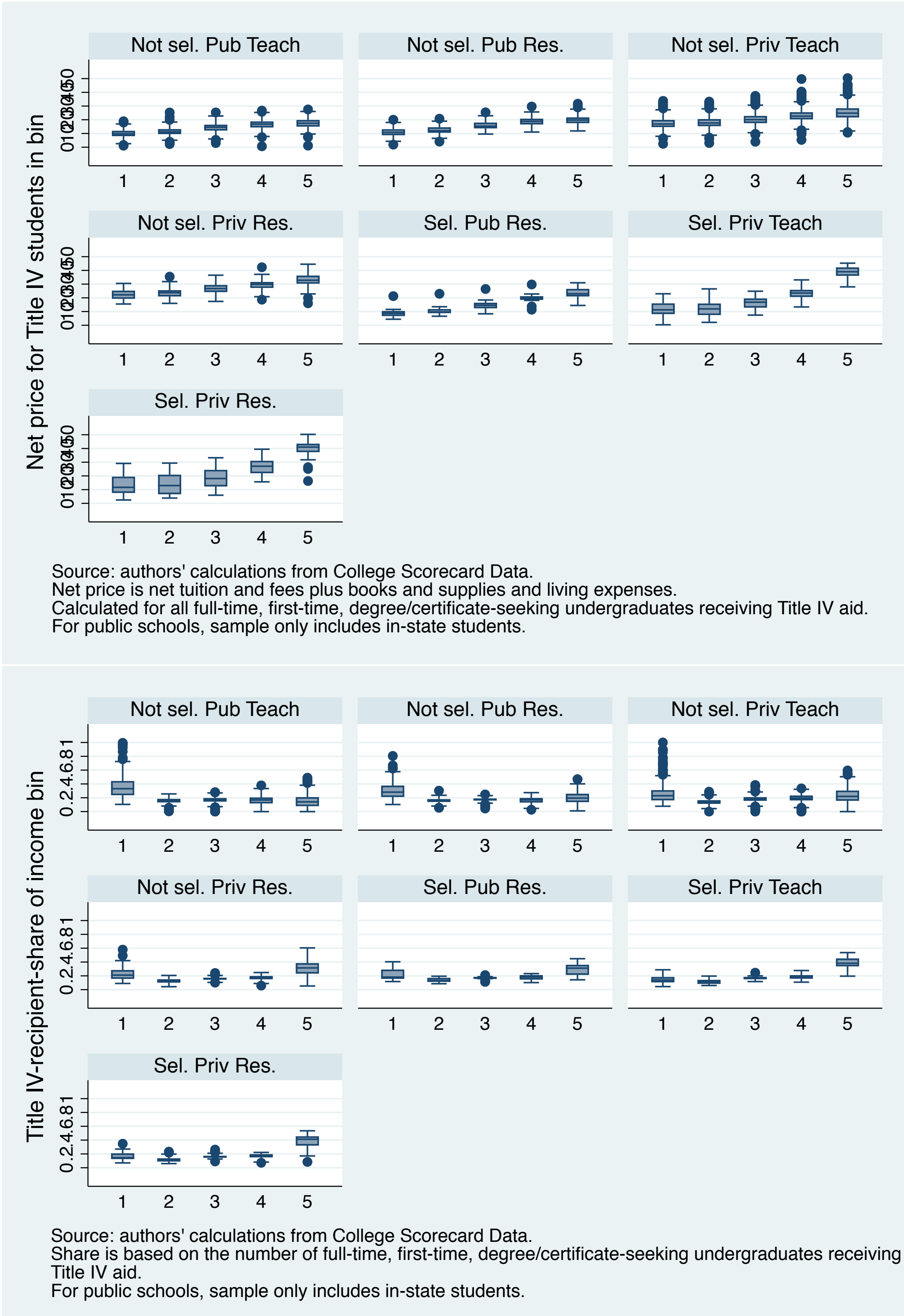


Figure 2: Parental Income Gradients and Enrollment by Parental Income Bins

where the subscripts have all been replaced with k to reflect the fact that posting costs in the model are specific to college type.

We have β_k from the previous estimation along with data on dropout rates (which enter into ω_k), average net tuition T_k^*, average parental income Y_k^*, and the standard deviation of parental income $\sigma_{Y,k}$. All that remains is choosing appropriate values for $\bar{n}$ and $\underline{n}$. We choose $\overline{n}$ and $\underline{n}$ such that 40% of students are on either side of each threshold. Section C.6 in the appendix provides a more detailed justification for these thresholds.

Matching Function Curvature Treating equation 29 as an empirical identity, γ controls the curvature of the relationship between net tuition T_{ik} and acceptance probabilities η_{ik} for students i with common characteristics $s(i)$ at college type k, as visualized in figure 3. Taking the expectation over enrollments and approximating by treating ω_k as a constant gives

$$T_k^* = \frac{\kappa_k}{\omega_k^*}\mathbb{E}[\eta]^{(1-\gamma)/\gamma} + \mathbb{E}[EMC_k] \tag{32}$$

If we assume sticker price tuition $T_k^{sticker}$ corresponds to the maximal markup (which occurs at $\eta = 1$), then $T^{sticker} = \kappa_k/\omega_k + \mathbb{E}[EMC_k]$. We can then difference and solve for type-specific γ_k via

$$\gamma_k = \left(1 + \log(1 - \frac{\omega_k^*}{\kappa_k}(T_k^{sticker} - T_k^*))/\log(\mathbb{E}(\eta))\right)^{-1}.$$

When we run this procedure to get a γ for each school, 4 of the 7 school types have estimates between 0.53 and 0.63, with one estimate not sensible and the other two being 0.18 and 0.36. Based on these estimates, we let $\gamma = 1/2$ for each college in the benchmark, which creates a linear relationship between acceptance rates and net tuition across submarkets.

3.1.7 Non-Tuition College Expenses

Recall that the total cost of college attendance includes non-tuition expenses, i.e. $COA(T_k) = T_k + \phi$. Because these non-tuition expenses grow over time in the data but are exogenous in the model, we follow Gordon and Hedlund (2019) to calibrate a sequence ϕ_t.

3.2 Households

This section describes the parametrization for households—namely, preferences, college-specific taste shocks and additive attendance utilities, college search disutility, parental transfers, earnings, and the distribution of student characteristics.

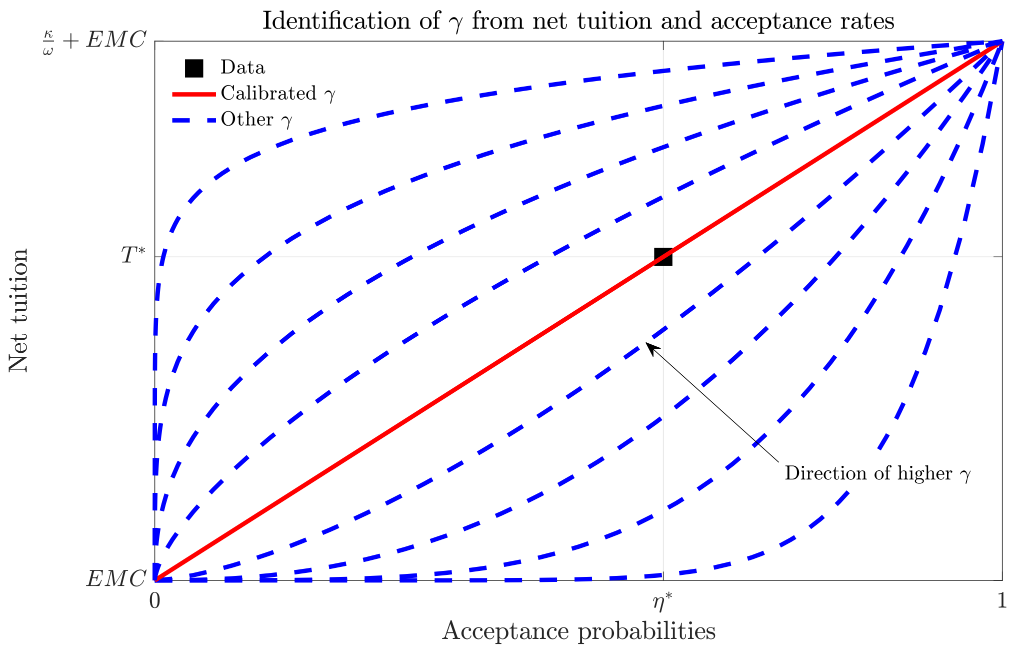


Figure 3: Identification Strategy for the Matching Function Elasticity

3.2.1 Preferences

We assume a constant relative risk aversion utility function with standard values of $\sigma = 2$ for risk aversion and $\beta = 0.96$ for the discount factor. The additive utility of college attendance is given by

$$v_k(I_k) = a_{0,public}\mathbf{1}_{[k,public]} + a_{0,private}\mathbf{1}_{[k,private]} + a_1 I_k + u_k. \tag{33}$$

This specification implies that attendance utility is increasing in college investment (assuming $a_1 > 0$) and depends on whether the college is public or private. The determination of the coefficients along with the residual terms u_k and the search disutility parameter ψ occurs as part of the joint parametrization in section 3.4. Lastly, for the college-specific taste shocks $\{\epsilon_k\}$, we set the standard deviation to be a small value of $\sigma_\epsilon = 0.02$ just to ensure that the college choice probabilities in equation 14 are nondegenerate, i.e. so that there is continuity in the decision of which (if any) college to attend.

3.2.2 The Distribution of Student Characteristics

We parametrize the joint distribution $\Gamma(x, y)$ of ability x and parental income y that comprise student characteristics $s = (x, y)$ following Gordon and Hedlund (2019). Specifically, we estimate a Tobit model with parental income as the dependent variable where parental income is censored below at 0 and above at 226.55 (in thousands of 2010 dollars). Table 5 reports the coefficients.

	Hh. income	
Ability	60.36	(23.19)
Constant	40.11	(26.44)
σ^2	2302.1	(43.97)
Observations	4102	
Note: t-statistics in parentheses.		

Table 5: Tobit Regression of Parental Income on Ability

3.2.3 Parental Transfers in College

We use NLSY97 data to calibrate the fraction ξ of parental transfers that appear directly in the student budget constraint, i.e. $\xi EFC(s)$. The first step involves computing parental income and applying the simplified formula from Epple et al. (2017) to get an EFC measure (the same as in the model). Next, we use data on family aid for college that is not expected to be paid back and find the annual level of support. Lastly, we regress this transfer measure on interaction terms between EFC and whether a student dropped out or graduated. We do this for two samples, the full sample and a subsample where EFC is less than net tuition, expecting transfers are not unconditional but contingent on having sufficiently large college costs. The results, which are given in Table 6, lead us to set $\xi = 0.7$, loosely the midpoint of 0.419 and 0.901.

	(1) Family grant	(2) Family grant
Dropped out × EFC (real)	0.0939***	0.419***
	(6.70)	(4.46)
Graduated × EFC (real)	0.185***	0.901***
	(27.31)	(30.16)
Observations	2063	771
R^2	0.277	0.547

t statistics in parentheses

(1) is the full sample; (2) includes only those with EFC < net tuition.

* $p < .1$, ** $p < .05$, *** $p < .01$

Table 6: Transfers as a Function of EFC

3.2.4 Earnings and Taxes

Using data from Heathcote, Perri, and Violante (2010), we estimate the tax τ on earnings along with the deterministic life cycle profile and stochastic innovations for earnings. Section D provides more details on the methodology. For the tax, we estimate a value of $\tau = 0.184$. After running the first-stage regression on observables for the deterministic profile, our second stage estimates the following stochastic process on the residuals with GMM:

$$\begin{aligned} \nu_{i,t} &= z_{i,t} + \varsigma_{i,t} \\ z_{i,t} &= z_{i,t-1} + \varepsilon_{i,t} \\ \varsigma_{i,t} &\sim N(0, \sigma_\varsigma^2) \\ \varepsilon_{i,t} &\sim N(0, \sigma_\varepsilon^2). \end{aligned} \tag{34}$$

We use the point estimate $\sigma_\varepsilon^2 = 0.00619$ for the random walk in the model.[14]

3.3 Federal Financial Aid

This section explains the parametrization of the Federal Student Loan Program and the Federal Pell Grant program. For student loans, we set the time-varying student loan rate i and loan limits $\bar{b}_j^{sub}$, $\bar{l}^{sub}$, $\bar{b}_j$, and $\bar{l}$ from the data following Gordon and Hedlund (2019). The student loan term is $t_{max} = 10$.

3.3.1 Expected Family Contribution

For our specification of the expected family contribution function $EFC(s)$, we use an approximation from Epple et al. (2017) to the true statutory formula. Specifically, we assume a mapping between raw and adjusted gross parental income of $\tilde{y}(y_p) = y(1 + 0.07 \cdot \mathbf{1}[y \geq \$50000])$ and an EFC formula given by $EFC(y_p) = \max\{\tilde{y}(y_p)/5.5 - \$5{,}000, \tilde{y}(y_p)/3.2 - \$16{,}000, 0\}$ in 2009 dollars.

3.3.2 Pell Grants

For our Pell grant estimation, we rely on detailed tabulations of EFC, COA, and awarded Pell grants published by the Department of Education.[15] Let the maximum Pell Grant mandated by law be $\bar{\zeta}$. Assume that the actual Pell grants take the form

$$\zeta(COA, EFC) = \min\{\bar{\zeta}, \max\{0, \zeta_0 + \zeta_{COA} COA + \zeta_{EFC} EFC\}\}$$

or, equivalently,

$$\frac{\zeta(COA, EFC)}{\bar{\zeta}} = \min\left\{1, \max\left\{0, \zeta_0 \frac{1}{\bar{\zeta}} + \zeta_{COA} \frac{COA}{\bar{\zeta}} + \zeta_{EFC} \frac{EFC}{\bar{\zeta}}\right\}\right\},$$

[14] The point estimate for σ_ς^2 is 0.226, but we do not include a transitory shock in the model, which is unlikely to affect college decisions.

[15] We use data from 2001 found here: https://ifap.ed.gov/dpcletters/attachments/p0003TableAFultime.PDF; 2018: https://ifap.ed.gov/dpcletters/attachments/GEN1804AttachRevised1819PellPaymntDisbSched.pdf.

which fits the data very well.[16] With this specification, we can recover the coefficients ζ_0, ζ_{COA}, and ζ_{EFC} by running a Tobit (censored) regression censoring both at zero and one.

Table 7 gives the results, both constraining $\zeta_0 = 0$ (as in specifications 1–3) and not (specifications 4–6). The results are stable over time. Because 2001 is in the middle of our sample, we use its coefficients $\zeta_{COA} = 1 = -\zeta_{EFC}$ with $\zeta_0 = 0$ (corresponding to the first specification). Under this specification, Pell Grants increase by one dollar for every dollar increase in COA or dollar decrease in EFC (when interior). Because of this, the value function will be inelastic to T when interior.

	(1) Pell/$\bar{\zeta}$	(2) Pell/$\bar{\zeta}$	(3) Pell/$\bar{\zeta}$	(4) Pell/$\bar{\zeta}$	(5) Pell/$\bar{\zeta}$	(6) Pell/$\bar{\zeta}$
Pell/$\bar{\zeta}$						
COA/$\bar{\zeta}$	0.999	1.018	1.001	0.994	1.067	0.999
	(691.12)	(806.29)	(399.96)	(394.53)	(508.76)	(248.57)
EFC/$\bar{\zeta}$	-0.994	-1.067	-1.000	-0.994	-1.065	-0.998
	(-391.56)	(-459.41)	(-228.91)	(-394.59)	(-500.91)	(-248.60)
COA/$\bar{\zeta}\times$2018			0.0170			0.0669
			(6.15)			(14.99)
EFC/$\bar{\zeta}\times$2018			-0.0658			-0.0656
			(-13.56)			(-14.67)
1/$\bar{\zeta}$				0.0161	-0.197	0.00423
				(2.25)	(-28.73)	(0.37)
1/$\bar{\zeta}\times$2018						-0.197
						(-15.01)
Constant included	No	No	No	No	No	No
Years	2001	2018	Both	2001	2018	Both

Note: t-statistics are in parentheses; all specifications use Tobit regressions; the unit of observation is a (COA,EFC) cell in a given year.

Table 7: Pell Grant Regressions

3.3.3 Consequences of Student Loan Default

In the model and data, garnishment for student loan applies only to earnings exceeding a threshold.[17] In the data, this threshold corresponds to 30 hours of work a week at the minimum wage. To map this to the model, we compute the real minimum wage in 2010 dollars over time. While the series is volatile, it does not exhibit a time trend. So we compute the average over 1987-2010,

[16] In the regressions below, a regression of the predicted values on actual gives an R^2 of at least 0.993.

[17] The statutory law for garnishment is summarized here: https://www.dol.gov/whd/regs/compliance/whdfs30.pdf (retrieved 12/20/2019).

finding it is \$6.32 per hour. We then take this real hourly wage and multiply by 30 * 52 to arrive at the after tax earnings an individual gets to keep per year. According to our estimates, the after tax earnings the individual gets to keep is $\underline{e} = 9.867$ in model units (\$9,867 in 2010 dollars). For any amount exceeding that, a fraction $\chi = 0.25$ is taken as in the law.

3.4 Parameters Determined Jointly Using the Model

The remaining parameters to identify are the quality function parameters $\alpha_{X,k}$, $\alpha_{N,k}$ (7 each), and ϵ, the search disutility ψ, and the coefficients of the college attendance utility function $v_k(I_k)$. To determine the parameters in $v_k(I_k)$, we first identify the level of utilities v_k (7 scalars) along with the other parameters above as part of the joint parametrization procedure, which we discuss momentarily. Then we project v_k onto $v_k = a_{0,public}\mathbf{1}_{[k,public]} + a_{0,private}\mathbf{1}_{[k,private]} + a_1 I_k + u_k$ using 1987 data on I_k to determine the coefficients $a_{0,public}$, $a_{0,private}$, and a_1 along with the residuals u_k.

3.4.1 GMM Procedure

The joint parametrization procedure sets out to identify the search disutility ψ, the 7 attendance utility scalars v_k just discussed, and the 15 quality function parameters. All but ϵ (i.e. 22 parameters in total) are used to minimize the distance between a set of moments in the initial equilibrium of the model and the 1987 data. The quality function curvature ϵ is set such that aggregate enrollment in the final equilibrium of the model matches the 2010 data, as will be discussed in detail below.

We target average net tuition T_k, ability X_k, and FTE enrollment N_k for each college type k. In addition, we target the FTE-weighted college acceptance probability $\mathbb{E}[\eta]$. At this stage, we have 22 parameters and 22 moments to allow for exact identification. However, it turns out that the estimation can be made more efficient by introducing some additional moments that exploit the model optimality conditions. Specifically, section C.7 derives a (net) tuition supply curve from

$$\alpha_{N,k} = \frac{\Delta_k(N_k)}{p^{1-1/\epsilon}} \left(\frac{N_k}{-\kappa \frac{V_k}{N_k} - \frac{pC_k(N_k)}{N_k} + \frac{G_k(N_k)}{N_k} + \frac{E_k(N_k)}{N_k} + T_k} \right)^{1/\epsilon} \tag{35}$$

where $\Delta_k(N_k)$ is the derivative of average custodial costs net of non-tuition revenue $G_k(N_k)$ and $E_k(N_k)$, while T_k is average net tuition (i.e. the expectation over enrollment) at college k.

Equation (35) defines a tuition supply curve in the sense that it provides the locus of points $\{(T_k, N_k, V_k)\}$ consistent with college optimality. To see the usefulness of this expression, note that for $\kappa_k = 0$, the average markup $\kappa_k V_k / N_k$ is null, which simplifies the locus of points to $\{(T_k, N_k)\}$. In this case, $\alpha_{N,k}$ is uniquely pinned down by plugging in T_k^* and N_k^* from the data. With $\kappa_k > 0$, the average markup matters, so we define $\tilde{\alpha}_{N,k}$ to be the solution to equation 35 when the right hand side is evaluated at the empirical values of T_k^* and N_k^* along with the *equilibrium* V_k of the model given a choice for all the other parameters, which includes $\alpha_{N,k}$. In other words, we get a mapping

$\tilde{\alpha}_{N,k} = f(\alpha_{N,k}, \text{other parameters})$. To increase estimation efficiency, we also target the fixed points $\tilde{\alpha}_{N,k} = \alpha_{N,k}$, resulting in 29 moments and 22 parameters that use the initial equilibrium. Before discussing the identification and model fit, it is worth remarking that the quality function curvature ϵ is not readily identified using just the initial equilibrium.[18] Instead, we use ϵ to target aggregate enrollment in 2010 using the terminal model equilibrium—the only 2010 moment that we target.

In terms of "intuitive" identification, $\alpha_{N,k}$ strongly influences enrollment N_k and also $\tilde{\alpha}_{N,k}$. In particular, when $\tilde{\alpha}_{N,k} = \alpha_{N,k}$, the empirical values of T_k^* and N_k^* are consistent with college supply as encapsulated by the tuition supply curve. However, to rationalize T_k^* and N_k^* in equilibrium, we must also ensure that T_k^* and N_k^* are consistent with college demand from household optimization, which is where the scalars v_k come into play in the identification. In particular, higher attendance utility v_k raises the demand for college k, which tends to increase net tuition. The quality function parameters $\alpha_{X,k}$ are identified by matching average ability by school type. Lastly, the search disutility ψ is identified by the enrollment-weighted acceptance probability. Figure 24 in the appendix shows that our identification strategy works as we claim. In particular, for each estimated

[18] To see why, suppose $\kappa = 0$ and one matches X_k, N_k, T_k perfectly, which then gives I_k matched perfectly for some $\epsilon^1, \{\alpha^1_{X,k}\}, \{\alpha^1_{N,k}\}$. Now consider a different ϵ^2, and adjust $\{\alpha^2_{X,k}\}$ and $\{\alpha^2_{N,k}\}$ such that the marginal rates of substitution q_N/q_I and q_X/q_I are unchanged when evaluated at the target moments. In this case, previously-optimal enrollment decisions are still optimal—because the ability and size premium are unchanged—and thus there are no demand changes. Without any change in demand, the old X_k, N_k, T_k, I_k still solve the college problem.

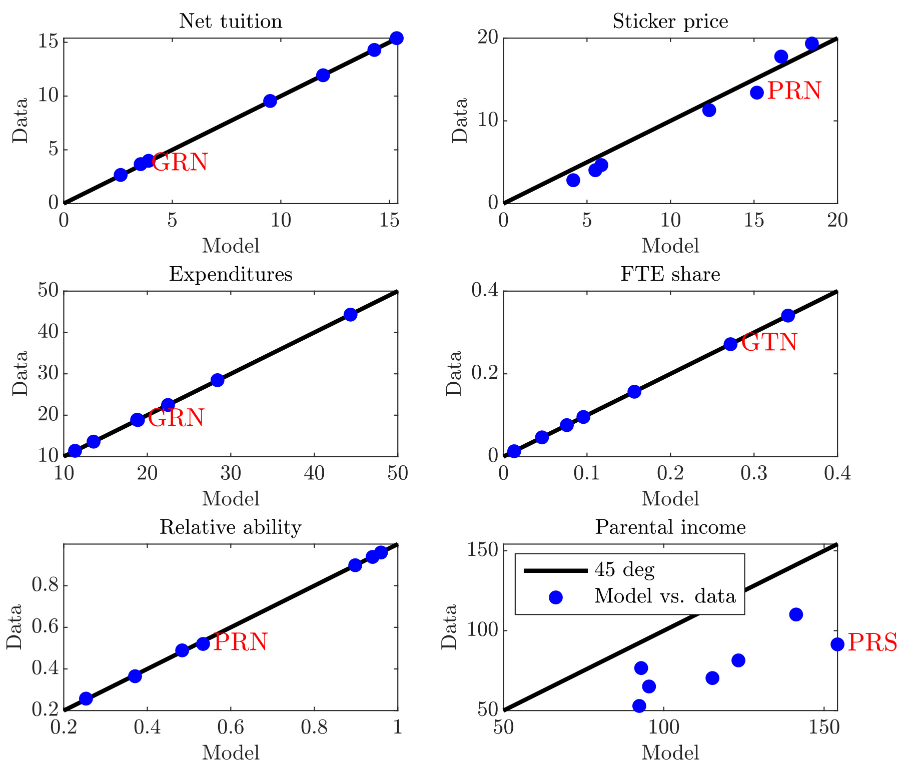


Figure 4: Joint Parametrization Goodness of Fit

parameter p and each moment m, it reports the elasticity $\epsilon_{p,m}$. The graph is a visualization of the Jacobian. The red rectangles highlights visually the "intuitive" identification scheme just discussed with v_k moving T_k, $\alpha_{X,k}$ moving X_k, $\alpha_{N,k}$ moving N_k and $\tilde{\alpha}_{N,k}$, and ψ moving $\mathbb{E}[\eta]$.[19]

Tables 15 and 16 in the appendix summarize the joint parametrization. Figure 4 shows that the model is able to successfully match not only the targeted moments but also provides a good fit for sticker price and total college expenditures by type in 1987. However, the model overshoots on parental income relative to the the 1987 data.

4 Results

The parametrization described in the preceding section ensured that the initial equilibrium of the model corresponding to 1987 in the data matches many salient features of the cross-section of the higher education market, including average net tuition, enrollment, and academic ability by college type. The main objectives of this section are to assess whether the model can successfully replicate the untargeted evolution of higher education outcomes between 1987 and 2010 and, if so, to use the model to understand the main driving forces behind such changes.

4.1 Comparative Statics in a Stylized "Toy" Model

Before delving into the full quantitative analysis, we turn to a static, stylized version of the model to glean qualitative insights into how different economic forces impact higher education. Specifically, we consider a representative college with quality function $q(I, N)$ that depends on investment I and enrollment N but not on student ability. Rather than explicitly model the decision of *who* the college admits, we assume that the college faces a downward sloping demand curve $T(N)$ and just chooses I and N to maximize $q(I, N)$ given the budget constraint. Specifically, the college solves

$$\begin{aligned} &\max_{I,N} q(I, N) \\ &\text{s.t. } pIN + pC(N) = T(N)N + \overline{G}N + \overline{E}N \end{aligned} \tag{36}$$

where $\overline{G}$ and $\overline{E}$ are constant per-pupil government appropriations and endowment funding, respectively.

Implicitly, the downward sloping $T(N)$ is akin to saying that, absent any dependence of q on academic ability, and conditional on targeting some level of enrollment N, the college will design its admissions strategy to maximize its per-pupil resources. Then, the higher the desired enrollment N,

[19] A quantitative metric proving the increased estimation efficiency from the overidentification is the condition number $J'J$ where J is the Jacobian. The Newton's method step (technically, the Levenberg-Marquardt algorithm, which is a damped version of Newton's method) solves for the step δ in $J'J\delta = J'e$ where e is the residual between actual and target moments. A well-conditioned $J'J$ leads to a more stable solution for δ. With $\tilde{\alpha}_N$ included, the condition number of $J'J$ is 3×10^5, while without it the number is 1×10^7 without it. One rule of thumb is that if the condition number is 10^n, then n digits of accuracy will be lost when solving for x in $Ax = b$.

the lower net tuition $T(N)$ it must charge to still attract the requisite number of students. Given $T(N)$, the budget constraint implies that

$$I(N) = -\frac{C(N)}{N} + \frac{1}{p}\left(T(N) + \overline{G} + \overline{E}\right). \tag{37}$$

For small N, the fixed cost component of $C(N)$ dominates, causing $I(N)$ to be a large negative number. As N increases, $I(N)$ first rises and then falls again given the convex shape of $C(N)$ and the decreasing average net tuition function $T(N)$, as captured by the blue curve in the top left panel of figure 5. The red dashed curve represents an "indifference curve" for the quality function q, and point A is a visual representation of the optimality condition $I'(N^*) = q_N(I(N^*), N^*)/q_I(I(N^*), N^*)$, with the asterisk directly below on the dashed black curve the average net tuition $T(N^*)$.

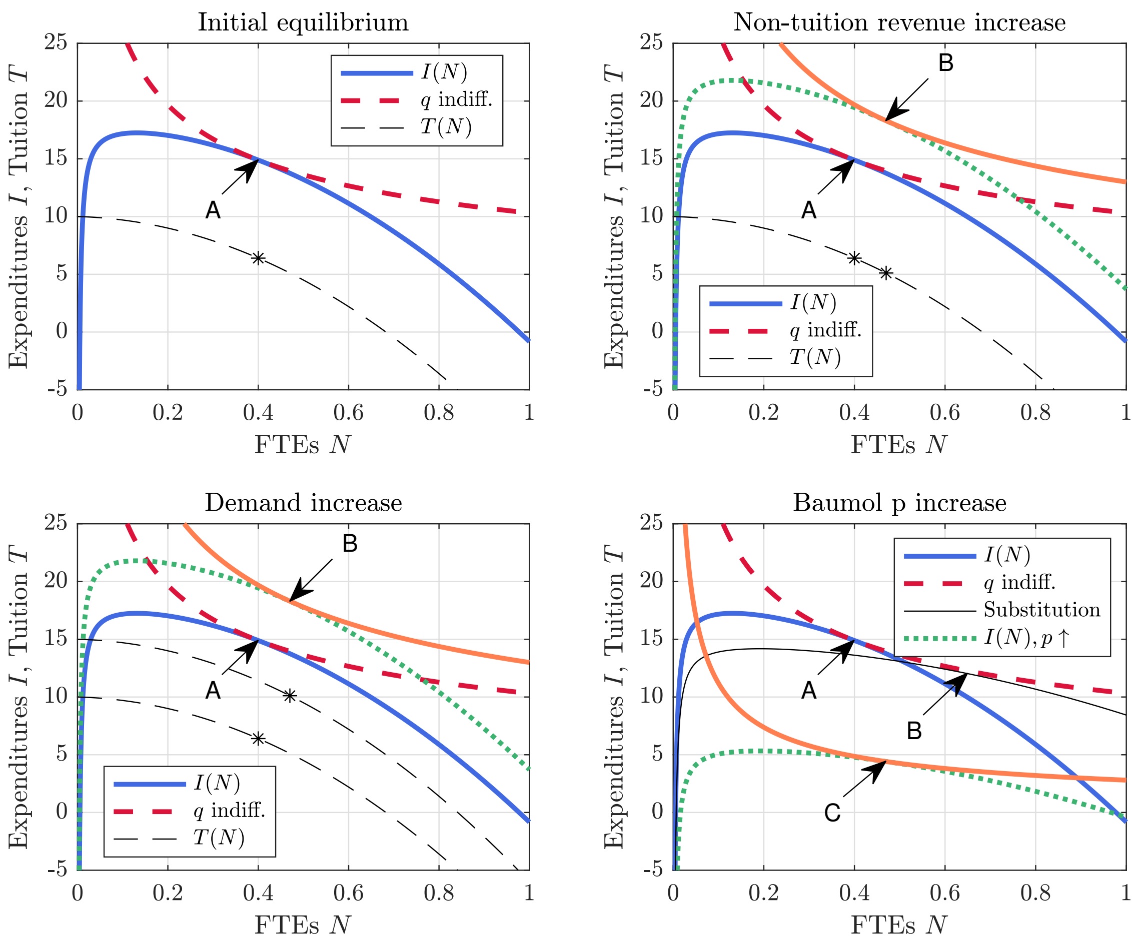


Figure 5: Comparative Statics in a Simple Model

4.1.1 An Increase in Non-Tuition Revenue

The top right panel depicts the impact of an increase to non-tuition revenue $\overline{G}$ or $\overline{E}$, which causes an outward shift in $I(N)$ from the blue to the green dotted curve. Akin to a pure income effect, we see that the new tangency point B occurs to the northeast of A at both higher enrollment $N_B > N_A$ and investment $I_B > I_A$. With no actual shift in the $T(N)$ curve, the higher level of enrollment is only possible if net tuition declines, i.e. $T(N_B) < T(N_A)$. Thus, net tuition tends to move in the opposite direction of non-tuition revenue. This result implies, for instance, that net tuition *increases* and quality-enhancing spending I *falls* if the government cuts its level of direct appropriations to colleges.

4.1.2 An Expansion in Government Financial Aid

The bottom left panel visualizes the impact of a demand increase—for example, from more generous government financial aid—manifested as an outward shift in $T(N)$ and therefore also $I(N)$. In principle, the shift to $\widetilde{T}(N)$ could take a number of different forms, resulting possibly in both income and substitution effects. If net tuition shifts in an approximately parallel fashion, as shown in the figure, then enrollment and investment both increase, i.e. $N_B > N_A$ and $I_B > I_A$, just like they did in response to higher non-tuition revenue. However, unlike in the case of non-tuition revenue, equilibrium net tuition rises after a positive demand shock as one might expect. The magnitude of the increase in net tuition is less than the demand shock, though, with $T(N_A) < \widetilde{T}(N_B) < \widetilde{T}(N_A)$. All together, these results suggest that net tuition absorbs part of the increase in demand, but the rest is passed through to higher investment and enrollment.

4.1.3 Baumol's Cost Disease

Whereas the previous two experiments yielded relatively straightforward predictions, the impact of Baumol's cost disease—implemented here as a rise in the relative price of college inputs p—on net tuition is ambiguous. From equation 37, the investment curve $I(N;p)$ undergoes a more noticeable shift to an increase in p at lower levels of enrollment where $T(N)$ is large. Mathematically, the change in the slope of the investment curve is $\partial^2 I/\partial N \partial p = -T'(N)/p^2 > 0$, which implies that the downward sloping portion of $I(N)$ becomes flatter (less negative). This rotation creates both income and substitution effects. The former induces a response tantamount to a cut in non-tuition revenue—namely, lower enrollment and thus higher net tuition. The substitution effect, however—as shown by the black curve in the bottom right panel—tends to reduce investment and increase enrollment, which leads to lower net tuition. The bottom right panel shows the case where the substitution effect dominates, i.e. $N_C > N_A$. In general, though, an increase in the relative price of college inputs has ambiguous effects on net tuition and enrollment absent a quantitative analysis.

4.2 Jointly Accounting for College Trends from 1987 to the Great Recession

While insightful, the previous stylized model ignores competition between colleges, heterogeneity in net prices across students within a college, and dynamics from forward-looking behavior.[20] This section assesses whether the theories from section 1 can jointly explain the large rise in net tuition between 1987 and 2010 prior to the full impact of the Great Recession-era policy and economic changes reaching the college market. After assessing whether the model can explain the observed trends with all forces present, we undertake a quantitative decomposition to understand how each force individually affects the aggregate and cross-sectional dynamics of the higher education market.

4.2.1 Implementing the Economic and Policy Changes

As outlined in section 1, we incorporate several economic and policy forces that have been put forward as possible theories behind the persistent rise in college tuition. Roughly speaking, these theories can be divided into those that primarily impact the equilibrium of the higher education market through the supply side and those that have more direct demand-side effects.

Factors Affecting College Supply On the supply side, colleges have been affected both by shifting cost structures and changes to non-tuition revenue. With regard to costs, we implement Baumol's cost disease as a rise in the relative price p_t of college inputs by feeding in the observed path of the CPI-adjusted Higher Education Price Index, which increased from 1.08 in 1987 to 1.30 in 2010. In addition, we incorporate the dynamics of the custodial cost function $C_k(N_{k,t};t)$ discussed in section 3.1.3. With regard to non-tuition revenue, we feed in the evolution over time of government appropriations at the Federal, State, and Local levels as well as that of endowment funding. Section 3.1.4 explained in greater detail the estimation of the functions $G_k(N_{k,t};t)$ and $E_k(N_{k,t};t)$.

Factors Affecting College Demand On the demand side, we incorporate a rise in the return to college enrollment (both because of higher post-graduation labor market returns and lower ex-ante dropout risk), an increase in average parental income from economic growth, and changes to financial aid, both in the form of loans and grants. Regarding the returns to college, we increase the post-graduation labor market premium λ to match the trends in Autor et al. (2008), and we adjust the exogenous dropout probabilities to reflect the rise in college completion rates over the past two decades.[21] To capture the effects of economic growth on parental income, we adjust

[20] Figures 12 in the appendix shows that the quantitative model generates significant within-school dispersion in net tuition. Some of this variation is because of the heterogeneity in students and therefore effective marginal cost $EMC_k(s)$. However, figure 13 demonstrates that the markup $T - EMC$ also features significant dispersion.

[21] The college graduate labor market premium data in Autor et al. (2008) stops in 2005, so we extrapolate to 2010 following the procedure in Gordon and Hedlund (2019). We move the college completion rates from their 2002 value (the earliest year for which we have data on this series from IPEDS/DCP) to their 2010 value.

$EFC(s)$ to reflect the 44% rise in real GDP per capita from 1987 to 2010. Lastly, to test the Bennett hypothesis—which postulates that colleges seek to capture increases in external financial aid by raising tuition—we carefully model the evolution of the Federal Student Loan Program and the Pell Grant program. Specifically, we incorporate shifts in borrowing limits, interest rates, Pell Grant amounts, and the introduction of supplemental unsubsidized loans in 1993. Lastly, because we seek to explain tuition and not other costs of college attendance, we increase the parameter ϕ for non-tuition expenses to reflect National Center for Education Statistics (NCES) estimates.

4.2.2 The Evolution of Higher Education 1987–2010: Model vs. Data

When subjected to all of the previously discussed forces, the model generates equilibrium dynamics that resemble quite closely the evolution of the data, both in the aggregate and the cross section. Figure 6 provides a visual representation of the model's performance in matching changes between the 1987—which was targeted in the joint parametrization—and 2010. The base of each segment represents the model (horizontal axis) and data (vertical axis) values for 1987, and the "cannonball" circle represents the 2010 values. Thus, a perfect match is represented by a trajectory that lies completely along the 45 degree line. Trajectories parallel to but not coinciding with the 45 degree line indicate that the model successfully matches the change from 1987 to 2010 while missing the initial level. Each college type is represented by a different color.

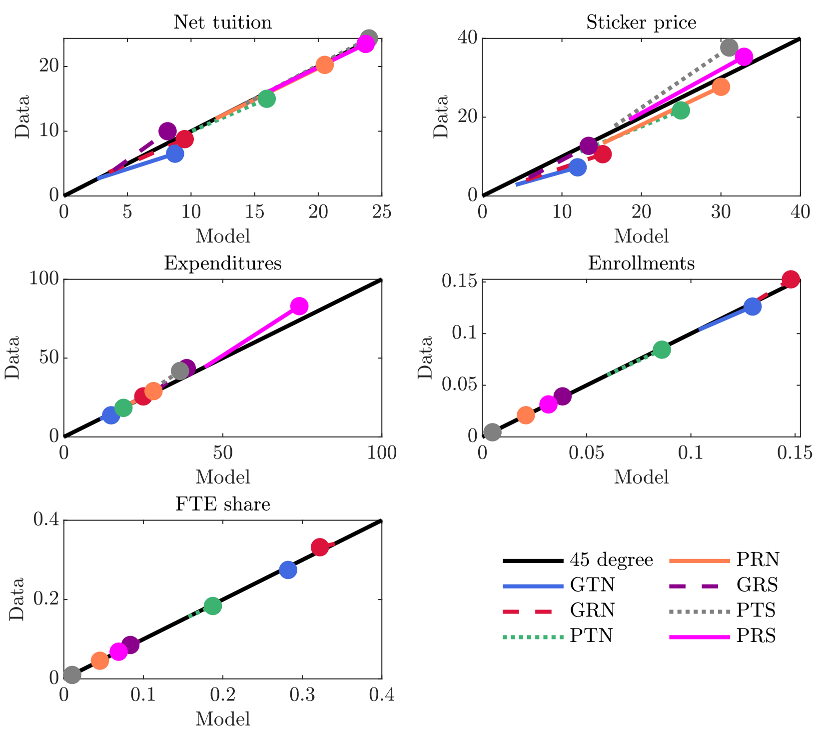


Figure 6: Data vs. Model, 1987 vs. 2010

The model captures the evolution of higher education between 1987 and 2010 quite well along several dimensions. For the main variable of interest—net tuition—the model generates an FTE-weighted 111% increase between 1987 and 2010 compared to 91% observed in the data, largely because of overshooting among GTN colleges, which comprise 27% of aggregate enrollment. The model almost exactly matches the rise in net tuition among the remaining college types. Both the model and data report that the largest *absolute* rise in net tuition comes from private colleges, and an even larger increase occurs for sticker price tuition. Thus, while private schools in 2010 are more expensive on average, they have also made institutional aid more generous to attract the most desirable students. On a percentage change basis, however, *public* colleges exhibit the most rapid net tuition inflation both in the model and data. On the spending side, a clear dichotomy emerges by degree of admissions selectivity. Expenditures per student at selective colleges, whether public or private, go up by 30% or more in the data, whereas they only rise by 15% for public research non-selective schools and remains stagnant or even declines for all other types. The model captures this dichotomy but overestimates the total rise in expenditures.

Regarding enrollment, figure 6 demonstrates that the model replicates almost perfectly the increase between 1987 and 2010 by school type. As a result, the model is able to reproduce the 13 percentage point rise in the data—from 35% to 48%—along with the fact that two-thirds of the increase accrues to public colleges. Delving into the cross section of students, figure 7 shows heat maps for equilibrium enrollment in the model for both 1987 and 2010. The distributions of student abilities within each college type remain mostly stable, though it is evident from the darkening of the shading in the 2010 plots that the largest enrollment increases occur among GTN and PTN colleges, particularly for students of moderate ability and higher parental income.

While we cannot compare the change in cross-sectional enrollment patterns empirically given lack of data, we can use the NLSY97 to look at enrollment patterns around 2000. These patterns are displayed in figure 8 broken down into public versus private and high (i.e., above median) sticker price versus low (below median) sticker price colleges. The sorting patterns between the model and data look strikingly similar. In particular, enrollment at high sticker price private schools (e.g. PRS) is concentrated among students that are both high ability and high income. In addition, public colleges exhibit relatively wide variation both in student ability and parental income, whereas low sticker price private schools cater almost exclusively to the more affluent, unless the student is of very high ability. Overall, the sorting of students across schools in the model looks reasonable both in 1987 and 2010 when compared to this data.

4.2.3 Tuition Dynamics

Before assessing the quantitative contribution of each driving force, figure 9 shows the dynamics (rather than just the endpoints) of net tuition in the model and data. Overall, the model does remarkably well at matching tuition over time across each of the college types, though it overshoots

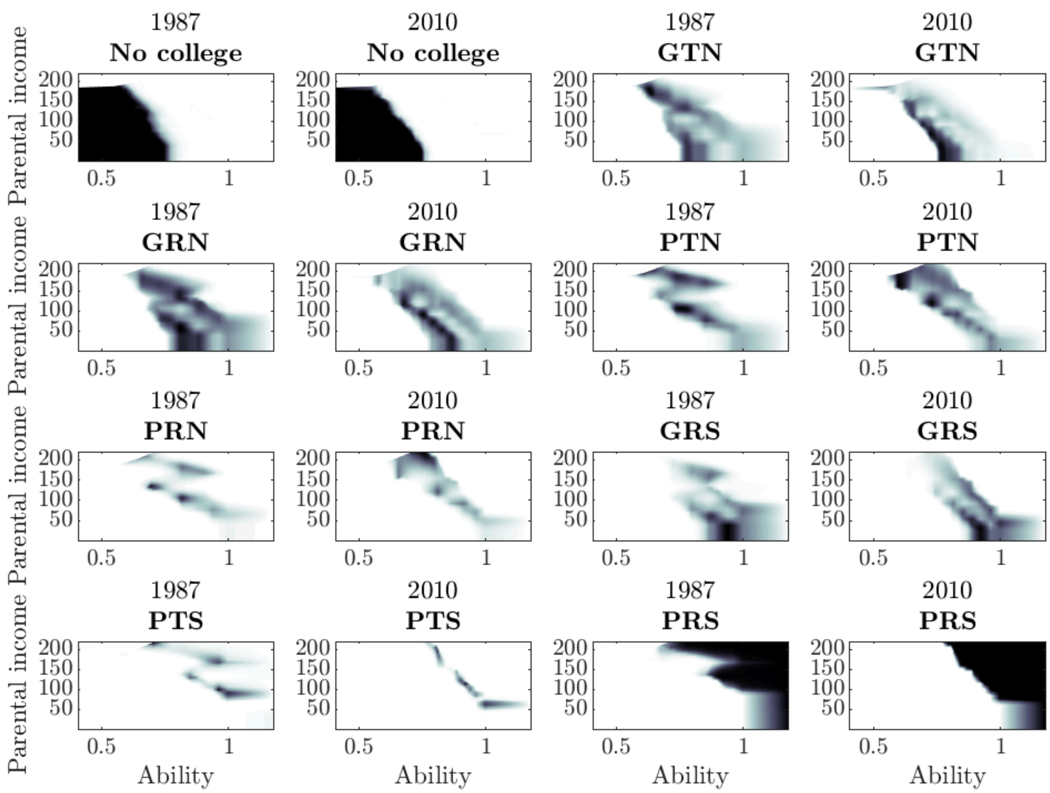


Figure 7: Sorting in 1987 and 2010

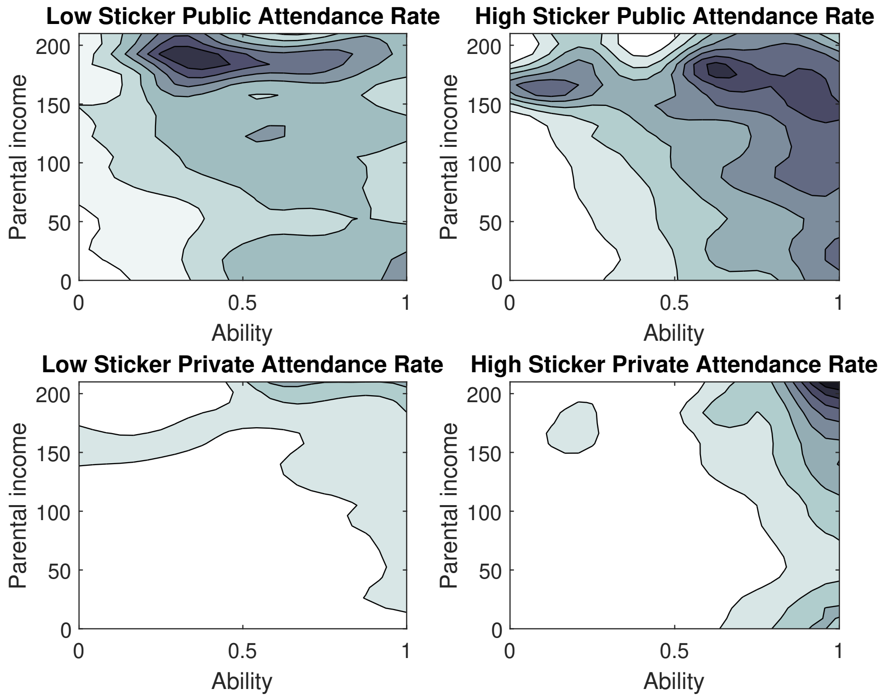


Figure 8: Sorting Patterns for Attendance in the NLSY97

the path of net tuition for PTS colleges, consistent with the discussion earlier. The same overshooting in the model occurs for PRS colleges in the late 1990s, but by 2010, the model and data are more or less in agreement. Net tuition dynamics for the other five college types are quite closely aligned during the entire time period.

Returning to the discussion earlier about institutional aid, figure 14 in the appendix plots the model dynamics of the ability premium q_X/q_I that determines the magnitude of the tuition discounting term $p\frac{q_X}{q_I}(x - X)$ for a student with ability x. As is evident in the figure, the ability premium rises steeply for all college types throughout almost the entire time period. The only exception is a leveling off starting in the mid-2000s for all types except private selective colleges. Next, figure 15 in the appendix plots the dynamics of the parental income gradient in the model. For every college type except GTN, this gradient increases dramatically in the mid-1990s after the expansion in financial aid allowing unsubsidized loans. This gradient then stabilizes or declines for most colleges except PRS, for which it continues to rise.

4.3 Explaining the Rise in Net Tuition and Other Trends

The success of the model at matching the evolution of U.S. higher education both in the aggregate and cross section makes it an appropriate laboratory to measure the relative contribution of each of the aforementioned demand and supply factors. We approach this decomposition from two sides. First, starting with the 1987 cohort-specific equilibrium, we introduce one force at a time by setting

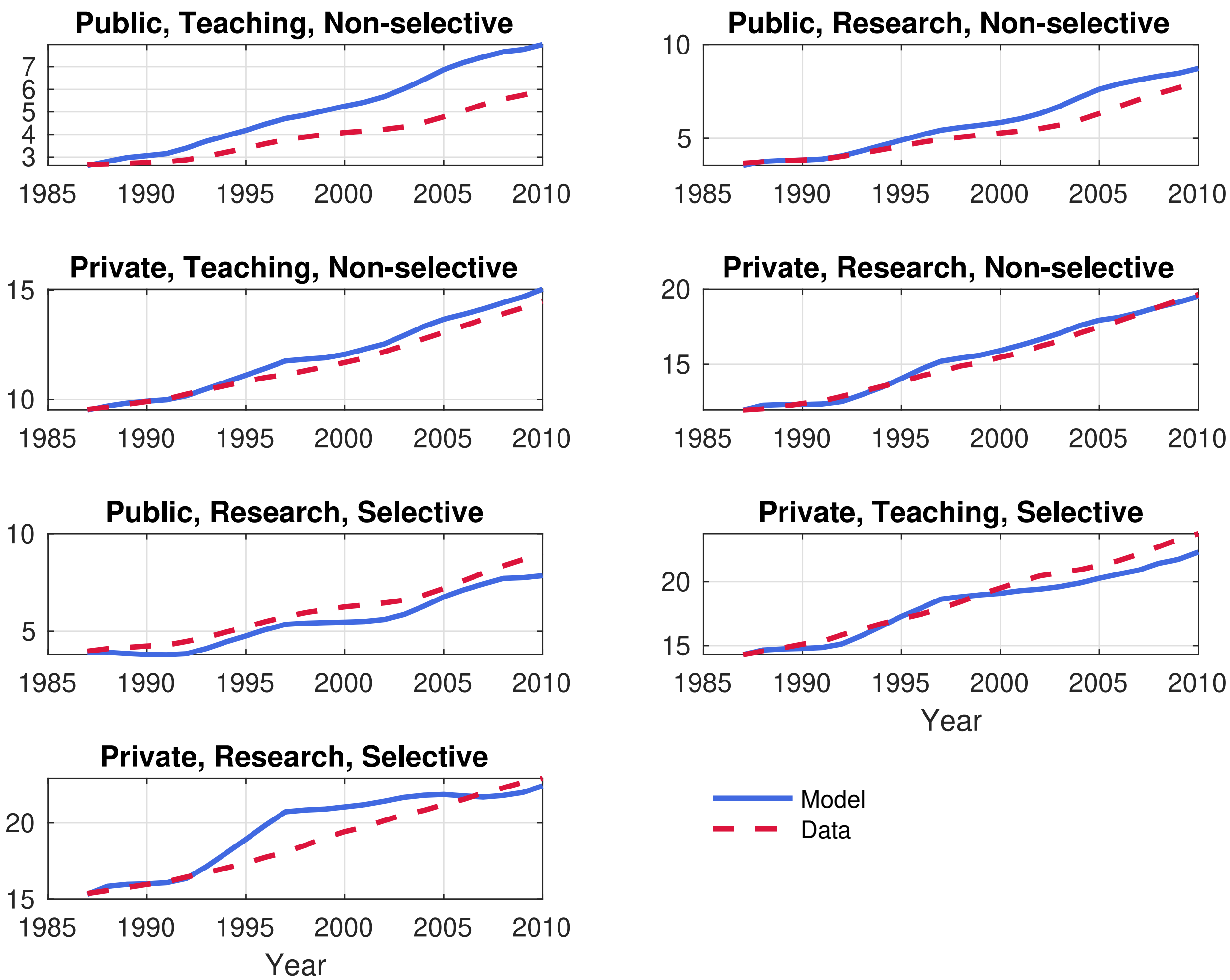


Figure 9: Net Tuition Dynamics: Model vs. Data

the relevant parameters to their 2010 values, such as changing loan limits and grant amounts to quantify just the Bennett hypothesis regarding financial aid. Then, we do the opposite by starting with the 2010 equilibrium and *removing* one force at a time, reverting the corresponding parameters to their 1987 values. These two decomposition approaches are necessary given possible interaction effects. Table 8 summarizes this decomposition for FTE-weighted net tuition, and figure 10 provides the breakdown by college type.

4.3.1 Supply: Changes in Government Appropriations

Beginning with supply factors, table 8 finds that changes to the amount of government appropriations colleges receive between 1987 and 2010 have actually contributed to a *decline* in net tuition of \$100–\$300, depending on whether we start from the 1987 equilibrium and implement the 2010 level of public appropriations or whether we start with the 2010 equilibrium and revert government appropriations from 2010 to 1987 levels. At first glance, this result may seem surprising in light of the comparative statics of the stylized model and extensive public discourse about government cutbacks fueling higher tuition. The reason for this counterintuitive finding is actually quite simple: total (Federal + State/Local) government appropriations have actually *gone up* in the aggregate, not declined. Only PTN and GTN colleges have experienced total cutbacks. Thus, consistent with the stylized model, higher non-tuition revenue in the form of government appropriations translates to lower net tuition. If we focus only on state appropriations—which have indeed fallen—table 8 finds that cutbacks have fueled a \$500–\$600 rise in real net tuition from 1987 to 2010. Broken down by college type, figure 10 (complemented by figure 10 in the appendix) indicates that declining trends in public appropriations created the largest upward pressure on net tuition at teaching-focused GTN colleges. By contrast, at research-intensive GRS and GRN colleges, the rise in federal appropriations more than offset state cutbacks.

In a sense, the above analysis which focuses on absolute levels of state appropriations may miss some of the narrative, because as a share of college revenues, *relative* state appropriations have indeed declined more noticeably. To evaluate the effects of state appropriations failing to keep up with tuition, we conduct another quantitative experiment in the model that keeps state appropriations stable relative to total college revenues between 1987 and 2010. This exercise is somewhat more complex, because college revenue at each school is an endogenous object that itself depends on the level of state appropriations and the pricing decisions of other colleges. To take into account such equilibrium feedback, this exercise solves for the average annual real growth rate of state appropriations that causes its share of equilibrium revenues in 2010 to remain the same as in 1987. A real growth rate of 2% emerges as the value that stabilizes state appropriations as a share of equilibrium revenues for each of the three public college types (GTN, GRN, and GRS) for which this exercise is most relevant.

This counterfactual exercise indicates that maintaining stability in the relative generosity of

		Net Tuition			
		Model: 1987 Baseline		Model: 2010 Baseline	
Experiment / change	Data	2010 Toggle	% Explained	1987 Toggle	% Explained
1987	5.8	5.7	0.0	5.7	-118.6
Baumol (p, C)	–	6.4	13.0	10.4	-31.0
Relative prices (p)	–	6.1	7.2	11.0	-19.9
Real costs (C)	–	6.1	7.3	11.5	-10.1
Pub. rev. (G)	–	5.6	-1.3	12.3	6.0
Pub. rev. federal (G^{fed})	–	5.0	-13.1	12.9	16.2
Pub. rev. state (G^{state})	–	6.2	10.4	11.4	-11.4
Priv. rev. (E)	–	5.2	-9.4	12.9	15.9
Bennett $(\bar{l}, i, \zeta, \phi)$	–	8.6	54.6	8.4	-67.1
Borrowing limits $(\bar{l})$	–	7.2	29.2	10.4	-30.3
Pell Grants (ζ)	–	6.5	16.0	11.2	-14.6
College prem, comp. rates	–	6.3	11.4	11.5	-10.1
Parental income / transfers	–	7.6	35.0	9.5	-47.9
Endogenous utility from q	–	5.7	0.0	11.6	-7.1
2010	11.1	12.0	118.6	12.0	0.0

Note: % explained is the model's change from the base year divided by the data's change from 1987 to 2010; all numbers are FTE weighted.

Table 8: The Contribution of Individual Forces to Average Net Tuition

state appropriations over time would have greatly slowed tuition inflation in the presence of other forces. For GTN colleges, real net tuition in this counterfactual increases by a cumulative 84% between 1987 and 2010 instead of the 234% from the baseline with the actual observed change in state appropriations, translating to a much smaller net tuition increase of \$2,200 versus \$6,100. At GRN colleges, the more generous state appropriations cut cumulative net tuition growth from 168% to 45%, thereby reducing the absolute rise in net tuition from nearly \$6,000 to only \$1,600. Among GRS colleges, maintaining state appropriations as a share of revenues at 1987 levels causes net tuition to *decline* by nearly \$1,700 instead of exhibiting a \$4,200 hike. By contrast, equilibrium net tuition at private colleges is nearly invariant to this change in state appropriations. Interestingly, despite the much wider gap in net tuition between public and private colleges that emerges in response to this policy—with net tuition rising rapidly at private colleges but not so much at public colleges—the predicted enrollment shares in 2010 barely budge. This inelastic response of enrollment shares to large changes in relative prices across institutions suggests a high degree of market segmentation.

4.3.2 Supply: Baumol's Cost Disease

Recall from the comparative statics of the stylized model that Baumol's cost disease—that is, a shift upward in the cost curve $pC(N)$ caused by some combination of rising p or $C(N)$—has ambiguous effects on net tuition and enrollment because of counteracting income and substitution effects, thereby necessitating the quantitative analysis. As reported in table 8, the model indicates that Baumol's cost disease is responsible for a \$700–\$1,600 rise in net tuition. Further decomposing the role of the relative price p and custodial cost function $C(N)$, table 8 reveals that the rise in p from 1987 to 2010 drives net tuition higher by \$400–\$1,000, while the shift in $C(N)$ by itself contributes to a \$400–\$500 tuition hike. Considering that net tuition more than doubles overall during this time period, these results suggest that Baumol's cost disease has been only a modest factor, albeit with figure 10 pointing to some heterogeneity across college types. In particular, the top panel shows that net tuition at public colleges tends to demonstrate a larger absolute response to Baumol's cost disease. However, moving to the second and third panels, private selective colleges are more sensitive to Baumol's cost disease in terms of declining enrollment and rising total expenditures $(pI+pC(N)+\kappa V)$—a mechanical result that owes to increases in p getting multiplied by the higher baseline level of quality-enhancing investment spending per student I at these institutions. The fact that net tuition increases by less than total expenditures indicates that investment I falls, which is consistent with the stylized model.

4.3.3 Demand: Expansions in Federal Financial Aid (Bennett's Hypothesis)

Switching focus to demand-side factors, the quantitative analysis underscores that the single largest factor driving up college tuition is the expansion in Federal financial aid, i.e. the Bennett Hypothesis.

Table 8 indicates that, in isolation, the combination of observed changes in student loan limits and interest rates as well as Pell grants and non-tuition expenses that enter aid formulas is responsible for 46–57% of the rise in equilibrium net tuition in the aggregate, which amounts to $2,900–$3,600 per student in real terms. Decomposing the contribution of each component of financial aid to tuition changes reveals that the expansion in borrowing limits is relatively more potent than that of Pell grants. Section 4.4 dives deeper into this point in relation to the empirical literature by pointing out the importance of distinguishing between the intensive and extensive margins of financial aid involving eligibility and utilization.

In the cross section of college types, the results shown in figure 10 reveal that net tuition at public colleges is much more responsive *in percentage terms* to expansions in Federal aid than it is at private colleges. However, reflecting the fact that percentage changes are affected by initial tuition levels, figure 17 reveals that the absolute change in net tuition caused by more generous financial aid is somewhat larger at private colleges. Looking beyond tuition, the degree of heterogeneity across college types with respect to the response of expenditures and enrollment to federal aid expansions is comparatively modest, with GRN and GTN schools exhibiting the largest absolute enrollment increases. Lastly, according to the bottom panel, average parental income actually *rises* in reaction to more generous financial aid, suggesting that in equilibrium, aid may not always effectively target help to lower-income families. Indeed, the introduction of unsubsidized loans directly increased the ability to borrow of families with incomes too high to otherwise qualify for need-based aid.

4.3.4 Demand: Family Income Growth

Family income growth (and the rising parental transfers to college students that accompany it) has also contributed meaningfully to higher tuition, accounting for between 35% and 48%—or $1,900 to $2,500—of the total increase in net tuition from 1987 to 2010, as shown in table 8. This result mirrors the finding in Cai and Heathcote (2020) about the importance of rising income dispersion and a fattening of the right tail as significant drivers of higher tuition. In percentage terms, figure 10 reveals that parental income growth is a more prominent driver of tuition growth at public colleges, but as was the case with financial aid expansion, base effects largely explain this pattern. In absolute levels, the effect of income growth on tuition is nearly twice as large among PRS, PTS, and PRN colleges relative to all other institution types, according to figure 17 in the appendix. In terms of enrollment, the biggest beneficiaries from family income growth are institutions at the bottom of the higher education market—GRN and GTN schools—where students are likely to be closer to the attendance vs. non-attendance margin.

4.3.5 Demand: Trends in the College Premium and Other Forces

Lastly, table 8 indicates that the higher return to college enrollment in 2010 compared to 1987—driven both by a higher labor market premium to holding a college degree and rising college completion rates (equivalently, falling dropout rates)—is responsible for a \$500–\$600 increase in net tuition, accounting for just over 11% of total tuition inflation over this time period. However, this tuition effect is almost entirely confined to public colleges, as shown in figure 10.

4.3.6 Taking Stock

The preceding results indicate that no single force is entirely responsible for the multi-decade upward march in net college prices. Instead, more expensive college is the result of a confluence of forces. Even so, some clear messages emerge from the decomposition exercises. First, the expansion in Federal aid has the largest quantitative effect on tuition inflation across all college types. Next up in importance are the demand-inducing effects of family income growth and parental transfers. At public colleges, cutbacks in government appropriations as a share of institutional revenue have also led to significantly higher net tuition charges for students and their families. Lastly, rising returns to college explain a modest fraction of the overall increase in net tuition, and Baumol's cost disease appears to play a relatively small role in creating tuition inflation. Instead, Baumol's cost disease primarily hurts enrollment and quality-enhancing investment.

4.4 Relation to Empirical Work on Financial Aid and Appropriations

The previous quantitative findings also relate to a growing empirical literature on the impact of financial aid and state appropriations on college pricing. This literature follows a range of approaches with regard to time horizon, geographic scope (i.e. state-specific vs. national), and the specific policies under question. To establish a common basis for comparison with this diverse empirical literature, this section undertakes some counterfactual experiments to compute tuition pass-through rates of the financial aid and state appropriations examined in sections 4.3.1 and 4.3.3.

4.4.1 Financial Aid

To calculate the transmission from financial aid to net tuition, the first set of counterfactual exercises takes turns exposing the economy to a \$1,000 increase either in maximum Pell grant amounts or in the annual loan limit for subsidized or unsubsidized loans (with a corresponding adjustment in the cumulative loan limit to allow students to borrow more each year). Importantly, the analysis allows for time-varying treatment effects given that conditions in the higher education market evolve significantly over time between 1987 and 2010.

As depicted in figure 11, the pass-through rate of increases in Pell grant amounts to equilibrium net tuition is stable at between 50% and 60% in the model over the sample period. This result stacks up favorably to the in-state tuition analysis in Rizzo and Ehrenberg (2004), which reports a 58% pass-through rate from increased Pell grant generosity. More recently, Lucca et al. (2019) estimate a smaller 21% pass-through rate of Pell grants to sticker price tuition and a more moderate

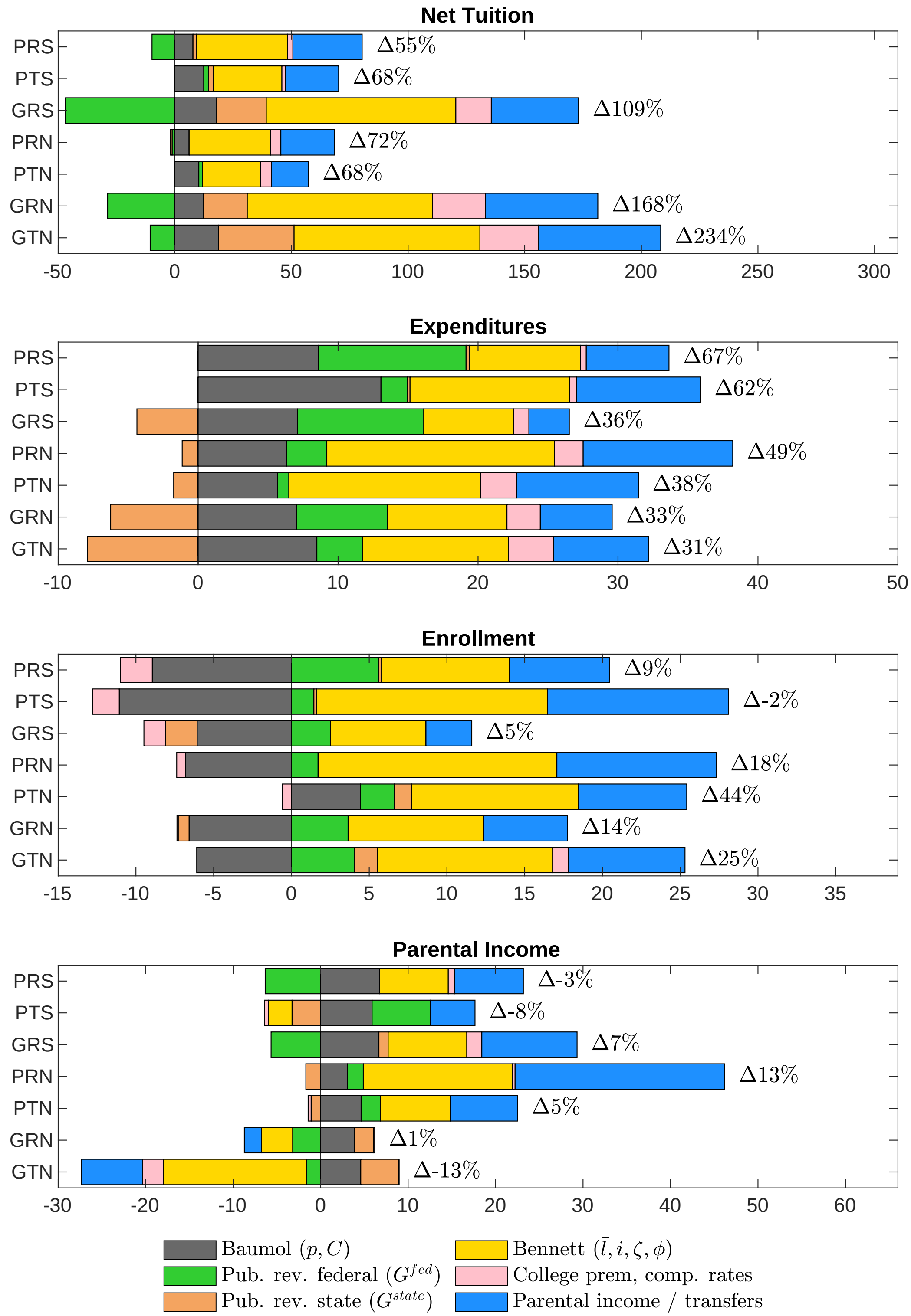


Figure 10: Percent Change Relative to 1987 from Adding One Force, Else Equal

pass-through of 36% to net tuition. In other words, as emphasized throughout this paper, colleges engage in substantial price discrimination, and therefore pricing adjustments may come in the form of changes to institutional aid that determine net tuition rather than the more noticed sticker tuition. Turner (2012) also mirrors this point in a student-level analysis of tax-based financial aid, simultaneously finding significant pass-through to the actual prices that students pay while failing to reject the possibility that overall sticker tuition is unaffected. Bridging the findings in Rizzo and Ehrenberg (2004) and Lucca et al. (2019), Singell and Stone (2007) deliver a range of estimates for the pass-through rate depending on methodology and the type of college. For in-state tuition, they report an OLS estimate for the pass-through rate of 36% but a smaller IV estimate of 13%. For out-of-state and private tuition, the study arrives at pass-through rates in excess of 80%. The elevated sensitivity of private college tuition to grant aid is reflected in figure 22 in the appendix, which portrays PRS institutions as having the highest pass-through rates that hover around 75%. By contrast, GTN colleges exhibit pass-through rates well below 50%. The empirical analysis in Turner (2017) confirms this extent of heterogeneity, reporting pass-through rates of around 15% overall but in excess of 75% at selective nonprofit schools.

Shifting attention from grants to student loans, figure 11 uncovers substantial time-variation in the pass-through rate of increased subsidized and unsubsidized loan limits to net tuition. In the late 1980s and early 1990s, subsidized loans had a nearly 20% pass-through rate to tuition, indicating that a $1,000 rise in the loan limit translated to an almost $200 increase in net tuition. By contrast, unsubsidized loans had nearly a 60% pass-through rate, which upon initial reflection may seem counterintuitive given that such loans are the less financially attractive of the two and would therefore be expected to translate less strongly into higher college demand. However, this intuition is incomplete, as it only considers the intensive utilization margin of college borrowing and not the extensive margin of loan eligibility. More concretely, while eligible students are indeed more responsive to increases in subsidized loan limits, they represent only a subset of all college students—that is, those with demonstrated need according to financial aid rules. Before unsubsidized loans became widely available in 1993, it was possible for students who did not qualify for need-based aid to nevertheless be credit-constrained and therefore quite responsive to being given the ability to borrow unsubsidized loans, whereas raising the amount of subsidized borrowing does nothing for them given their ineligibility status. Notably, figure 11 reveals that, after loan limits were expanded in the early 1990s, the pass-through rates for further marginal expansions plummet, indicating that borrowing needs were satiated. However, as tuition continued to rise through the early-mid 2000s amidst flat nominal loan limits, students became more credit-constrained and the pass-through rates began to again approach 15–20% until the eventual post-2008 loan expansion re-satiated borrowing demand. Empirically, Lucca et al. (2019) report a similar pass-through rate of unsubsidized loans but much larger values in excess of 60% for subsidized loans. Cellini and Goldin (2014) and Frederick et al. (2012) also uncover evidence linking student aid to tuition increases, but they examine for-profit and community colleges, respectively, which fall outside the scope of this paper. To summarize, the findings from the model suggest that there is no such thing as “the” pass-through rate from student loan expansions to net tuition. Instead, the sensitivity of college pricing to loan availability depends on the existing tightness of credit constraints, which is related to prevailing prices, the available borrowing instruments, and eligibility criteria.

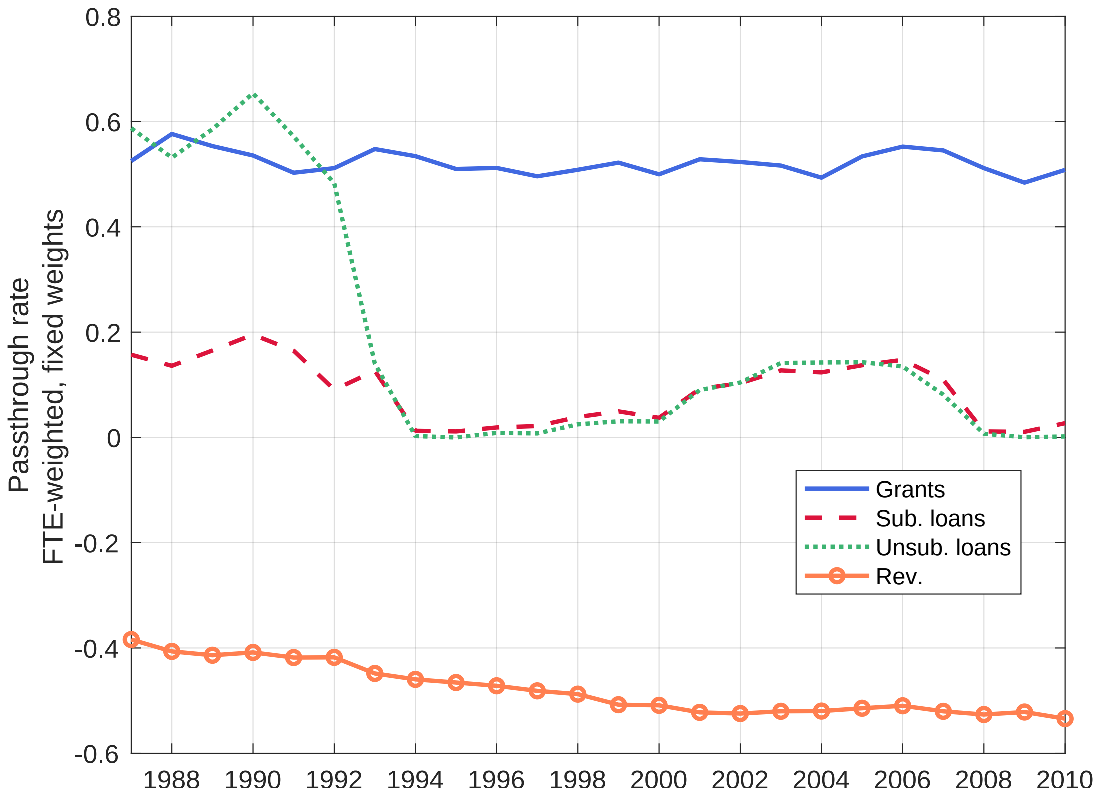


Figure 11: The Dynamics of Equilibrium Tuition Pass-Through Rates

4.4.2 State Appropriations

Similar to the counterfactual experiment in the previous section, the analysis here considers a \$1,000 increase in state appropriations for higher education. Figure 11 reveals that the pass-through rate to equilibrium net tuition is relatively stable over time between -40% and -50%, indicating a decline in net tuition of \$400–\$500 for every \$1,000 in more generous state appropriations. One of the most frequently referenced empirical studies that evaluates the relationship between state appropriations and tuition, Koshal and Koshal (2000), estimates a similar -40% pass-through rate. More recently, Webber (2017) estimates a -26% pass-through rate of state appropriations to net tuition, pointing out that the salience of public support has risen over time. In particular, the paper reports that the pass-through rate has grown from 10% prior to the year 2000 to 32% post-2000. While the model provides evidence in favor of an inverse link between state appropriations cut and tuition changes, the magnitude is far below a $1-for-$1 relationship. Rather than pass on such changes fully to prices, colleges also adjust quality-enhancing spending, which could have real-world implications for dropout rates and degree attainment, as confirmed empirically by Deming and Walters (2018).

5 Conclusion

Many explanations have been proffered for the rise in college tuition over the past few decades, ranging from Baumol's cost disease to labor market shifts to financial aid changes, just to name a few. Ample empirical evidence points to the *existence* of all these channels—for example, the labor market premium for college graduates has clearly gone up—but what is unclear absent a structural analysis is the extent to which each one is responsible for tuition inflation. The analysis in this paper suggests that, collectively, these existing hypothesis are sufficient to explain the path that U.S. higher education has taken since at least the late 1980s. In other words, the analysis in this paper does not point to any urgent need for an entirely new theory of tuition inflation. More importantly, the framework in this paper also sheds light on which of these factors matters the most, and it turns out the answer varies to some extent by institution type. In the aggregate, demand-side forces—notably, changes in the return to college and policy-induced increases in financial aid—are the primary drivers of average tuition growth. However, in the cross-section, the return to college matters much more for tuition at public institutions than at private colleges, while increases in endowment income have actually restrained tuition growth, but only at research-intensive colleges.

Going forward, many fruitful extensions emerge for future research. First, whereas this paper studies the long-run determinants of college tuition at a national level, further work is warranted to understand the short-run dynamics of tuition at an even more disaggregated level along with the impact of different forms of state funding. In addition, numerous reforms have either been recently implemented or proposed to increase college access and reduce the burden of student loan debt, ranging from a greater array of income-based repayment options to free public college. Further study is needed to fully understand the potential impacts of these reforms both on higher education outcomes (e.g. tuition, enrollment, completion, etc.) and on the broader economy.

References

B. Abbott, G. Gallipoli, C. Meghir, and G. Violante. Education policy and intergenerational transfers in equilibrium. *Journal of Political Economy*, 127(6):2569–2624, 2019.

R. J. Andrews, J. Li, and M. F. Lovenheim. Quantile treatment effects of college quality on earnings: Evidence from administrative data in texas. Mimeo, 2012.

R. B. Archibald and D. H. Feldman. Explaining increases in higher education costs. *The Journal of Higher Education*, 79(3):268–295, 2008.

K. Athreya and J. Eberly. Risk, the college premium, and aggregate human capital investment. Mimeo, 2016.

D. H. Autor, L. F. Katz, and M. S. Kearney. Trends in U.S. wage inequality: Revising the revisionists. *The Review of Economics and Statistics*, 90(2):300–323, May 2008.

W. J. Baumol. Macroeconomics of unbalanced growth: The anatomy of urban crisis. *The American Economic Review*, 57(3):415–426, 1967.

W. J. Baumol and W. G. Bowen. *Performing Arts: The Economic Dilemma; a Study of Problems Common to Theater, Opera, Music, and Dance*. Twentieth Century Fund, 1966.

P. Belley and L. Lochner. The changing role of family income and ability in determining educational achievement. *Journal of Human Capital*, 1(1):37–89, 2007.

Z. Cai and J. Heathcote. College tuition and income inequality. Working Paper, 2020.

D. Card and T. Lemieux. Can falling supply explain the rising return to college for younger men? *Quarterly Journal of Economics*, 116:705–746, 2001.

S. R. Cellini and C. Goldin. Does federal aid raise tuition? new evidence on for-profit colleges. *American Economic Journal: Economic Policy*, 6:174–206, 2014.

R. Chakrabarty, M. Mabutas, and B. Zafar. Soaring tuitions: Are public funding cuts to blame? http://libertystreeteconomics.newyorkfed.org/2012/09/soaring-tuitions-are-public-funding-cuts-to-blame.html#.VeDDrPlVhBc, 2012. Accessed: 2015-08-28.

S. Chatterjee and F. Ionescu. Insuring student loans against the risk of college failure. *Quantitative Economics*, 3(3):393–420, 2012.

A. F. Cunningham, J. V. Wellman, M. E. Clinedinst, J. P. Merisotis, and C. D. Carroll. Study of college costs and prices, 1988 - 89 to 1997 - 98, volume 1. Report NCES 2002-157, National Center for Education Statistics, 2001a.

A. F. Cunningham, J. V. Wellman, M. E. Clinedinst, J. P. Merisotis, and C. D. Carroll. Study of college costs and prices, 1988 - 89 to 1997 - 98, volume 2: Commissioned papers. Report NCES 2002-157, National Center for Education Statistics, 2001b.

DCP. Delta cost project documentation of IPEDS database and related products. Available: http://nces.ed.gov/ipeds/deltacostproject/download/DCP_History_Documentation.pdf [Last accessed: April 5, 2014], December 2011.

D. J. Deming and C. R. Walters. The impact of state budget cuts on u.s. postsecondary attainment. Working paper, 2018.

D. Epple, R. Romano, and H. Sieg. Admission, tuition, and financial aid policies in the market for higher education. *Econometrica*, 74(4):885–928, 2006.

D. Epple, R. Romano, S. Sarpca, and H. Sieg. A general equilibrium analysis of state and private colleges and access to higher education in the u.s. *Journal of Public Economics*, 155, 2017.

I. Fillmore. Price discrimination and public policy in the U.S. college market. Mimeo, 2016.

A. B. Frederick, S. J. Schmidt, and L. S. Davis. Federal policies, state responses, and community college outcomes: Testing an augmented bennett hypothesis. *Economics of Education Review*, 31(6):908–917, 2012.

C. Fu. Equilibrium tuition, applications, admissions, and enrollment in the college market. *Journal of Political Economy*, 122(2):225–281, 2014.

C. Garriga and M. P. Keightley. A general equilibrium theory of college with education subsidies, in-school labor supply, and borrowing constraints. Mimeo, 2010.

C. Goldin and L. F. Katz. The race between education and technology: The evolution of u.s. educational wage differentials, 1890 to 2005. NBER Working Paper, 2007.

G. Gordon and A. Hedlund. Accounting for the rise in college tuition. In C. R. Hulten and V. A. Ramey, editors, *Education, Skills, and Technical Change: Implications for Future U.S. GDP Growth*, pages 357 – 394. NBER and University of Chicago Press, 2019.

J. Heathcote, F. Perri, and G. Violante. Unequal we stand: An empirical analysis of economic inequality in the united states 1967-2006. *Review of Economic Dynamics*, 13(1):15–51, 2010.

D. E. Heller. The effects of tuition and state financial aid on public college enrollment. *The Review of Higher Education*, 23(1):65–89, 1999.

L. Hendricks and O. Leukhina. The return to college: Selection bias and dropout risk. Mimeo, 2016.

M. Hoekstra. The effect of attending the flagship state university on earnings. *The Review of Economics and Statistics*, 91(4):717–724, 2009.

D. A. Jaeger and M. E. Page. Degrees matter: New evidence on sheepskin effects in the returns to education. *The Review of Economics and Statistics*, 78(4), 1996.

J. B. Jones and F. Yang. Skill-biased technological change and the cost of higher education. *Journal of Labor Economics*, 34(3), 2016.

L. F. Katz and K. M. Murphy. Changes in relative wages, 1963 - 87: Supply and demand factors. *Quarterly Journal of Economics*, 107:35–78, 1992.

M. P. Keane and K. I. Wolpin. The effect of parental transfers and borrowing constraints on educational attainment. *International Economic Review*, 42(4):1051–1103, 2001.

R. K. Koshal and M. Koshal. State appropriation and higher education tuition: What is the relationship? *Education Economics*, 8(1), 2000.

L. J. Lochner and A. Monge-Naranjo. The nature of credit constraints and human capital. *American Economic Review*, 101(6):2487–2529, 2011.

B. T. Long. How do financial aid policies affect colleges? the institutional impact of the georgia hope scholarship. *Journal of Human Resources*, 39(4):1045–1066, 2004a.

B. T. Long. The impact of federal tax credits for higher education expenses. In C. M. Hoxby, editor, *College Choices: The Economics of Where to Go, When to Go, and How to Pay for It*, pages 101 – 168. University of Chicago Press, 2004b.

B. T. Long. College tuition pricing and federal financial aid: Is there a connection? Technical report, Testimony before the U.S. Senate Committee on Finance, 2006.

D. O. Lucca, T. Nadauld, and K. Shen. Credit supply and the rise in college tuition: Evidence from the expansion in federal student aid programs. *The Review of Financial Studies*, 32(2):423–466, 2019.

M. S. McPherson and M. O. Shapiro. *Keeping College Affordable: Government and Educational Opportunity*. Brookings Institution Press, 1991.

M. J. Rizzo and R. G. Ehrenberg. Resident and nonresident tuition and enrollment at flagship state universities. In C. M. Hoxby, editor, *College Choices: The Economics of Where to Go, When to Go, and How to Pay for It*, pages 303 – 353. University of Chicago Press, 2004.

L. D. Singell, Jr. and J. A. Stone. For whom the Pell tolls: The response of university tuition to federal grants-in-aid. *Economics of Education Review*, 26:285–295, 2007.

M. A. Titus, S. Simone, and A. Gupta. Investigating state appropriations and net tuition revenue for public higher education: A vector error correction modeling approach. Working paper, Institute for Higher Education Law and Governance Institute Monograph Series, 2010.

L. J. Turner. The road to Pell is paved with good intentions: The economic incidence of federal student grant aid. Mimeo, 2017.

N. Turner. Who benefits from student aid: The economic incidence of tax-based aid. *Economics of Education Review*, 31(4):463–481, 2012.

D. A. Webber. State divestment and tuition at public institutions. *Economics of Education Review*, 60:1–4, 2017.

A Supplementary Tables and Figures

A.1 The Distribution of Net Tuition and Markups

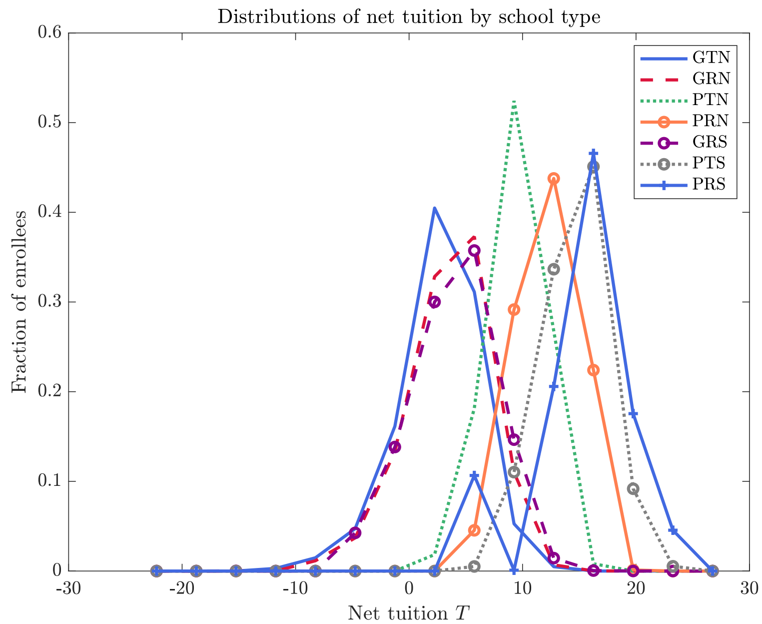


Figure 12: Within-School Distributions of Net Tuition

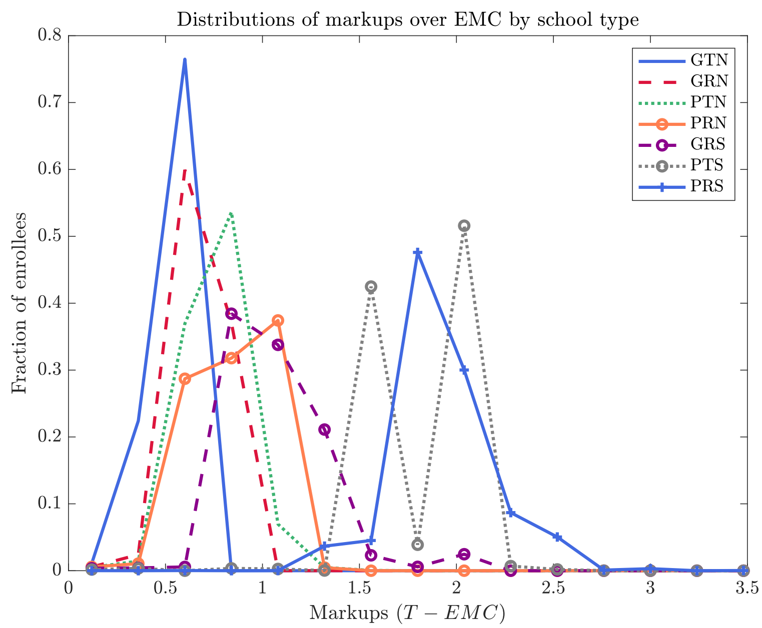


Figure 13: Distribution of Net Tuition Markups

A.2 Additional Benchmark Dynamics

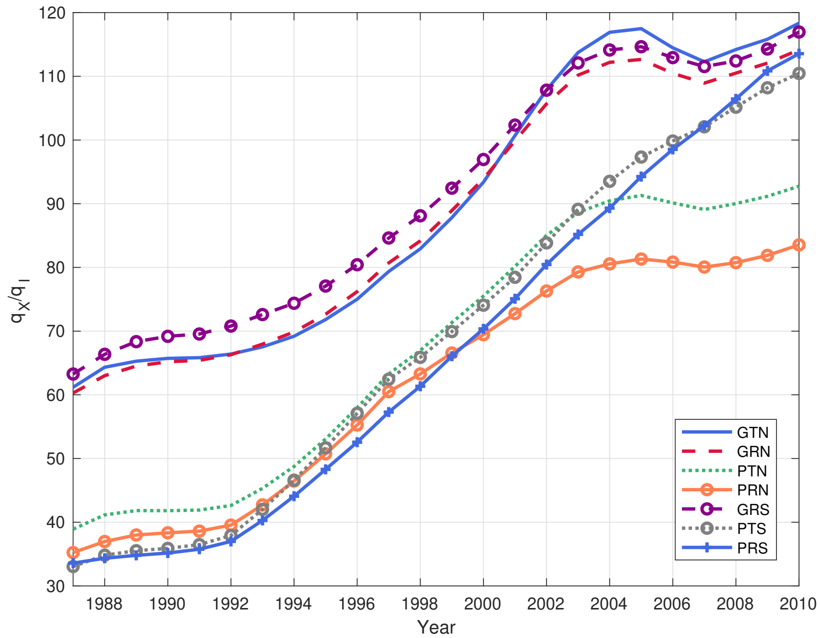


Figure 14: Ability Premia in the Model

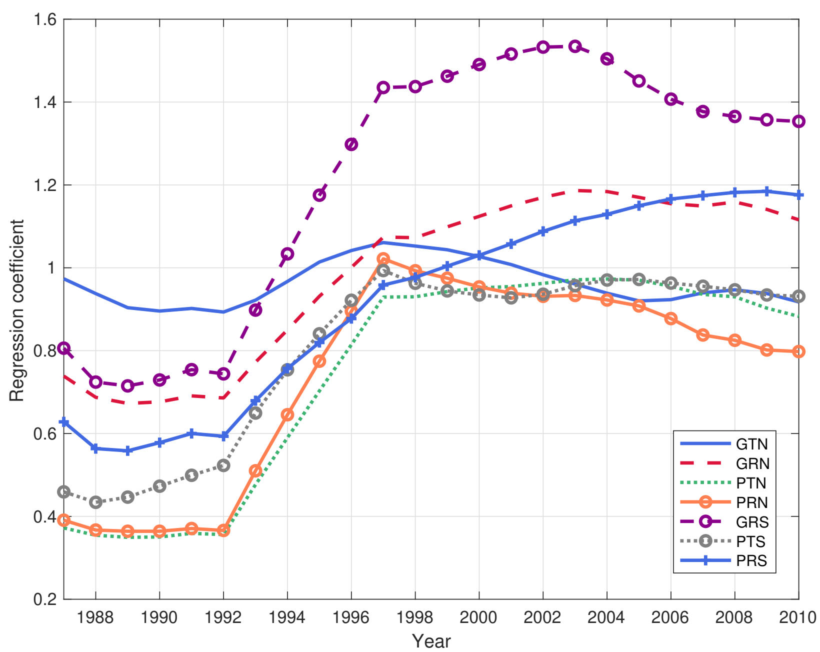


Figure 15: Parental Income Gradients in the Model

A.3 Decomposition: Additional Heterogeneous Effects

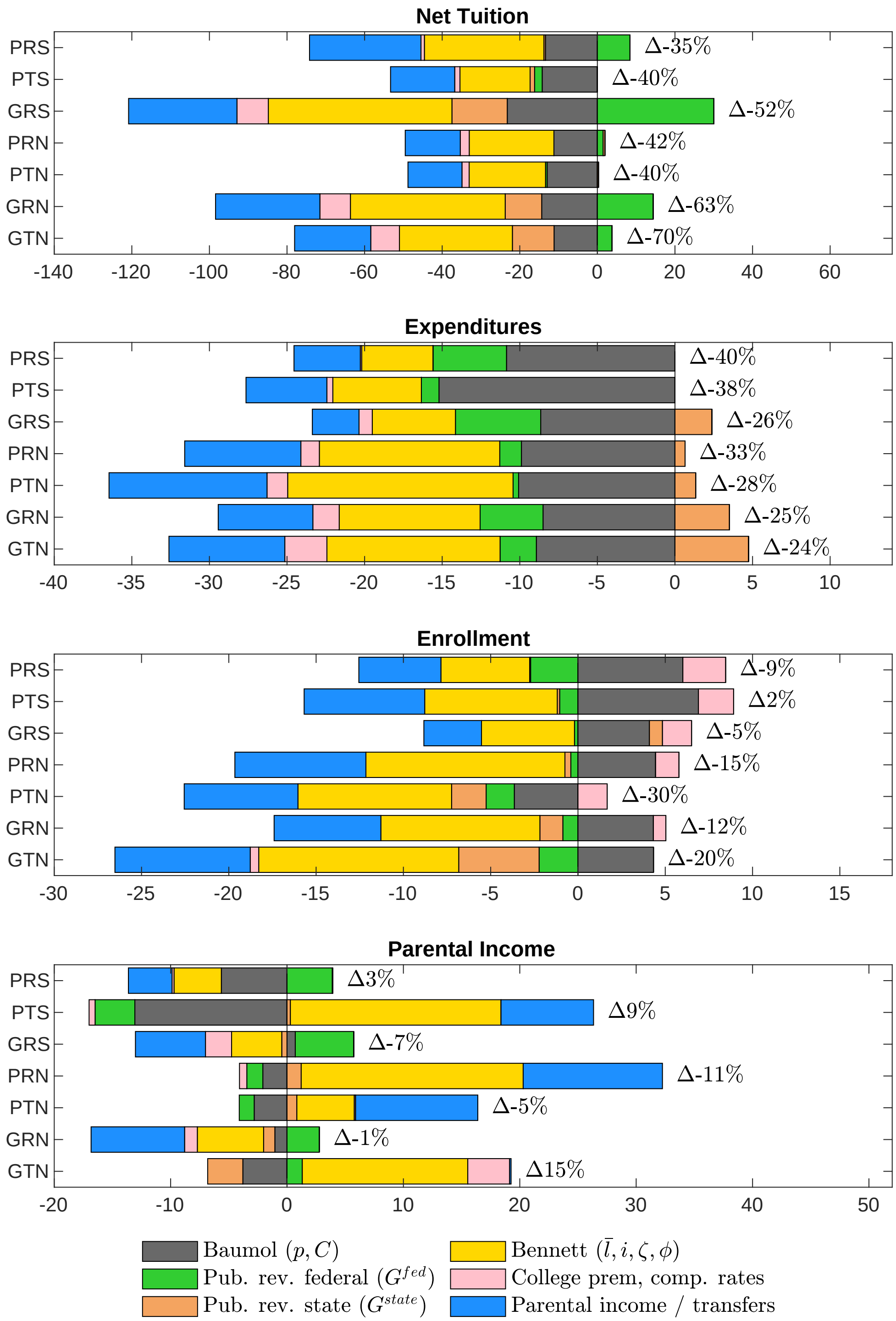


Figure 16: Percent change relative to 2010 from subtracting one force, else equal

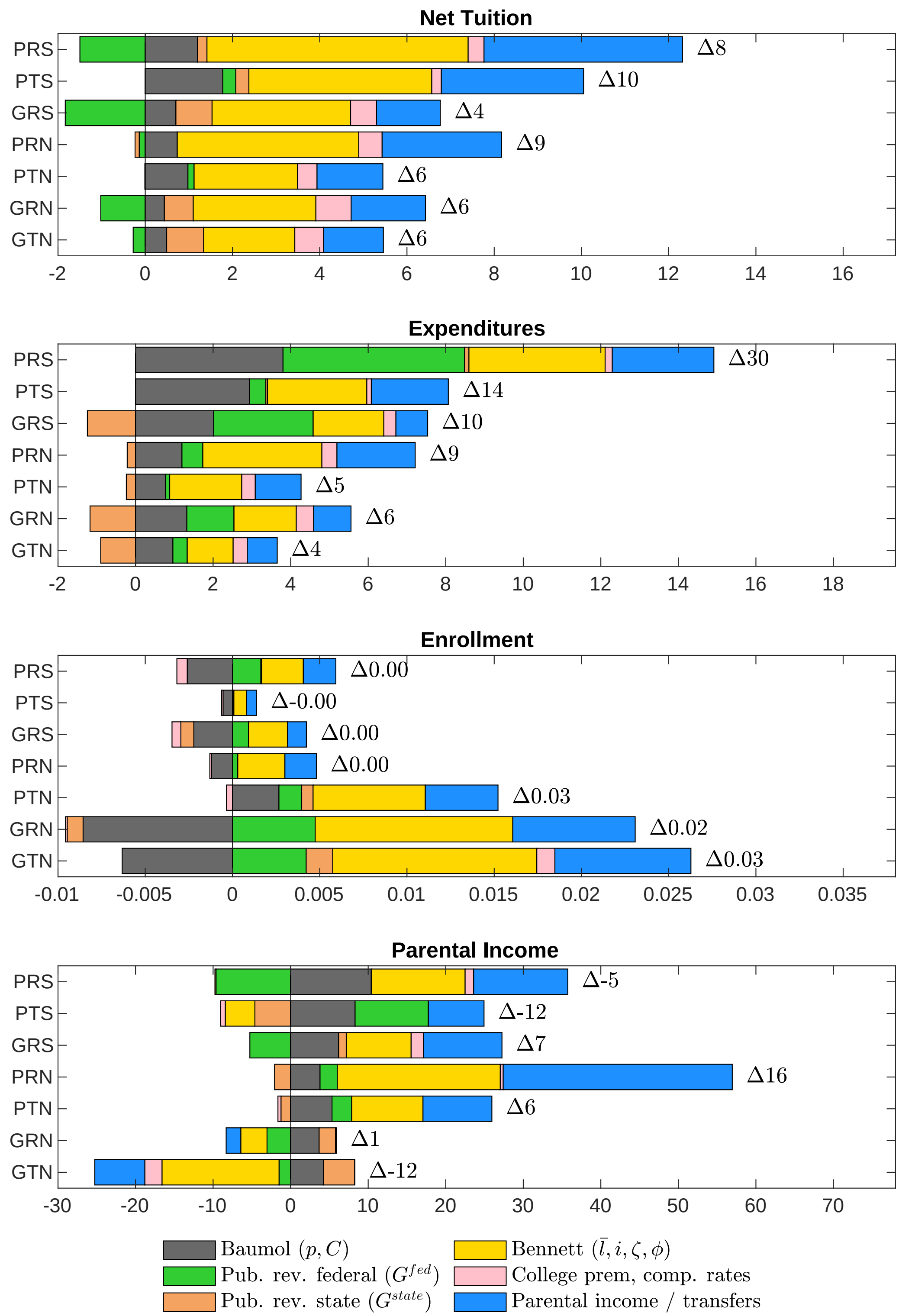


Figure 17: Absolute Change Relative to 1987 from Adding One Force, Else Equal

A.4 Decomposition: Dynamics from Adding One Force at a Time

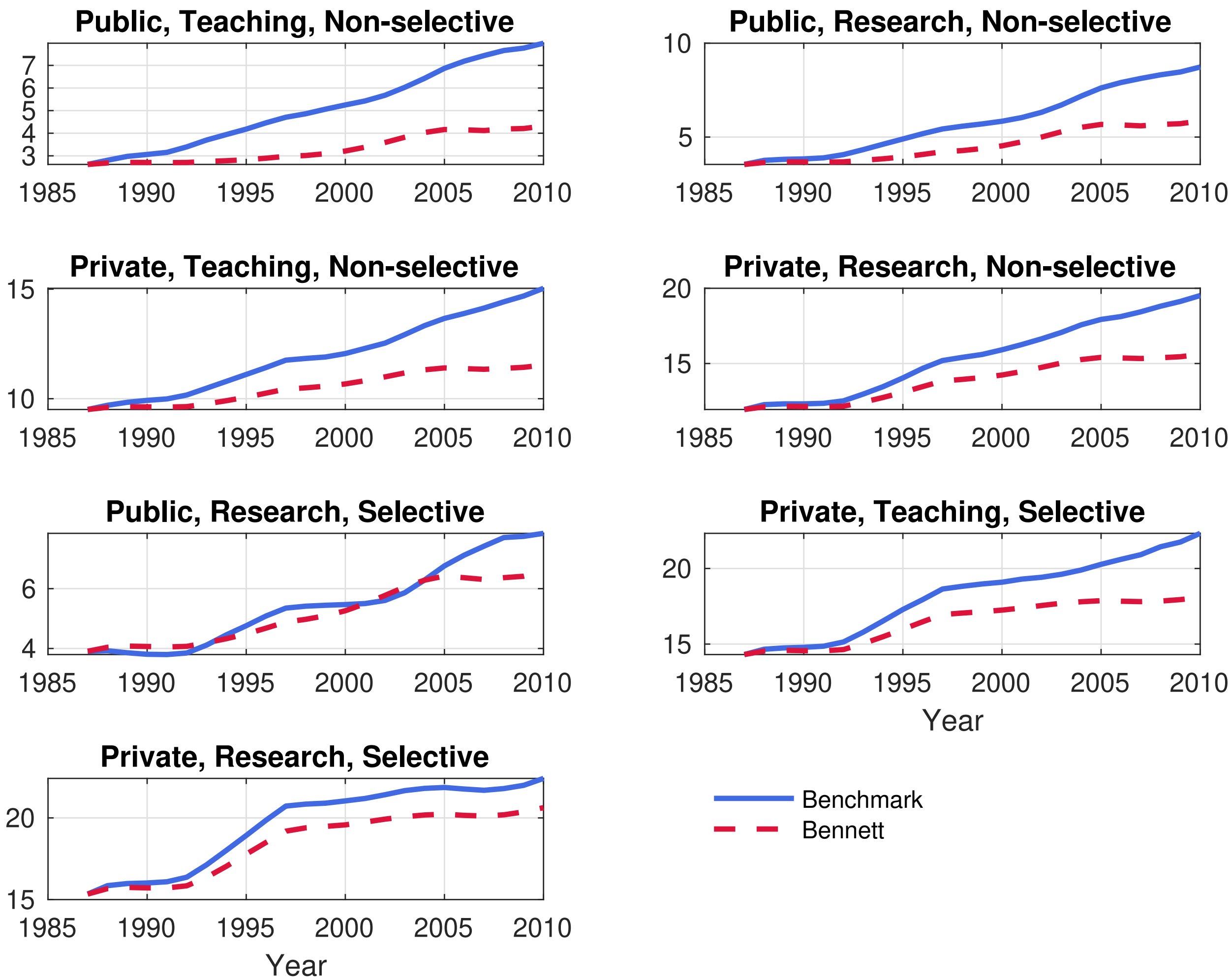


Figure 18: Net Tuition: Bennett Hypothesis Only

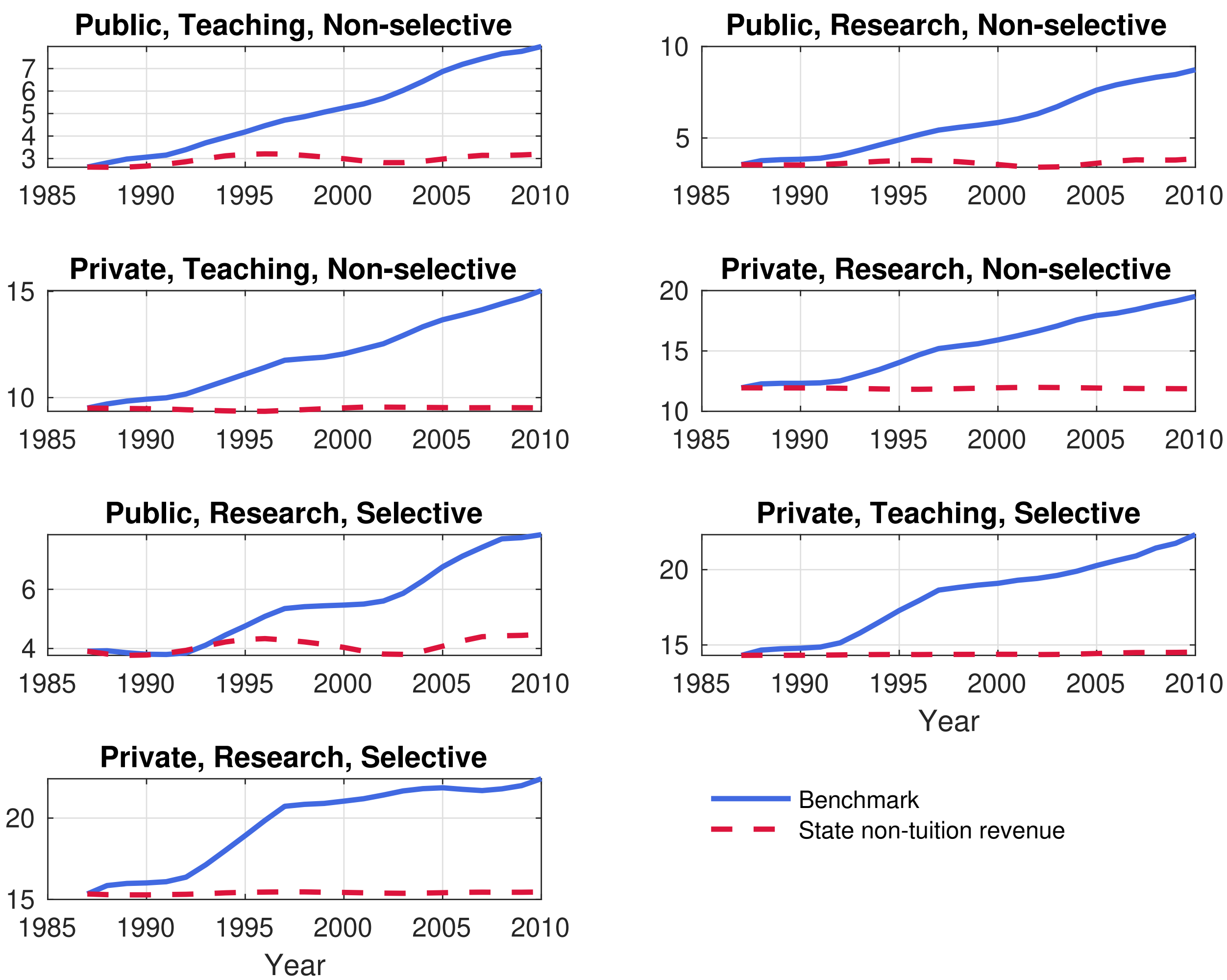


Figure 19: Net Tuition: State Support Only

A.5 Decomposition: Dynamics from Removing One Force at a Time

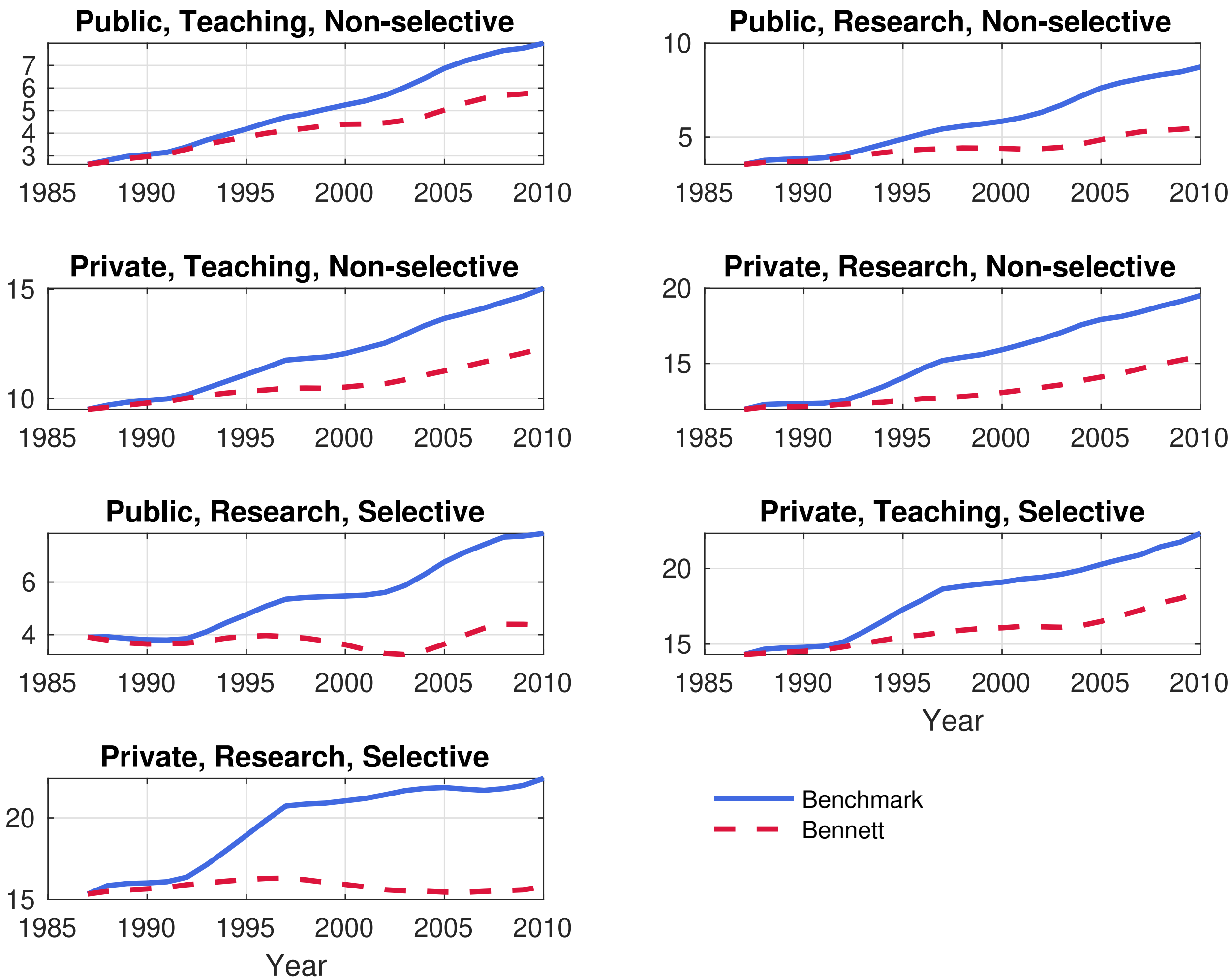


Figure 20: Net Tuition: FLSP Fixed to 1987

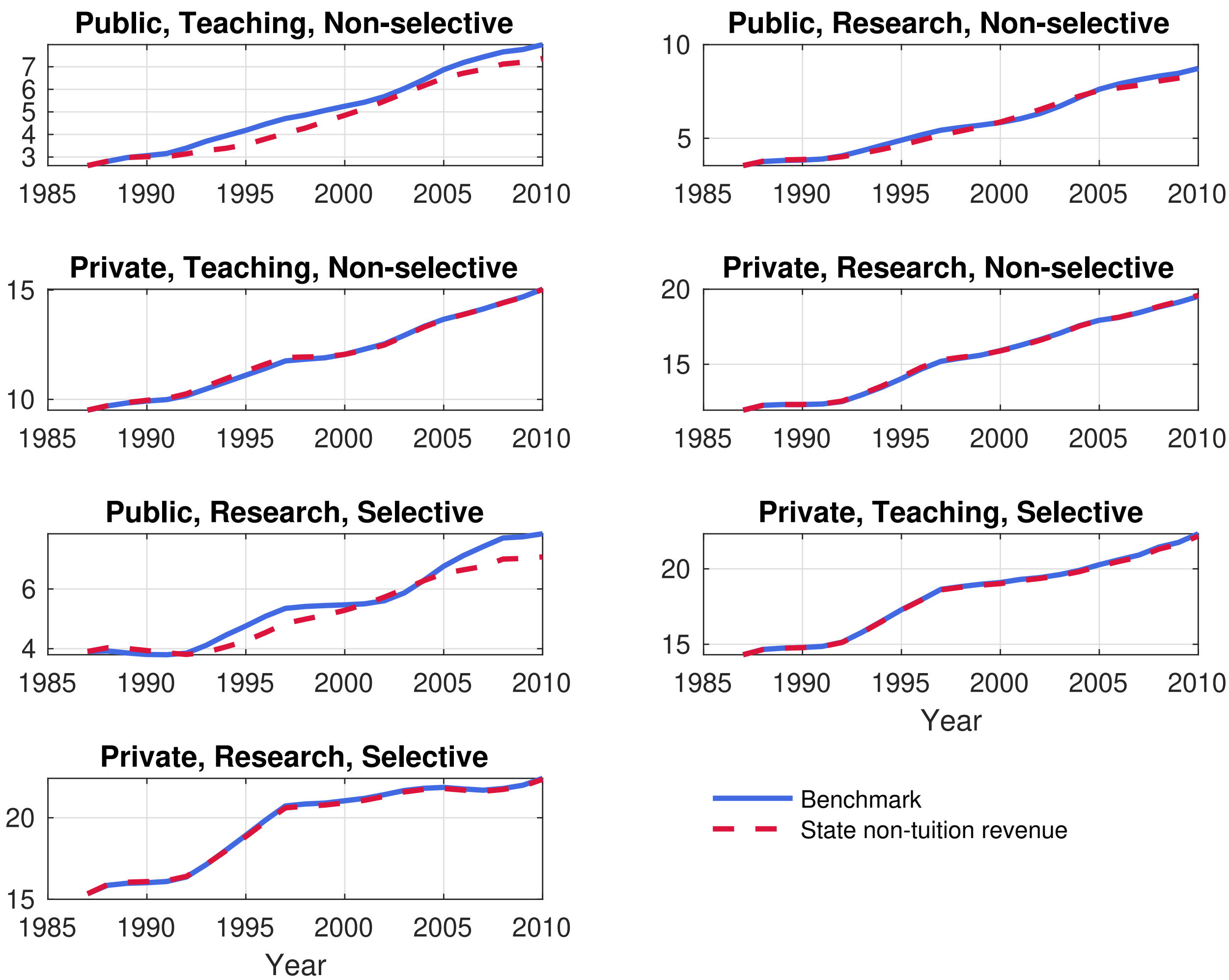


Figure 21: Net Tuition: State Support Fixed to 1987

A.6 Summary of Predictions: Stylized vs. Quantitative Models

The table below summarizes the comparison between some of the theoretical predictions of the stylized model from section 4.1 and the quantitative results from the full model.

		Changes in public support G					
		Simple intuition			Quantitative model		
College type	$\bar{G}$ change	T	pI	N	T	Expend.	N
Private, Research, Non-selective	+0.5	↓	↑	↑	−0.2	+0.3	+1.7
Private, Research, Selective	+8.3	↓	↑	↑	−1.2	+4.8	+5.8
Private, Teaching, Non-selective	−0.3	↑	↓	↓	+0.1	−0.1	+2.6
Private, Teaching, Selective	+0.2	↓	↑	↑	+0.6	+0.5	+1.6
Public, Research, Non-selective	+0.1	↓	↑	↑	−0.2	+0.2	+3.4
Public, Research, Selective	+3.1	↓	↑	↑	−0.8	+1.5	+0.9
Public, Teaching, Non-selective	−1.4	↑	↓	↓	+0.6	−0.5	+5.5
		Changes in private support E					
		Simple intuition			Quantitative model		
College type	$\bar{E}$ change	T	pI	N	T	Expend.	N
Private, Research, Non-selective	+1.4	↓	↑	↑	−0.6	+1.2	+1.3
Private, Research, Selective	+22.3	↓	↑	↑	−4.0	+13.5	+6.2
Private, Teaching, Non-selective	−0.4	↑	↓	↓	+0.0	−0.1	+14.3
Private, Teaching, Selective	+9.1	↓	↑	↑	−2.0	+4.9	−8.2
Public, Research, Non-selective	+1.6	↓	↑	↑	−0.5	+0.9	+2.4
Public, Research, Selective	+6.1	↓	↑	↑	−1.6	+3.1	+4.0
Public, Teaching, Non-selective	−0.1	↑	↓	↓	+0.3	+0.1	+1.1
		Bennet hypothesis changes					
		Simple intuition			Quantitative model		
College type		T	pI	N	T	Expend.	N
Private, Research, Non-selective		↑	↑	↑	+4.2	+3.1	+15.3
Private, Research, Selective		↑	↑	↑	+6.0	+3.5	+8.2
Private, Teaching, Non-selective		↑	↑	↑	+2.4	+1.9	+10.7
Private, Teaching, Selective		↑	↑	↑	+4.2	+2.6	+14.8
Public, Research, Non-selective		↑	↑	↑	+2.8	+1.6	+8.7
Public, Research, Selective		↑	↑	↑	+3.2	+1.8	+6.1
Public, Teaching, Non-selective		↑	↑	↑	+2.1	+1.2	+11.3

Note: financial variables are in thousands of 2010 dollars; enrollments are percent change from 1987 values.

Table 9: Predicted Changes Based on Simple Intuition and Actual Model Implied Changes

B Heterogeneous Pass-Through Rates

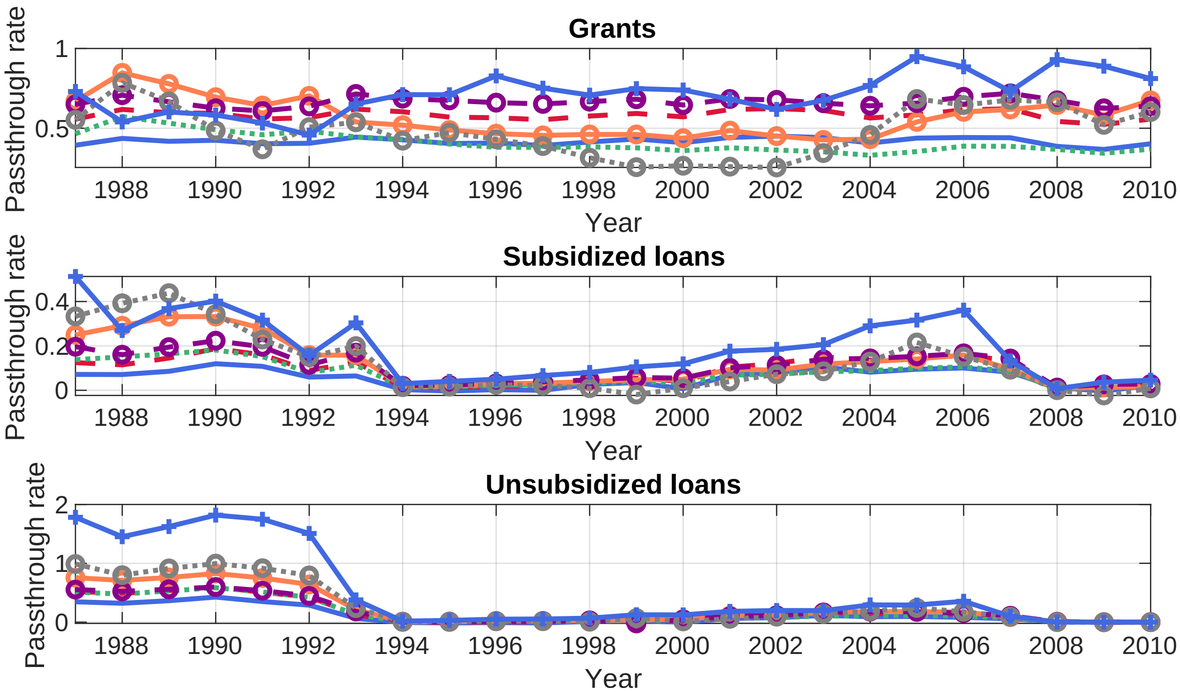


Figure 22: Heterogeneous Pass-Through Rates of Federal Financial Aid to Equilibrium Net Tuition

C Additional Details of College Data-Model Mappings

This section discusses how we selected our sample from the IPEDS/Delta Cost Project data and how we map the expenditure, revenues, and FTEs from the data to the model.

C.1 Sample Selection

Some institutions are "grouped" together, while some are not. For example, Indiana University is not a grouped institution, so we have data on each of the several campuses (Bloomington, South Bend, etc.). In contrast, the University of Missouri is a grouped institution, so we only have consolidated numbers for the University of Missouri system but not the individual campuses (Columbia, Kansas City, etc.).

For our sample selection in the Delta Cost Project (DCP), we require that the institution be present from 1987 to 2010, that they be a four-year, non-specialty institution according to the Carnegie Classification, that they be either public or a non-profit private, and that we are able to determine their school type.

C.2 Categorizing College Types

We categorize schools into one of potentially 8 different types, with one type not having any schools. The school types are all possible combinations of Public vs. Private (G/P), Research Intensive vs. Not Research Intensive (R/T), and Selective vs. Not Selective (S/N). (The type that does not exist is GTS.) Public vs. Private is a well known distinction. We say the school is research intensive if its 2005 Carnegie Classification is "very high research activity." We say a school is selective if their mean SAT score (either reported or imputed) is 1250 or higher (on a 1600 point scale). For schools without a reported SAT score, we impute a value by regressing SAT scores on a large number of school type dummies, along with log FTE and log FTE interacted with a public school dummy.[22] There are 1032 observations for this regression, with an R^2 of 0.61. We then use a linear prediction of the SAT score as the imputed value, which is applied to 232 schools, giving an SAT score for all of the 1264 schools. The mean of the SAT score is 1065 and the standard deviation is 130, hence being 1.5 standard deviations above the (institutional) mean classifies a school as selective.

C.3 Classifying College Balance Sheets

We categorize different components of the budget constraint into model-comparable measures. In particular, the model's budget constraint can be written

$$pC + pI + \kappa V = T + G + E$$

[22] Specifically, the 2005 Carnegie Classification, state, flagship status, land grant status, HBCU status, HSI status, and whether the institution is grouped or not.

where we are V denotes vacancies. Mapping the data's budget constraints to the model is complicated by five main issues:

1. Schools add institutional aid as both a revenue and expense. Consequently, letting A denote total institutional aid and $T^{sticker} = T + A$ denote sticker tuition and fees, the data's budget constraint is more like
$$pC + pI + \kappa V + A = T^{sticker} + G + E.$$
We deal with this by netting out A from both sides to get the model's budget constraint.

2. Schools in the data run surpluses and deficits. Specifically, the "gross operating margin," which is the difference between revenue and expenditures, can be positive or negative. We deal with this by including the the gross operating margin in E.

3. Local appropriations, grants, and contracts are mostly unreported prior to 2002. Consequently, to prevent a jump in G in 2002 (which would be driven just by accounting), we categorize local funding as part of E.

4. Financial variables that are reported as zero are converted to missing values (p. 14 DCP). Moreover, there are a large number of missing values for certain measures, including things like state support (where probably for private schools this is because they had no state support). We deal with this in the following ways:

   - First, we try to use larger categories of spending and revenue where there is less zero data and hence less messing.
   - Second, we compute E as a residual and put some of the most problematic measures (such as local support discussed above) into it. Private support is particularly well-suited for this because there are a number of problematic private non-tuition revenue measures such as endowment income (where many schools have no endowment).
   - Third, for state and federal support, we treat missing values as zeros.
   - Fourth, for the main expenditure categories (listed in Table 10), we impute values using predicted values from fixed effects regressions, which only allows us to impute values for schools where we have at least two observations for that school category.[23] We then sum over the subcategories, treating the resulting value as missing only if all the subcategories are missing.

[23]For the imputation, we express the financial variables as a share of total revenue (DCP variable eandg01_w_auxother_sum). We then use as independent variables net tuition and instruction (nettuition01 and instruction01, as shares of revenue), log FTEs, log FTEs squared, and all of these interacted with the academic year (as continuous) and schooltype (as discrete). Hence, our imputation procedure tries to get at the typical "portfolio share " of expenditures, allowing those shares to change over time and by type.

5. There is no subcategory of expenditures that only contains positing costs. Rather, there is a larger category, “academic support,” that includes admissions but several other things. Hence, we can only bound κV.

The categorization of the main balance sheet items of colleges, along with the DCP variable, are summarized in Table 10.

Our mapping of the individual expenditure components to pI or pC or κV is based on qualitative evaluation of their definitions. Table 11 highlights parts of the definitions of the specific variables we used.

While our mapping is qualitative, it also correlates in the way one would expect. In particular, in the model, I, as well as X, are “normal goods” in the sense that positive wealth effects increase them. In contrast, C is fixed in that it is normal operating expenses. Consequently, one would expect spending on I-type (C-type goods) to be increasing (be decreasing) in wealth. Now, we cannot isolate pure wealth effects in the data, but we can deliver three proxies: average ability, total spending per FTE, and research spending per FTE. Table 12 presents how the variables—as a share of total expenditures—are correlated with the three wealth proxies. Research is the most positively correlated with the wealth proxies, while the two custodial cost items (opermain01 and instsupp01) are negatively correlated. Student services, which we assume includes pI and κV, can be positively or negatively correlated depending on the measure, consistent with its conflating of different goods. Perhaps the most surprising is instruction, which is positively correlated (weaklty) with ability but negatively correlated with the other measures. However, we conclude that for the most part our qualitatively defined categories line up nicely with theoretically-guided quantitative results.

Summary statistics for each of the expenditure categories we use are presented in Table 13.

C.4 Mapping FTEs to Model-Consistent FTEs

In the data, we construct a model-consistent FTE number that

- matches our assumed initial mass of youth (which we take to be 1),
- matches our assumed enrollment rate (R), which reflects enrollment only of high school graduates, and
- matches the data’s FTE shares.

We do this because an important discrepancy between the model and the data is that we only allow youth to enroll in college (whom we think of as high school graduates), while in reality people also enroll at older ages.

From the NCES, we have the enrollment rate of high school graduates R. From DCP we also have FTE shares by school type θ_k, and from merged College ScoreCard data we have the 6-year

Balance sheet item	Model equivalent	Measurement method
Total Expenditures	$pI + pC + \kappa V + T^s - T$	(calculated)
Educ & General spending	Part of $pI + pC + \kappa V$	(calculated)
Instruction	Part of pI	instruction01
Research	Part of pI	research01
Academic support	Part of pI	acadsupp01
Public service	Part of pI	pubserv01
Student services	Part of $pI + \kappa V$	studserv01
Operation, maintenance of plant	Part of pC	opermain01
Institutional support	Part of pC	instsupp01
Grants and fellowships	$T^{sticker} - T$	(calculated)
Auxiliary and "other" spending	Part of E (reduces)	(in residual)
Total Revenue	$T^s + G$+part of E	
Sticker tuition and fees	T^s	tuition03
Net tuition and fees	T	nettuition01
Directly from student	Out of pocket for T	(not measured)
From government	Students apply to T	(not measured)
Pell	Students apply to T	(not used)
Local, state, and other federal	Students apply to T	(not used)
Grants and fellowships	$T^s - T$	(calculated)
Approp., contracts, excluding Pell	G and part of pC	
Federal grants, contracts (w/o Pell)	Part of G	federal10_net_pell
State approp., grants and contracts	Part of G	state03+state06
Local approp., grants and contracts	Part of E (see note)	(in residual)
Auxiliary and "other" revenue	Part of E	(in residual)
Endowment revenue, gifts	Part of E	(in residual)
Gross operating margin (rev. - exp.)	Part of E	(in residual)

Note: E is the sum of "Part of E" and pC is the sum of "Part of pC;" T^s denotes sticker tuition; a component of Educ & General spending is expenditures on scholarships and fellowships (see the text for details); local appropriations, grants, and contracts are excluded from G because they are inconsistently reported over time.

Table 10: College Balance Sheet

Variable	Category	Definition
instruction01	pI	Instruction - … Includes **general academic instruction**, … for both credit and non-credit activities. Excludes expenses for academic administration … Information technology expenses related to instructional activities [may be] included …
research01	pI	Research - … expenses for activities specifically organized to produce research outcomes … includes **institutes and research centers**, and **individual and project research**.… [possibly] included are information technology expenses related to research activities …
acadsupp01	pI	Academic support - … **libraries**, museums, and galleries; … academic **administration** (including academic **deans** but not department chairpersons); and formally organized and separately budgeted academic personnel development and course and curriculum development expenses. … [Possibly] included are information technology expenses …
pubserv01	pI	Public service - … **noninstructional services** beneficial to individuals and groups external to the institution. Examples are **conferences**, institutes, general advisory service, … includes expenses for community services, cooperative extension services, and **public broadcasting services**. Also includes information technology expenses [possibly] …
studserv01	$pI/\kappa V$	Student services - … **admissions**, registrar activities, and activities whose primary purpose is to contribute to students emotional and physical well-being and to their intellectual, cultural, and social development outside the context of the formal instructional program. Examples include **student activities, cultural events, student newspapers, intramural athletics**, … may include information technology expenses …
opermain01	pC	Operation and maintenance of plant - … **service and maintenance** related to campus grounds and facilities … [s]pecific expenses include **utilities**, fire protection, property **insurance**, and similar items. … does not include amounts charged to auxiliary enterprises, hospitals, and independent operations …
instsupp01	pC	Institutional support - … **day-to-day operational support** of the institution. … general administrative services, central executive-level activities concerned with management and long range planning, **legal and fiscal operations**, space management, employee personnel and **records**, **logistical services such as purchasing and printing**, and public relations and development …

Note: Emphasis added; definitions are from the Delta Cost Project data dictionary.

Table 11: Qualitative Categorization of Expenditure Types

	Wealth Effect Proxies		
	Ability	Expenditures	Research
research01	0.42	0.27	0.66
pubserv01	0.04	0.08	0.15
acadsupp01	0.06	-0.06	-0.09
instruction01	-0.06	-0.22	-0.25
studserv01	-0.24	-0.18	-0.32
opermain01	-0.23	-0.15	-0.20
instsupp01	-0.26	-0.15	-0.27

Note: the variables (research01, ...) are expressed as a share of total expenditures, while the proxies Expenditures and Research are real, per FTE measures.

Table 12: Pairwise Correlations by Expenditure Category Variable

completion rate δ_k^{total}. Given our assumption that graduation occurs after 5 completed years of college, we compute a model retention rate of $\delta_k = (\delta_k^{total})^{1/5}$ so that the model's completion rate is the same as the data's.[24] Then if e_k individuals enroll in schools of type k, there will be $N_k = e_k(1 + \delta_k + \delta_k^2 + \delta_k^3 + \delta_k^4)$ model FTEs. Define $\Delta_k := (1 + \delta_k + \delta_k^2 + \delta_k^3 + \delta_k^4)$, so $N_k = e_k\Delta_k$.

Stack e_k, θ_k, and Δ_k into column vectors e, θ, Δ. Define D as a diagonal matrix, all zero except for Δ_k on the diagonal.

Then $\frac{\Delta_k e_k}{\sum_{\tilde{k}} \Delta_{\tilde{k}} e_{\tilde{k}}} = \theta_k \Leftrightarrow \Delta_k e_k = \theta_k(\Delta' e)$ can be stacked into

$$D_{K\times K} e_{K\times 1} = \theta_{K\times 1} \underbrace{\Delta'}_{1\times K} e_{K\times 1}$$
$$\Leftrightarrow (D - \theta\Delta')e = 0$$

If e satisfies this, then the enrollments will be consistent FTE. The final restriction is $\mathbf{1}e = R$, which says that given the mass 1 of individuals, the enrollment rate R must equal the mass of enrollees (which is also R).

Once we have found an e solving this system of equations, we can get $N = De$. This model-consistent N measure satisfies our desired criteria. The last step is to convert this type-specific FTE count to a school-specific FTE count by dividing by the number of schools within the type.

[24] Note that the model allows for completion rates to vary by student type, but we calibrate the model in such a way that we necessarily match the aggregate.

	School Type						
	GTN	GRN	PTN	PRN	GRS	PTS	PRS
studserv01	1.2	1.1	2.7	2.1	1.4	4.5	3.3
	(0.6)	(0.5)	(1.4)	(0.9)	(0.7)	(1.8)	(2.8)
research01	0.4	3.9	0.5	2.5	10.3	0.9	14.5
	(2.0)	(3.5)	(1.3)	(5.9)	(5.8)	(1.1)	(15.7)
pubserv01	0.5	1.6	0.5	0.9	2.2	0.6	1.9
	(0.7)	(2.0)	(1.2)	(2.3)	(1.8)	(1.1)	(3.2)
acadsupp01	1.3	2.2	1.8	3.4	3.6	4.1	6.4
	(0.6)	(1.3)	(1.2)	(6.6)	(1.9)	(1.6)	(5.8)
instruction01	5.7	8.4	7.4	11.1	13.3	14.2	23.7
	(1.5)	(2.9)	(3.5)	(6.2)	(4.4)	(4.2)	(15.0)
opermain01	1.4	1.7	1.8	2.1	2.6	3.5	4.8
	(0.7)	(0.7)	(1.0)	(1.4)	(1.0)	(1.7)	(4.2)
instsupp01	1.8	2.0	4.1	4.4	2.8	6.6	6.9
	(1.0)	(1.0)	(1.9)	(2.7)	(1.0)	(2.6)	(4.3)
auxother_cost	2.5	5.8	4.2	5.6	14.7	7.4	23.4
	(2.4)	(8.4)	(3.2)	(8.7)	(14.8)	(2.5)	(34.3)
grants01	1.4	1.5	3.5	2.9	2.0	5.1	4.3
	(0.9)	(0.8)	(2.4)	(2.6)	(1.1)	(2.9)	(3.1)

Note: displayed as mean (standard deviations) in thousands of 2010 dollars.

Table 13: Summary Statistics for Subcomponents of Expenditure by School

C.5 Non-Tuition Revenue Parametrization

Figure 23 numerically illustrates what the parameterization delivers for different values of γ. The top panel plots the functional form used both for G and E, while the bottom panel plots the elasticity with respect to enrollment. Given our local solution approach, any γ can be supported in the sense of permitting an equilibrium that matches our targeted moments. However, the estimation implicitly assumes a constant elasticity. Hence, we choose γ to try to keep a near constant elasticity, which suggests a high value of γ, as can be seen in the bottom panel of figure 23. A second concern is that we want functions that look nearly quadratic to ensure that the quadratic approximation of the Newton-type solver is accurate. This consideration suggests a lower value of γ. We found $\gamma = 0.75$ was a high value that worked well computationally.

C.6 Vacancy Posting Costs

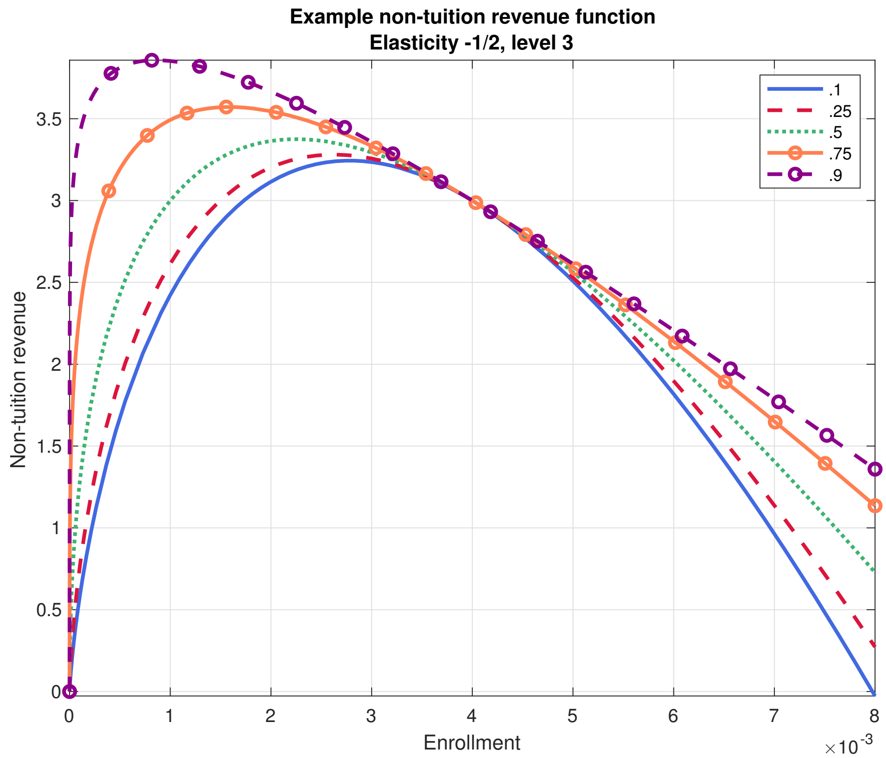
Because $\overline{n}$ corresponds to paying full price, we can discipline it using two pieces of evidence. First, we can use the fraction paying sticker price. This fraction varies by school, but at selective schools it is 40-60%. Second, we note that data limitations prevent us from zooming in beyond the 5 income brackets, and the largest bracket holds around 40% of students at PRS, PTS, GRS, and PRN. These lead us to select $\overline{n}$ such that the mass above $\overline{n}$ is 40%.

On the other end, we have $\underline{n}$, which corresponds to the threshold such that a student gets in "at cost." We note here that the parental income gradient levels off at at the first two income brackets. The mass in these two brackets is around 40% (except at GTN and GRN where it is closer to 60%), and we choose $\underline{n}$ to match this fraction.

We also have three sources of validation to lend credibility to this approach. The first comes from the college budget constraint. There we can compare the posting costs per FTE, $\kappa(\int v d\mu)/N$, with the data's student services category, which contains both admissions-related activity (which we think of as posting costs) and other expenditures. The results are displayed in table 14, and for each school type the results show that the equilibrium posting costs fall within the upper bound provided from the data. If the posting costs had exceeded student services, then we could have rejected our posting costs as unreasonably large. In reality, they seem fine by this measure.

The second validation comes from matching the parental income gradients. The comparison of the model and data's parental income gradients can be seen in table 16. For private schools, the model undershoots the gradient at selective schools and overshoots at non-selective colleges, but the magnitudes are not very far off. Interpretation for the public schools is problematic because the public school gradient in the data only depends on in-state tuition, but they may suggest that the posting costs are too large at GTN and GRN.

The final validation comes from matching the parental income distribution across schools. This distribution is influenced by posting costs because the greater κ is, the more high-parental-income students tend to pay. These moments are also displayed in table 16, and there the model matches



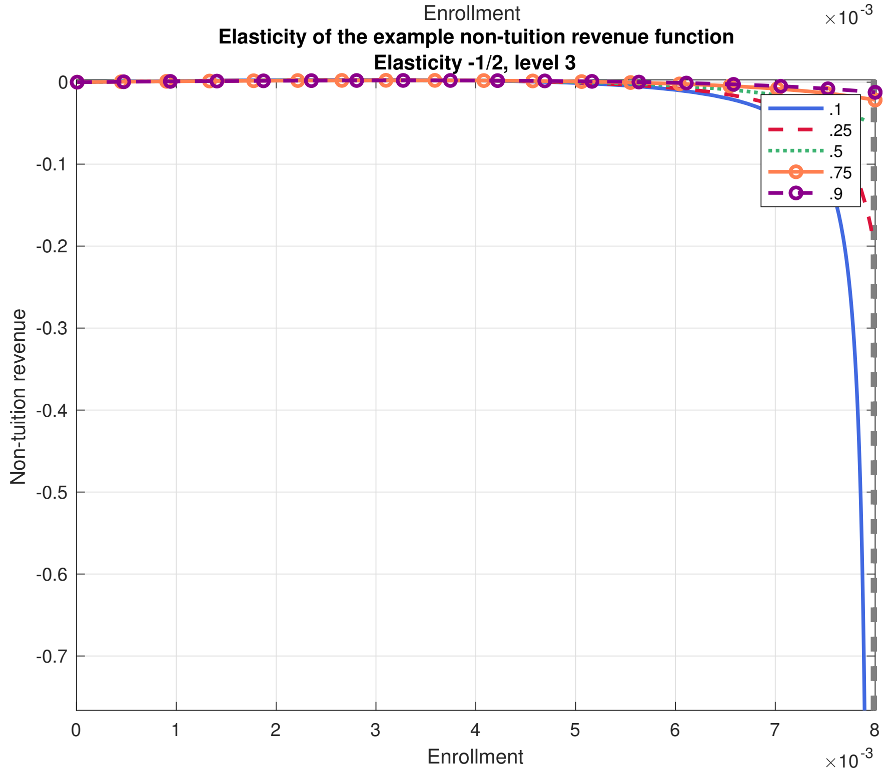


Figure 23: Non-Tuition Revenue Function Example

School type	Posting costs	Student services	Pct. of Stud. Serv.
GTN	0.5	1.2	44
GRN	0.7	1.1	63
PTN	0.8	2.7	29
PRN	0.8	2.1	41
GRS	1.1	1.4	75
PTS	1.8	4.5	40
PRS	1.9	3.3	59

Note: postings costs are per-FTE averages from the benchmark; student services is studserv01 per FTE in thousands of 2010 dollars over the sample.

Table 14: Posting Cost Validation: Comparison with IPEDS Admissions Category

well the ordering and magnitude of parental incomes (while somewhat exaggerating parental income at GRS and PTS).

C.7 Joint Parametrization

This section gives additional details on the joint parametrization procedure of section 3.4

C.7.1 Deriving Tuition Supply

The first step to arriving at the tuition supply curve is to take the expectation over enrollment (i.e. integrate over $\omega(m)v(m)\rho(\theta(m))/N$) of equation 2 that characterizes active submarkets, giving

$$T = -p\frac{q_N}{q_I}N + \kappa\frac{V}{N} + pI + pC'(N) - G'(N) - E'(N),$$

where T is average net tuition per student, V is total vacancies, and $\kappa V/N$ is the average markup. The ability discount term drops out. Substituting in the CES functional form for q gives

$$T = -p\frac{\alpha_N I^{1/\epsilon}}{\alpha_I N^{1/\epsilon}}N + \frac{\kappa V}{N} + pI + pC'(N) - G'(N) - E'(N). \tag{38}$$

Now, consider the budget constraint expressed in per FTE terms:

$$\kappa\frac{V}{N} + pI + \frac{pC(N)}{N} = T + \frac{G(N)}{N} + \frac{E(N)}{N}. \tag{39}$$

After combining equations 38 and 39 by substitution for T, one has

$$p\frac{\alpha_N I^{1/\epsilon}}{\alpha_I N^{1/\epsilon}}N = pC'(N) - \frac{pC(N)}{N} + \frac{G(N)}{N} - G'(N) + \frac{E(N)}{N} - E'(N)$$

Note that this expression can be rewritten as

$$p\frac{\alpha_N I^{1/\epsilon}}{\alpha_I N^{1/\epsilon}}N = N\frac{d(pC(N)/N)}{dN} - N\frac{d(G(N)/N)}{dN} - N\frac{d(E(N)/N)}{dN}.$$

Some simplification yields

$$p\frac{\alpha_N I^{1/\epsilon}}{\alpha_I N^{1/\epsilon}} = \frac{d\left(\frac{pC(N) - G(N) - E(N)}{N}\right)}{dN}$$

where the right hand side, $\Delta(N)$, is the derivative of average custodial costs net of non-tuition revenue. This expression implies that, absent college preferences over enrollment size, i.e. when $\alpha_N = 0$, the college is an average total cost (ATC) minimizer.

To further simplify, a little bit of algebra yields

$$\frac{\alpha_N}{\alpha_I} = \frac{\Delta(N)}{p}\left(\frac{N}{I}\right)^{1/\epsilon}.$$

Finally, replacing I with

$$I = \frac{1}{p}\left(-\kappa\frac{V}{N} - \frac{pC(N)}{N} + \frac{G(N)}{N} + \frac{E(N)}{N} + T\right)$$

from the budget constraint gives

$$\frac{\alpha_N}{\alpha_I} = \frac{\Delta(N)}{p^{1-1/\epsilon}}\left(\frac{N}{-\kappa\frac{V}{N} - \frac{pC(N)}{N} + \frac{G(N)}{N} + \frac{E(N)}{N} + T}\right)^{1/\epsilon},$$

which is the same as in equation 35 in the main text, except with the normalization $\alpha_I = 1$.

C.7.2 Identification and Model Fit

Figure 24 provides a visual summary of the parameter identification, depicting the sensitivity of different model moments to each of the parameters.

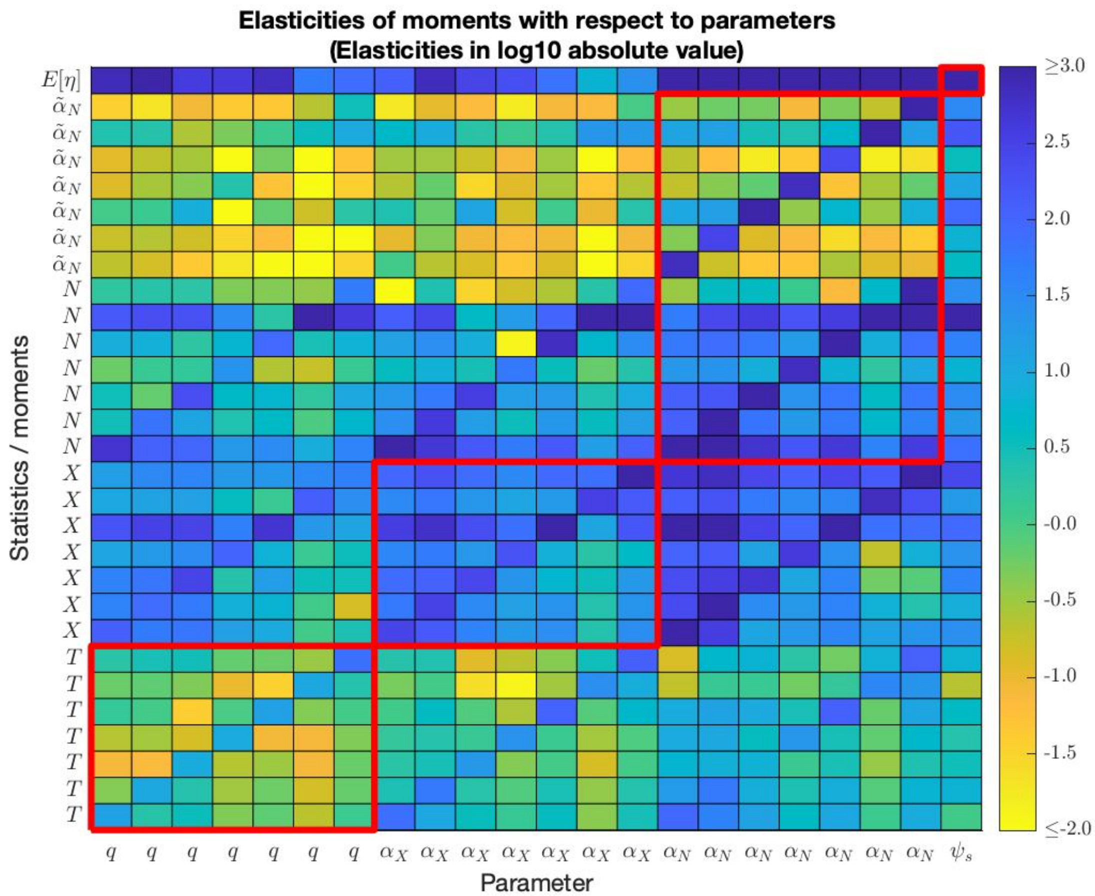


Figure 24: Estimated Parameter Identification

Structurally-estimated parameters varying by school

	GTN	GRN	PTN	PRN	GRS	PTS	PRS
Enrollment weight α_N, log	-20.6	-19.4	-25.0	-22.4	-18.9	-24.3	-22.4
Ability weight α_X, log	-3.9	-5.6	-4.4	-5.9	-6.8	-5.7	-8.5
Student valuation of quality q, initial s.s.	0.01	0.02	0.06	0.07	0.04	0.07	0.11
Residuals from projection on I and public	0.01	0.00	-0.01	-0.01	-0.01	0.02	0.01

Structurally-estimated parameters common to schools

Search intensity disutility ψ_s	0.0075
CES elasticity ϵ of quality (see note)	0.3

Independently-determined parameters varying by school

	GTN	GRN	PTN	PRN	GRS	PTS	PRS
Vacancy posting cost κ	2.1	3.7	6.2	8.3	8.8	36.4	44.1
Elasticity of G at N^*	0.10	0.10	0.37	0.37	0.10	0.37	0.37
Elasticity of E at N^*	0.12	0.12	-0.41	-0.41	0.12	-0.41	-0.41
Expenditure weight α_I (normalization)	1.0	1.0	1.0	1.0	1.0	1.0	1.0

Independently-determined parameters common to schools

Match elasticity γ	0.50
Independent fraction of earnings premium μ_λ	0.66
Independent fraction of continuation rate μ_δ	0.66

Note: The CES elasticity is manually adjusted to match enrollments in the terminal steady state.

Table 15: College Parameters

	Net tuition T		Sticker tuition		Expenditures		E^g revenue		E^p revenue	
School	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data
GTN	2.6	2.7	4.2	2.8	11.4	11.4	8.8	8.8	-0.1	-0.1
GRN	3.5	3.7	5.5	4	18.8	18.9	13.6	13.6	1.6	1.6
PTN	9.5	9.5	12.3	11.3	13.6	13.6	1.3	1.3	2.7	2.7
PRN	11.9	11.9	15.2	13.4	18.9	18.8	3.5	3.5	3.4	3.4
GRS	3.9	4	5.9	4.7	28.4	28.5	21.2	21.2	3.3	3.3
PTS	14.3	14.3	16.6	17.8	22.5	22.5	1	1	7.2	7.2
PRS	15.3	15.4	18.5	19.3	44.3	44.3	14	14	15	15

	Log FTEs		FTE share		College premium		Ann. dropouts		Accept. rates	
School	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data
GTN	-6.58	-6.58	0.27	0.27	1.32	1.32	0.16	0.16	0.91	0.67
GRN	-5.53	-5.53	0.34	0.34	1.52	1.52	0.12	0.12	0.74	0.74
PTN	-7.96	-7.96	0.16	0.16	1.41	1.41	0.11	0.11	0.51	0.72
PRN	-6.6	-6.59	0.05	0.05	1.73	1.73	0.09	0.09	0.43	0.73
GRS	-4.93	-4.93	0.1	0.1	1.9	1.9	0.08	0.08	0.52	0.55
PTS	-7.53	-7.53	0.01	0.01	2.04	2.04	0.03	0.03	0.23	0.45
PRS	-5.93	-5.93	0.08	0.08	2.6	2.6	0.04	0.04	0.2	0.38

	Rel. ability		Rel. ability s.d.		Relative p. inc.		P. inc. gradient*	
School	Model	Data	Model	Data	Model	Data	Model	Data
GTN	0.25	0.26	0.65	0.37	0.89	0.79	0.97	0.23
GRN	0.48	0.49	0.46	0.34	0.92	0.97	0.74	0.28
PTN	0.37	0.37	0.56	0.37	1.11	1.05	0.37	0.18
PRN	0.53	0.52	0.44	0.32	1.19	1.22	0.39	0.2
GRS	0.9	0.9	0.09	0.09	0.9	1.15	0.81	0.6
PTS	0.94	0.94	0.05	0.06	1.36	1.65	0.46	0.83
PRS	0.96	0.96	0.03	0.04	1.49	1.37	0.63	0.8

Note: The data's parental income gradient measure for public schools is based only on in-state tuition; FTEs are stated in model units; all financial variables are thousands of 2010 dollars.

Table 16: Model Fit (values in 1987)

D Earnings and Tax Estimates from the PSID

For earnings data, we use the cleaned data from Heathcote et al. (2010). Specifically, we begin with sample C of their data, which includes heads of households and their "wives" (in the particular PSID definition) when the individuals satisfy a few cleaning criteria (see their paper for more details). We then take their data, which is in constant 2000 dollars, and convert it to constant 2010 dollars using the CPI.

Our main variable is `redlabplus`, which is household labor income plus *private* transfers. We equivalize this in a simple way: dividing by 2 (1) if there is (is not) a wife present. Doing so preserves the aggregate numbers (which might be important for aggregate tuition) but accounts for risk-sharing and marriage/cohabitation patterns. We do the same thing for the variable `redpostgovinc`, which is household labor income plus private transfers and government transfers less taxes. Call these variables $e_{i,t}$ and $y_{i,t}$, respectively.

With this equivalized metric, we have one observation for each household, which is the same for the head or wife. We then keep only one observation for the household, effectively dropping wives when present. We then keep heads if their ages are between 18 and 65 and if the year is greater than or equal to 1987.

Because the model has a flat tax, we want the closest corresponding metric in the data. To this end, we regress

$$y_{i,t} = (1 - \tau)e_{i,t} + \varepsilon_{i,t}$$

to recover τ. The estimates are presented in table 17, and give an implied tax estimate of 0.184.

	Post-tax earnings
Pre-tax earnings	0.816
	(787.90)
Observations	39986
Note: t-statistics in parentheses.	

Table 17: Tax Estimate Regression

Then, we estimate earnings dynamics by running a first stage equation on observables and, in a second stage, modeling the dynamics of the residual. Specifically, our first stage is a cubic polynomial in age with year, educational attainment, and year by educational attainment with the dependent variable being log pretax earnings from above. The educational attainment variable is in 3 groups, weakly fewer than 12 years, strictly between 12 and 16 years, and weakly greater than 16 years. In the regression, we also require the additional sample restriction that the age less years of education is strictly greater than 6. That way 18 year olds who just completed their 12th year (high school) are excluded. The estimates are given in Table 18.

	Log pre-tax earnings	
Age/10	0.774	(4.17)
$\text{Age}^2/100$	-0.0706	(-1.58)
$\text{Age}^3/1000$	-0.00196	(-0.57)
Some College	0.270	(7.53)
College Grad	0.595	(18.18)
Constant	1.530	(6.13)
Observations	39308	
Year effects	Yes	
Year × education effects	Yes	
Note: t-statistics in parentheses.		

Table 18: First Stage Regression

In the second stage, we estimate dynamics with GMM. We use a permanent-transitory specification of

$$\nu_{i,t} = z_{i,t} + \varsigma_{i,t}$$
$$z_{i,t} = z_{i,t-1} + \varepsilon_{i,t}$$
$$\varsigma_{i,t} \sim N(0, \sigma^2_\varsigma)$$
$$\varepsilon_{i,t} \sim N(0, \sigma^2_\varepsilon).$$

where $\nu_{i,t}$ is the residual from the first stage. We follow the identification strategy of Heathcote et al. (2010) by looking at two year changes (because the PSID earnings are biannual after 1996) and in levels. See equation 5 and 6 of their paper. This procedure gives an estimate by cohort and year. We then take the average across cohorts within each year, and then the average across years. Heathcote et al. (2010) produce estimates year by year which have a mean very close to our point estimate (see figure 18 of their paper, on page 40).

E NLSY97

The NLSY97 includes very detailed information on an individual's schooling experience for different schools, colleges, terms, and years.[25] In particular, the survey collects data regarding the respondent's educational experience prior to high school, in high school, and in college. Information is stored in different types of variables and rosters are used to store retrospective and current information about all schools and colleges the respondent has attended since the last interview. Since we are primarily interested in an individual's aggregate schooling experience, i.e. how many

[25] This section was prepared in large part by our research assistant, Kathrin Ellieroth, whom we thank.

years of schooling does the individual have in total, how much tuition did the respondent spend on average/in total, etc., we explain in the following how we take the very detailed NLSY97 data that allows for multiple colleges/years/terms and process it into a format that allows us to observe all educational information for each individual.

In order to understand the way we process the data, let us briefly describe how NLSY97 data on education is organized. In round 1, the NLSY collects data about the current school (K-12 or college) attended as well retrospective questions regarding the individual's classes, grades, GPA, and diploma in high school if the individual has completed high school at the time of the round 1 interview. In all following rounds, the NLSY97 creates a roster for each respondent to collect information for both current and all previously enrolled in schools. The roster contains information on the periods of enrollment at each school, the level of school attended, and the round in which the school was first reported.[26] Thus, the way to track schools in the NLSY97 is to use the variable `NEWSCHOOL_PUBID_XX_YYYY` which gives a unique identification number (for that individual) for each school attended. This identification number is equal to three digits which identifies the school and the round in which the school was attended. For example, an id equal to 201 means that the respondent attended school 01 in round 2. So if `NEWSCHOOL_PUBID_03_1998`= `NEWSCHOOL_PUBID_01_2002`, then that means that all the `COLL03` variables in 1998 correspond to the `COLL01` variables in 2002.

We are interested in a person's schooling experience, e.g. did the individual ever obtain a BA, what was the average net tuition, etc., so we will describe the steps we do to process and aggregate the data by each respondent.

1. In general, when loading the data, the NLSY data consists of three types of variables (left), which are processed into new variables formatted in the following way (right)
   (a) `V_YYYY`: variable V from year YYYY $\rightarrow$ *pers(i).v*: single variable v
   (b) `V_XX_YYYY`: variable V from college XX and year YYYY $\rightarrow$ *pers(i).schoolinfo(is).v*: row vector containing information from variable v for school *is* and person i for each year in a different column
   (c) `V_XX_TT_YYYY`: variable V from college XX, term TT, and year YYYY $\rightarrow$ *pers(i).schoolinfo(is)*: row vector containing information from variable v for school *is* and person i for each term in a different column
2. After processing the three types of variables, we need to aggregate the information for each individual.
   - For the yearly data on colleges (the `V_XX_YYYY` from above), there is usually one relevant statistic we seek to find such as did the individual ever work on a BA (this is usually reported as 1 in every interview). In this example we would compute

[26] See https://www.nlsinfo.org/content/cohorts/nlsy97/topical-guide/education for more details.

pers(i).schoolinfo(is).maxBAwork=max{*pers(i).schoolinfo(is).BAwork*},
which converts the vector to a useful summary (scalar) statistic.

- For the term data on colleges (the `V_XX_TT_YYYY` from above), we also take into consideration whether the respondent was enrolled full-time or part-time. Therefore, we compute averages per term while weighting by enrollment with part-time being counted as 1/2. This is consistent with the concept of full-time equivalent. Once we obtain averages per term after weighting accordingly, we multiply the per term average by the number of terms per year to get annual amounts and save it in a variable of type *pers(i).schoolinfo(is).v* where each column correspond to a different year.
- To further aggregate the information for each respondent, we compute the total/average of each variable by college to get the total per school per FTE year. Then we sum across all schools and divide by the total of FTE years to get an average measure per individual.

In the following subsections, we describe in detail how we process each variable by variable type.

E.1 Yearly Variables

- *pers(i).abil*:
  We take the ASVAB score as reported in NLSY and convert it onto the 0 to 1 range by dividing `ASVAB_MATH_VERBAL_SCORE_PCT` by 10^5.

- *pers(i).pinc*:
  In order to compute this variable we combine information from parents' earnings and business income. Information on earnings and income is collected in a categorical variable which reflects income brackets, e.g. the respective variable equals 1 if earnings/income are between \$0 and \$5000. For the earnings variable, this is the first bracket, for income, however, the first bracket collects losses, and then the second bracket is equal to the first earnings bracket. Therefore, in the case of income losses we recode the variable to be zero, and then shift the brackets so that for both income and earnings, the first bracket captures \$0 to \$5,000.
  If earnings are unknown or refused, we use the estimate provided by NLSY instead. Lastly, we sum parental income from all sources and deflate the data using the 2010 CPI.

- *pers(i).age0*:
  This variable indicates the individual's age as of 12/31/1996.

- *pers(i).hhinc*:
  This variable captures the household income. We recode all refusals/ don't know/skips into NaNs and deflate the data using the 2010 CPI.

- *pers(i).efc*:
  This variable indicates the expected family contribution (EFC), it uses adjusted parental

income and is converted to 2009 dollars. We use the same conversion as in the model, which comes from the approximation by Epple et al. (2017).

- *pers(i).age*: Current age of respondent
- *pers(i).income*: Gross income, deflated
- *pers(i).income2*: Family income, deflated
- *pers(i).kidslt6*: Children under 6 years present in hh
- *pers(i).kidslt18*: Children under 18 years present in hh
- *pers(i).hhsize*: Household size
- *pers(i).enrolledatDLI*: Whether respondent was enrolled at DLI (date of last interview)
- *pers(i).reenrolled*: Whether the student reenrolled.
- *pers(i).schoolQ*:

E.2 College Variables

Variables regarding the schooling experience at different colleges are formatted as row vectors. Each row of the row vector contains information for the respective variables for a different college. If the information furthermore varies by year, then each column of the row vector corresponds to a particular survey round. For example, for the variable *pers(i).schoolinfo(is).BAwork*, which is equal to 1 if the student worked towards a BA in the survey round in that school, the data would be stored as follows:

$$\textit{pers(i).schoolinfo(is).BAwork} = [1 \;\; 1 \;\; 1 \;\; 1 \;\; 1]$$

i.e. the respondent reported working towards a BA at school "*is*" for 5 consecutive survey rounds.

- *pers(i).schoolID*:
  In order to store information in the above mentioned format, we need a way to identify all colleges/schools uniquely. For each individual we save the unique values from *NEWSCHOOL_PUBID* as a vector, so if *pers(i).schoolID* is a length 3 vector, this means we found 3 schools.

The following variables contain information for each unique school attended/enrolled in using the generated variable *pers(i).schoolID* to identify each unique school. Therefore, the length of each of the following row vectors is equal to the number of unique schools attended.

- *pers(i).schoolinfo(is).schoolGRP*:
  This variable captures the type of each school *is*, in particular, it takes the following values: = 0 if elementary to high school, = 1 if 2-year college, and = 2 if 4-year college

- *pers(i).schoolinfo(is).is4Ycoll*: indicates whether the respondent is enrolled in a 4-year college. We generate this from the previous school type variable being equal to two.

- *pers(i).schoolinfo(is).colltype*: equal to `CV_COLLEGE_TYPE` for that school.

- *pers(i).schoolinfo(is).coll_isnonprof*: = 1 if public (non profit), = 2 if private non-profit, = 3 if private for profit

- *pers(i).schoolinfo(is).coll_ispub*: = 1 if public

- *pers(i).schoolinfo(is).coll_isprivnonprof*: = 1 if private non-profit

- *pers(i).schoolinfo(is).BAwork*: whether was working on a BA.

- *pers(i).schoolinfo(is).grad*: = 1 if respondent left because graduated and received degree, = 0 if respondent left because of some reason other than graduating

- *pers(i).schoolinfo(is).grad2*

- *pers(i).schoolinfo(is).termtype*:

- *pers(i).schoolinfo(is).termsperyear*: This variable is important in obtaining average/total amounts per year for each individual. The variable = 2 if the school is on a semester or trimester system since this implies 2 terms per year (See https://en.wikipedia.org/wiki/Academic_term for more information). If the school is on a quarter system, the variable equals 3 and it implies that the individual attended 3 terms.

E.3 College/Term Variables

These variables are stored in a row vector format as well. Each column of the row vector contains information for the respective variable for a different term and the length of the row vector will be as long as the number of terms reported. For example, for the variable *pers(i).schoolinfo(is).full* (whether the respondent is enrolled full-time or part-time), the data looks like

$$\textit{pers(i).schoolinfo(is).full} = [0.00 \quad 1.00 \quad 1.00 \quad 1.00 \quad 1.00]$$

This individual has five terms reported, the first one he/she was enrolled part-time and for the remaining four terms the individual was enrolled full-time.

- *pers(i).schoolinfo(is).full*: = 1 if respondent is enrolled full-time in the particular term, = 0 if part-time enrolled. The underlying variable begins with `YSCH_21800`.

- *pers(i).schoolinfo(is).anychgfin*: This variable only applies to term > 1 and asks whether there was any change in financing. The underlying variable is `YSCH_22005`.

For the following education finance variables, two cases arise. (i) If the respondent is in the first term or in a higher term and a change in financing occured and a valid skip was reported, we change the value of the variable to zero, since in this case, the skip means the respondent did not receive any transfers. (ii) If the term is two and up and there was no change to financing since the last term, we just carry over the information from the previous term.
All variables are deflated.

- *pers(i).schoolinfo(is).famtran*: categorical variable which captures the transfers from family/friends the respondent is not expected to repay for attendance at each school in each term. The underlying variable begins with `YSCH_24600`.

- *pers(i).schoolinfo(is).famloan*: categorical variable which captures loans from family/friends to help pay for attendance at each school in each term. The underlying variable begins with `YSCH_24700`.

- *pers(i).schoolinfo(is).grant*: categorical variable which captures the amount of financial aid the respondent received in grants, tuition or fee waivers or reductions, and fellowships or scholarships for each school in each term. The underlying variable begins with `YSCH_25400`.

- *pers(i).schoolinfo(is).loans*: categorical variable which captures the amount of government subsidized loans or other loans while attending each school in each term. The underlying variable begins with `YSCH_25600`.

- *pers(i).schoolinfo(is).workstud*: The underlying variable begins with `YSCH_26000`.

- *pers(i).schoolinfo(is).employaid*: The underlying variable begins with `YSCH_26200`.

- *pers(i).schoolinfo(is).otheraid*: categorical variable which captures other types of assistance while attending each school in each term. The underlying variable begins with `YSCH_26400`.

- *pers(i).schoolinfo(is).oop*: categorical variable which captures amount paid out of own pocket from earnings or savings at each school in each term. The underlying variable begins with `YSCH_26500`.

E.4 Aggregating Variables by School for Each Individual

Ultimately, we are interested in education variables aggregated for each respondent across terms/years and for each school.
So, in the following we summarize how we aggregate each of the different types of variables.

1. **College variables**
   First, we compute aggregate summary statistics for the following characteristics that should not vary across years, but are reported each year, by taking the median for each person and each school:

   - *pers(i).schoolinfo(is).medcolltype* = median(*pers(i).schoolinfo(is).colltype*)
   - *pers(i).schoolinfo(is).medcoll_isnonprof* = median(*pers(i).schoolinfo(is).coll_isnonprof*)
   - *pers(i).schoolinfo(is).medcoll_ispub* median(*pers(i).schoolinfo(is).coll_ispub*)
   - *pers(i).schoolinfo(is).medcoll_isprivnonprof* = median(*pers(i).schoolinfo(is).coll_isprivnonprof*)

2. **College/Term variables** Next, we use the variables that vary across terms for each school attended for each individual and average across terms for each school and each individual. We observe whether the respondent was enrolled full-time or part-time and weigh variables accordingly.

   - *pers(i).schoolinfo(is).avgsticker*:
     This variable is an estimate of the average sticker price of each school attended. We start by getting the FT/PT status for each term and assign a weight of 1 if the student was enrolled full-time in the term and a weight of 0.5 if the student was enrolled part-time in the term. Next, we sum the total number of full-time terms based on the full-time/part-time classification.
     We estimate the average sticker price as the sum of the following 8 variables:
     famtran, *famloan*, *grant*, *loans*, *workstud*, *employaid*, *otheraid*, *oop*.
     For each of the 8 variables, we compute the average amount per term by summing (while weigthing by FT/PT status) across all terms and then dividing by the total number of FTE terms. (We exclude NaNs from the calculation of the averages.) Lastly, we sum up the weighted averages of all of the eight variables to obtain the average sticker price per school per term for each student.
   - *pers(i).schoolinfo(is).avgnet*:
     Net tuition is the difference between the sticker price and the total grants.
   - *pers(i).schoolinfo(is).avgtermsperyear*:
     Terms per year should be/are tied to the college, so they should be invariant to the term and we simply take the average (excluding NaNs).

- *pers(i).schoolinfo(is).yearsAttendedFTE*:
  We compute how many "FTE" years each person attended a school by dividing the total number of FTE terms by the average number of terms per year
- *pers(i).schoolinfo(is).maxBAwork*:
  We use the information from the variable *pers(i).schoolinfo(is).BAwork*, which is coded 1 if the person was working toward a BA at the respective school, and 0 otherwise. We then obtain *pers(i).schoolinfo(is).maxBAwork* by simply taking the max over the row vector (each column indicates a term at this school) of the dummy variable and the new variable tells us whether the individual ever worked towards a BA at each school.
- *pers(i).schoolinfo(is).maxgrad*:
  We compute this variable in the same way as the previous one, we take the max of the row vector *pers(i).schoolinfo(is).grad* and if this is equal 1 it means the respondent graduated from this school and 0 otherwise.
- *pers(i).schoolinfo(is).maxgrad2*: Same calculation as the previous two variables.
- *pers(i).schoolinfo(is).maxBArecv*: Similar calculation as the previous variables. This variable captures whether the individual worked towards a BA at the school and graduated and received a degree. We compute this by checking whether *.maxBAwork* and the max of *pers(i).schoolinfo(is).grad* or *pers(i).schoolinfo(is).grad2* are both equal to 1.

3. **College/Year/Term variables**
   After we obtained averages per term per year for each school as well as averages per year per school, the last thing we need are aggregates across schools, terms, and years per student. So that we have variables capturing an individual's average education and college experience, i.e. variables *pers(i).avgv* for each student i and variable v.
   In order to compute averages, we loop over all relevant schools and add up total numbers for each variable and total years and divide by total years to receive the averages.
   We compute the following aggregates per student for respondents who ever enrolled at a 4-year school and were working towards a BA (We can furthermore distinguish between all 4-year school and non-profit 4-year schools only.):

   - *pers(i).totyearsAttendedFTE*: We sum over all years the respondent was enrolled in full-time status.
   - Financial variables: *pers(i).avgavgsticker*, *pers(i).avgavgnet*, *pers(i).avgavgfamtran*, *pers(i).avgavggrant*, *pers(i).avgavgloans*
     Since all financial variables are computed as averages per terms, we do the following for each variable to compute averages for each student across terms, years, and schools: First, we multiply each financial variable by the number of terms per year and the number of

years and then we divide them by the total years enrolled in full-time status. Thus, we get the mean weighted by terms across schools and years for each financial variable.

- *pers(i).avgmedcoll_ispub*: We simply take the raw mean over all schools and years.
- *pers(i).maxmaxgrad*, *pers(i).maxmaxgrad2*, *pers(i).maxmaxBAwork*, *pers(i).maxmaxBArecv*: To obtain these variables, we simply take the max over all schools for each individual.
- *pers(i).everWorkForBABS*:
  = 1 if the respondent ever attended a 4-year college and worked towards a BA, = 0 otherwise
- *pers(i).everGrad*:
  = 1 if the respondent ever graduated and received a degree from any of the school he/she attended, = 0 otherwise
- *pers(i).everRecvBABs*:
  = 1 if the respondent ever graduated and received a BA/BS degree from any of the schools he/she attended, = 0 otherwise

E.5 Processed Data

In the end, we the obtain a processed data matrix which contains the following variables for each student:

1. Per individual:
   - *abil*, *pinc*, *age0*, *hhinc*, *efc*
2. Per survey round per individual:
   - *year*, *age*, *income*, *income2*, *kidslt6*, *kidslt18*, *hhsize*
3. Per school per term/per round per individual:
   - *schoolIDs*, *schoolGRP*, all *schoolinfo* variables
4. Aggregates/Averages per individual:
   - *totyearsAttendedFTE*, *avgavgnet*, *avgavgsticker*, *avgavgfamtran*, *avgavggrant*, *avgavgloans*, *avgmedcoll_ispub*, *maxmaxgrad*, *maxmaxgrad2*, *maxmaxBAwork*, *maxmaxBArecv*, *everWorkForBABS*, *everGrad*, *everRecvBABS*, *avgeinc*

E.6 Summary Statistics

Table 19 summarizes key variables, both unconditional, conditional on enrolling, and conditional on graduating.

	(1) Mean	(2) Mean	(3) Mean	(4) Mean	(5) Mean	(6) Mean
Enrolled	0.428	1	1	0.460	1	1
Graduated	0.300	0.714	1	0.325	0.719	1
Years college	1.628	3.867	4.488	1.779	3.919	4.535
Sticker tuition estimate (real)		14.10	16.08		14.33	16.29
Net tuition estimate (real)		8.792	10.16		8.933	10.22
Family transfers (real)		3.657	4.588		3.641	4.481
Grants (school or gov.) (real)		5.311	5.920		5.401	6.069
Loans (private or gov.) (real)		3.197	3.515		3.301	3.647
Took out a loan		0.560	0.604		0.587	0.634
Ability				0.506	0.677	0.709
Household income in 1996 (real)				73.37	92.71	99.10
EFC (real)				10.86	15.48	17.04
Observations	6536	2616	1868	4102	1778	1278

Note: All estimates are means from the NLSY97 data, unweighted using the cross-section sample.
In the full sample, 21.1% are missing ASVAB scores; 26.6% are missing household income;
and 40.1% are missing ASVAB or household income.
Enrollment is defined as any enrollment in a 4-year nonprofit college while working towards a BA/BS or MA.
Sticker and net tuition are approximate and computed by adding aid from various sources.
All financial variables are in thousands of 2010 dollars.

Table 19: NLSY97 Data Summary

F Summary Statistics by School Type

School type	1987 financial measures and shares				
	T	Expend	G	E	FTE share
Public, Teaching, Non-selective	2.7	14.9	9.2	3.0	0.25
Public, Research, Non-selective	3.7	25.9	13.7	8.5	0.36
Private, Teaching, Non-selective	9.6	19.9	1.4	9.0	0.15
Private, Research, Non-selective	11.9	27.0	3.8	11.3	0.05
Public, Research, Selective	4.0	39.5	21.3	14.3	0.10
Private, Teaching, Selective	14.3	32.6	1.0	17.3	0.01
Private, Research, Selective	15.5	72.2	14.1	42.7	0.08

School type	2010 financial measures and shares				
	T	Expend	G	E	FTE share
Public, Teaching, Non-selective	6.4	17.8	7.9	3.5	0.25
Public, Research, Non-selective	8.8	35.5	14.9	11.8	0.35
Private, Teaching, Non-selective	15.1	22.5	1.1	6.3	0.18
Private, Research, Non-selective	20.3	34.0	4.1	9.6	0.05
Public, Research, Selective	10.0	65.3	29.1	26.2	0.09
Private, Teaching, Selective	24.3	50.0	1.2	24.5	0.01
Private, Research, Selective	23.7	115.4	22.0	69.6	0.07

School type	Additional 2010 measures				
	Rel. premium	Comp. rate	P. inc.	Rel. X	# schools
Public, Teaching, Non-selective	0.83	0.47	53	0.26	242
Public, Research, Non-selective	0.95	0.58	65	0.48	129
Private, Teaching, Non-selective	0.89	0.58	71	0.34	639
Private, Research, Non-selective	1.08	0.65	81	0.51	50
Public, Research, Selective	1.19	0.73	77	0.90	20
Private, Teaching, Selective	1.29	0.89	110	0.94	36
Private, Research, Selective	1.63	0.87	91	0.96	42

Note: Monetary values are in 2010 dollars deflated using the CPI.

Table 20: Data Measures in 1987 and 2010

G Additional Empirical Support for the Model

G.1 Tuition Discounting

Table 21 provides some empirical evidence that colleges discount tuition based on both ability and parental income. Appendix G reports similar results broken out by ability decile, as well as additional regressors of net tuition or sticker tuition.

	Discount (% off)
Ability	7.472**
Parental income in 1996 (real)	-0.0972***
Constant	34.15***
Observations	1609
R^2	0.047

* $p < .1$, ** $p < .05$, *** $p < .01$

Table 21: Tuition discounting (source: IPEDS)

	(1) % off	(2) % off	(3) % off	(4) % off	(5) % off	(6) % off
Ability	7.472**	12.82***	2.573			
	(2.29)	(4.00)	(0.78)			
95th Abil pctile				8.576***	13.27***	4.468
				(3.13)	(4.95)	(1.61)
90-95th Abil pctile				4.445	6.866**	2.329
				(1.57)	(2.50)	(0.83)
75-90th Abil pctile				-0.474	1.724	-2.224
				(-0.22)	(0.82)	(-1.03)
50-75th Abil pctile				-1.219	-0.555	-1.934
				(-0.59)	(-0.28)	(-0.94)
Parental income in 1996 (real)	-0.0972***	-0.0776***	-0.102***	-0.0982***	-0.0782***	-0.102***
	(-8.89)	(-7.22)	(-9.43)	(-9.01)	(-7.33)	(-9.51)
Net tuition estimate (real)		-0.724***			-0.748***	
		(-10.48)			(-10.85)	
Sticker tuition estimate (real)			0.363***			0.348***
			(7.10)			(6.78)
Constant	34.15***	35.81***	32.44***	38.48***	42.48***	34.94***
	(14.27)	(15.43)	(13.69)	(21.55)	(24.09)	(19.02)
Observations	1609	1609	1609	1609	1609	1609
R^2	0.047	0.108	0.076	0.055	0.119	0.081

t statistics in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Table 22: Tuition discounting (source: NLSY97)

G.2 The Role of Student Characteristics

	(1) Enrolled	(2) Graduated	(3) Took out a loan
Ability	0.837***	0.405***	0.165***
	(35.32)	(9.34)	(3.44)
Household income in 1996 (real)	0.00124***	0.000717***	-0.00142***
	(10.99)	(4.84)	(-8.67)
Constant	-0.0548***	0.367***	0.607***
	(-3.94)	(11.69)	(17.48)
Observations	4102	1888	1867

t statistics in parentheses

Note: (2) and (3) are conditional on enrollment.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 23: How select variables vary in initial conditions

Table 24: Correlations

Variables	Enrollment	Parental income (real)	Ability (ASVAB pctile)
Enrollment	1.000		
Parental income (real)	0.299	1.000	
Ability (ASVAB pctile)	0.475	0.310	1.000

Table 25: Correlations conditional on enrollment

Variables	Graduation	Parental income (real)	Ability (ASVAB pctile)
Graduation	1.000		
Parental income (real)	0.118	1.000	
Ability (ASVAB pctile)	0.211	0.187	1.000