Supplement to
Selective College Access and Intergenerational Mobility

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Abstract

This document contains supplementary material for the paper "Selective College Access and Intergenerational Mobility" by the same authors.

JEL: J24; J31; I23; I26

Key Words: college quality; human capital; selective college access; intergenerational mobility; income-adjusted admissions

1 Calibration

This section describes the calibration in detail.

High school graduates draw a vector of endowments (a, p, g, h_1) from a Gaussian copula. In order to reduce the number of calibrated parameters that govern endowment correlations, we proceed as follows. We draw (a, p) from a bivariate normal distribution with zero means and unit standard deviations. The correlation parameter $(\rho_{a,p})$ is calibrated. We then set $g = \beta_{g,a}a + \beta_{g,p}p + \varepsilon_g$ and $h_1 = \beta_{h,a}a + \beta_{h,p}p + \varepsilon_h$. The error

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terms $(\varepsilon_h, \varepsilon_g)$ are drawn from independent, standard normal distributions. College admission scores are given by $z = 0.5h_1 + \beta_{z,g}g$. We rescale the endowments to have the desired marginal distributions: $p \sim U[0,1]$, $g \sim U[0,1]$, and $h_1 \sim U[1, 1+\Delta h_1]$, where Δh_1 is calibrated.

For each candidate set of parameters, the calibration algorithm calculates the probability of all possible life histories for $10,000$ students. It constructs model counterparts of the target moments and searches for the parameter vector that minimizes a weighted sum of squared deviations between model and data moments.

While the calibration algorithm searches over all parameter values to jointly match all target moments, it may be helpful to think of the following mapping from target moments to parameter values.

- The earnings regressions help identify the human capital technologies.
- Dropout and graduation patterns help identify $\Pr_d$ and $\Pr_g$.
- Because both earnings and graduation depend strongly on g, our calibration assigns a high degree of correlation between a and g. It follows that high-ability students face high financial returns to college quality, which helps the model match the strong correlation between college quality choice and g.
- Dropout earnings premiums help identify the correlation between h_1 and a as well as the dispersion of h_1 (i.e. Δh_1).
- The observed joint distribution of g and p disciplines the joint distribution of a and p in the model.
- Preference shocks introduce noise in college selection. Their scale is identified by the observed undermatch of students with high g and high p. These students face strong financial returns to high-quality colleges and are unlikely to be affected by other constraints. They forgo attending $q4$ due to preference shocks. The responsiveness of college enrollment to changes in tuition is also informative about the scale of preference shocks.
- The remaining targets relate to the relationship between college quality choice and parental background (for given g). In the model, higher-income students tend to choose better colleges for three reasons. First, parental income affects consumption in college. Data on financial variables reveal how tight this friction is. Second, information frictions prevent low-income students from entering high-quality colleges. The information friction is calibrated to match the quasi-experimental evidence of Hoxby and Turner (2013). Finally, lower-income

students are less likely to be admitted to high-quality colleges because they have lower initial human capital. With the scale of preference draws identified, this channel is the residual explanation for the undermatch of the lower-income students, and is identified as such.[1]

1.1 Fixed Parameters

How the fixed model parameters are set is described in the main text. Figure 1 shows the estimated experience-wage profiles. Financial variables are set as follows.

- The annual net cost of attending college, $\tau_{total}(s)$, is the sum of an observed cost $\tau(s)$ and an additional (calibrated) unobserved cost τ_{4y} that is paid by all four-year college students. The observable cost is estimated by regressing tuition charges, net of grants and scholarships, on family income, test scores, and college quality (see Table 1). As expected, observed college costs increase with college quality and parental income, but decline with test scores. The additional cost of attending a four-year college helps the model match the fact that higher-income students are more likely to attend such colleges.
- Parental transfers: We set parental transfers, $\mathcal{T}(s)$, to their observed means for each combination of family income quartile and college quality (see Table 2). The lifetime transfer is set to the sum of the transfers received while attending a $q4$ college for six years. The difference between the lifetime transfer and the transfers received while enrolled in college is paid out at the start of work. Students who never attend college also receive the lifetime transfer.
- Student debt: We find that, for given college quality, debt varies little with AFQT scores or parental incomes. We therefore set debt for all students to the estimated means by college quality and year (see Table 3). We assume that annual borrowing stays constant after year four, which is the last year for which we have enough observations to estimate debt with reasonable precision. In our data, students rarely borrow large amounts. At the end of their fourth year in college, mean debt is just over \$10,000 and almost half of students have no debt at all.
- Student earnings: In our data, student earnings vary little with parental incomes or student test scores. We therefore set student earnings to their estimated

[1] As explained in the main text, model-implied access rates do not map directly into observed admission rates. However, we do verify that, for each ability quartile, the model-implied $q4$ access rate does not exceed the observed q4 admission rate.

means for all students in a given college. Earnings are similar for all four-year colleges, but higher for two-year colleges.[2]

- Student consumption: We infer consumption from the student budget constraint. Our data imply that consumption levels are quite low for lower-income students who enroll in selective colleges, suggesting that these students may face binding financial constraints. The reason is that college costs rise with quality, but parental transfers do not. Higher-income students, on the other hand, receive large parental transfers when they enroll in selective colleges, ensuring that their consumption levels are far greater than those of lower-income students.

1.2 Calibrated Parameters

Table 4 through Table 7 show the values of the calibrated parameters. Students' graduation and dropout probabilities are linear functions of ability percentiles. Specifically, we assume that $\Pr_g(s) = \gamma_{1,q} + \gamma_{2,q}\hat{a}$, where $\gamma_{1,q}, \gamma_{2,q} \geq 0$, and that $\Pr_d(s) = \gamma_{4,q} - \gamma_{5,q}\hat{a}$, where $\gamma_{4,q}, \gamma_{5,q} \geq 0$. All probabilities are truncated into the unit interval. As shown in Figure 2a and Figure 2b, for a given student, attending a higher quality college increases the likelihood of graduating, but reduces the likelihood of dropping out. Taken together, the probability of eventually graduating from college rises substantially with college quality, especially for high-ability students.

2 Model Fit

This section shows all target moments used in the calibration, except for those already displayed in the main text.

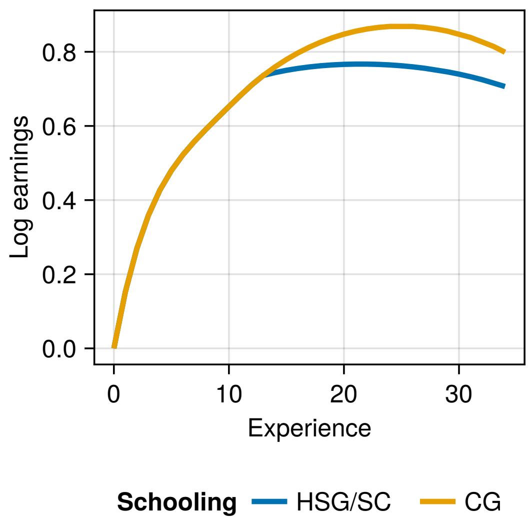
2.1 College Entry Patterns

The target moments that characterize college entry patterns are:

1. The fraction of high school graduates in each AFQT or parental income quartile who enter any college (Figure 3 and Figure 4).
2. College quality choice for students in each AFQT and parental income quartile (Figure 5).
3. AFQT distribution of freshmen by college (Figure 6) and mean AFQT percentiles of freshmen in each college (Figure 7).

[2] Average annual earnings by college quality are: $q1 : \$8,100, q2 : \$5,442, q3 : \$4,651, q4 : \$4,430$.

Figure 1: Experience Profiles



Note: The figure shows the estimated experience profiles for log earnings.

Table 1: College Costs

Regressor	**Coefficient (s.e.)**
AFQT 2	-261.65 (615.46)
AFQT 3	39.27 (573.69)
AFQT 4	-1,198.1 (629.19)
Quality 2	35.69 (600.22)
Quality 3	1,679.4 (546.53)
Quality 4	4,307.6 (882.17)
Parental income 2	921.85 (1,005.6)
Parental income 3	1,825.0 (974.64)
Parental income 4	2,938.7 (1,023.4)
Constant	-720.65 (801.01)

Note: The table shows the results of regressing the net cost of college on AFQT quartile dummies, parental quartile dummies, and quality dummies. The regression implies negative net costs for some students with low incomes but high test scores. Such cases, where financial aid covers more than the total cost of college, are observed in the data.

Table 2: Parental Transfers

	$p1$	$p2$	$p3$	$p4$
Quality 1	626.6	1,032.1	2,442.7	2,796.4
Quality 2	2,079.1	2,237.4	4,186.2	5,274.6
Quality 3	1,700.3	3,913.6	5,289.6	9,998.7
Quality 4	4,171.0	4,896.5	11,095.6	17,218.7

Note: The table shows mean parental transfers for each combination of family income quartile and college quality.

Table 3: Student Debt

Year	**1**	**2**	**3**	**4**
Quality 1	374.0	794.2	n/a	n/a
Quality 2	2,569.5	5,671.5	7,756.1	10,773.1
Quality 3	2,070.5	4,515.3	7,159.0	10,064.8
Quality 4	2,717.5	5,395.5	7,574.9	11,121.2

Note: The table shows mean student debt at the end of each year in college for each quality.

Table 4: Preference parameters

Symbol	Description	Value
$\mathcal{U}_e$	Fixed utility at work; by education	3.00, 2.63, 3.50
$\mathcal{U}_{2y}$	Utility from attending 2 year college	6.97
$\Delta\mathcal{U}$	Range of idiosyncratic college preferences	5.14

Table 5: Endowment Parameters

Symbol	Description	Value
$\rho_{a,p}$	Correlation (a,p)	0.340
$\beta_{h,a}$	Weight on ability when drawing h_1	1.29
$\beta_{h,p}$	Weight on parental when drawing h_1	0.518
Δh_1	Range of h endowments	0.118
$\beta_{g,a}$	Weight on ability when drawing g	3.70
$\beta_{g,p}$	Weight on parental when drawing g	0.0278
$\beta_{z,g}$	Weight on g in admissions score	0.119
π	Prob of observing true quality	0.335, 0.403, 0.462, 0.518

Note: The probability of observing the true college quality varies with parental income quartile.

Table 6: Financial Parameters

Symbol	Description	Value
τ_{4y}	Cost of attending four year college	4.12
w_{HSG}	Log wage HSG	2.39
Δw	College wage premium	0.105

Note: The college wage premium is the log difference between w_{CG} and w_{HSG}.

Table 7: College-Related Parameters

Symbol	Description	Value
A_q	College productivities	-2.77, -2.08, -2.00, -2.00
ϕ_q	Ability scale	0.000, 0.000, 0.169, 0.381
ζ	Exponent on h	0.011

4. Total freshman enrollment by college quality (Figure 8).

2.2 College Dropout and Graduation

Target moments that relate to college dropout and graduation patterns are:

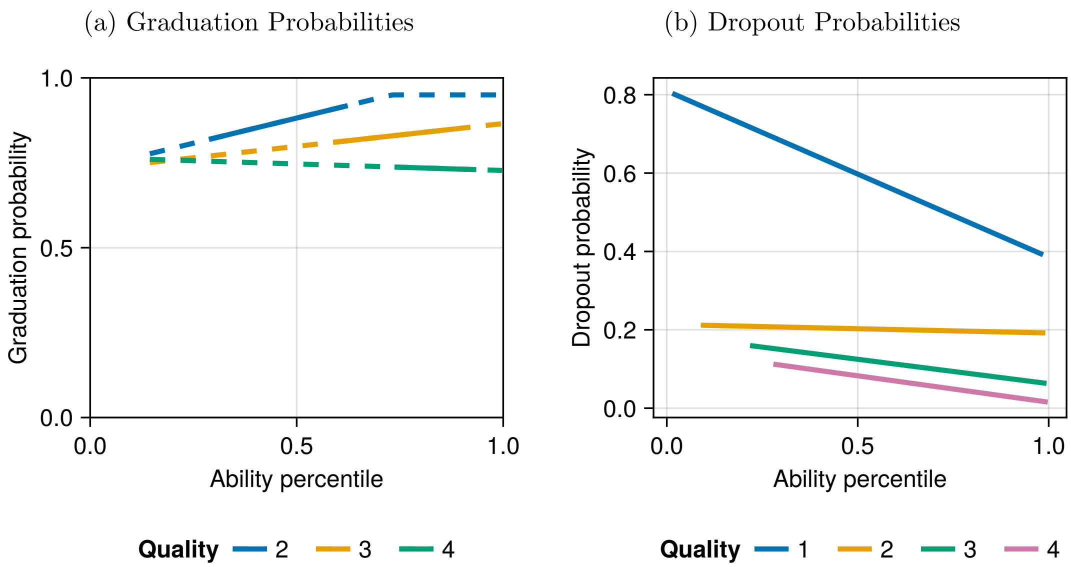
1. The fraction of college entrants who graduate within six years by college quality, AFQT quartile, and parental income quartile (Figure 9 through Figure 11).
2. The fraction of college entrants dropping out by the end of the second year by AFQT and college quality (Figure 12).
3. The fraction of college entrants dropping out at the end of each year for each college quality (Figure 13).
4. The average number of years students spend in college before either dropping out or graduating (Figure 14).

2.3 Other Target Moments

Target moments that characterize worker earnings are:

1. The coefficients of a regression of log earnings (net of experience effects) on AFQT and education dummies (Table 8). Even controlling for AFQT scores, college graduates earn far more than dropouts.
2. Mean log earnings fixed effects by education, AFQT, and college quality (Figure 15 through Figure 17).

Figure 2: Graduation and Dropout Probabilities



Note: The figure shows the annual graduation and dropout probabilities for students of different ability levels. Students can graduate after attending a four-year college for at least 3 years. The solid sections in the graduation probability plot represent interquartile ranges of students enrolled in each college.

Scalar target moments are shown in Table 9. The last two rows show the quasi-experimental moments described in the main text.

1. The "tuition subsidy" entry shows the change in college enrollment due to a \$5,000 decrease in tuition. A random subset of 40 percent of high school graduates receive the treatment. The target moment is based on (Dynarski et al., 2023).
2. The "full information" entry shows the change in college enrollment for lower-income, high AFQT students who are given full information ($\pi = 1$). The target moment is based on Hoxby and Turner (2013).

In both cases, the enrollment changes are calculated as the difference between the mean enrollment change of the treated and the untreated students.

Figure 3: College Entry by AFQT or Parental Income

(a) College Entry by AFQT (b) College Entry by Parental Income

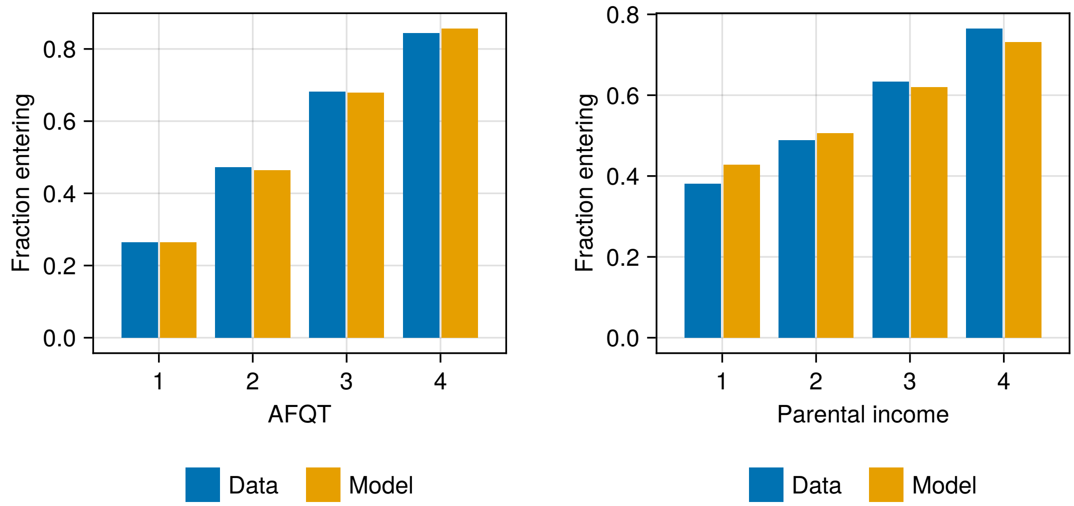


Figure 4: College Entry by AFQT and Parental Income

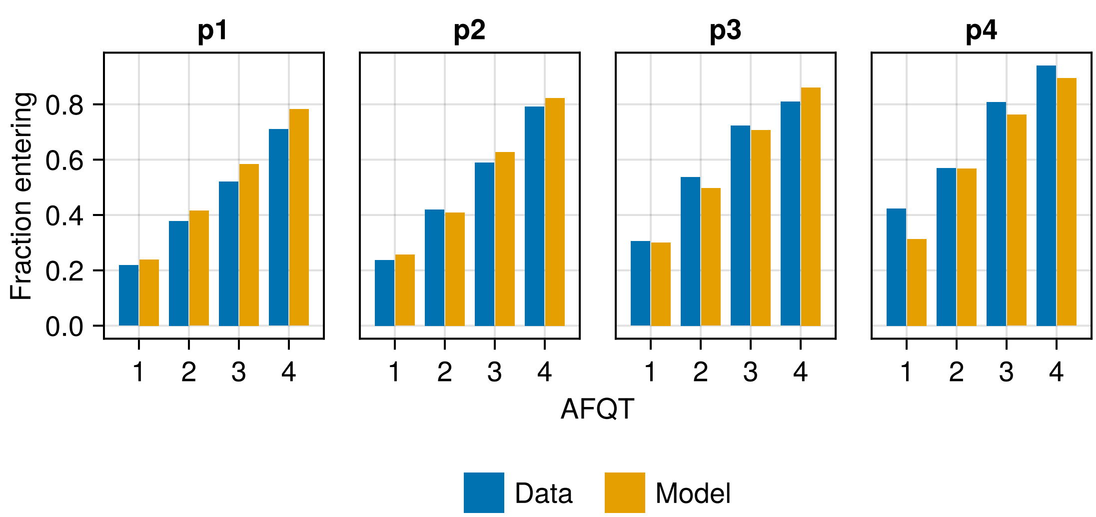


Figure 5: College Quality Choice

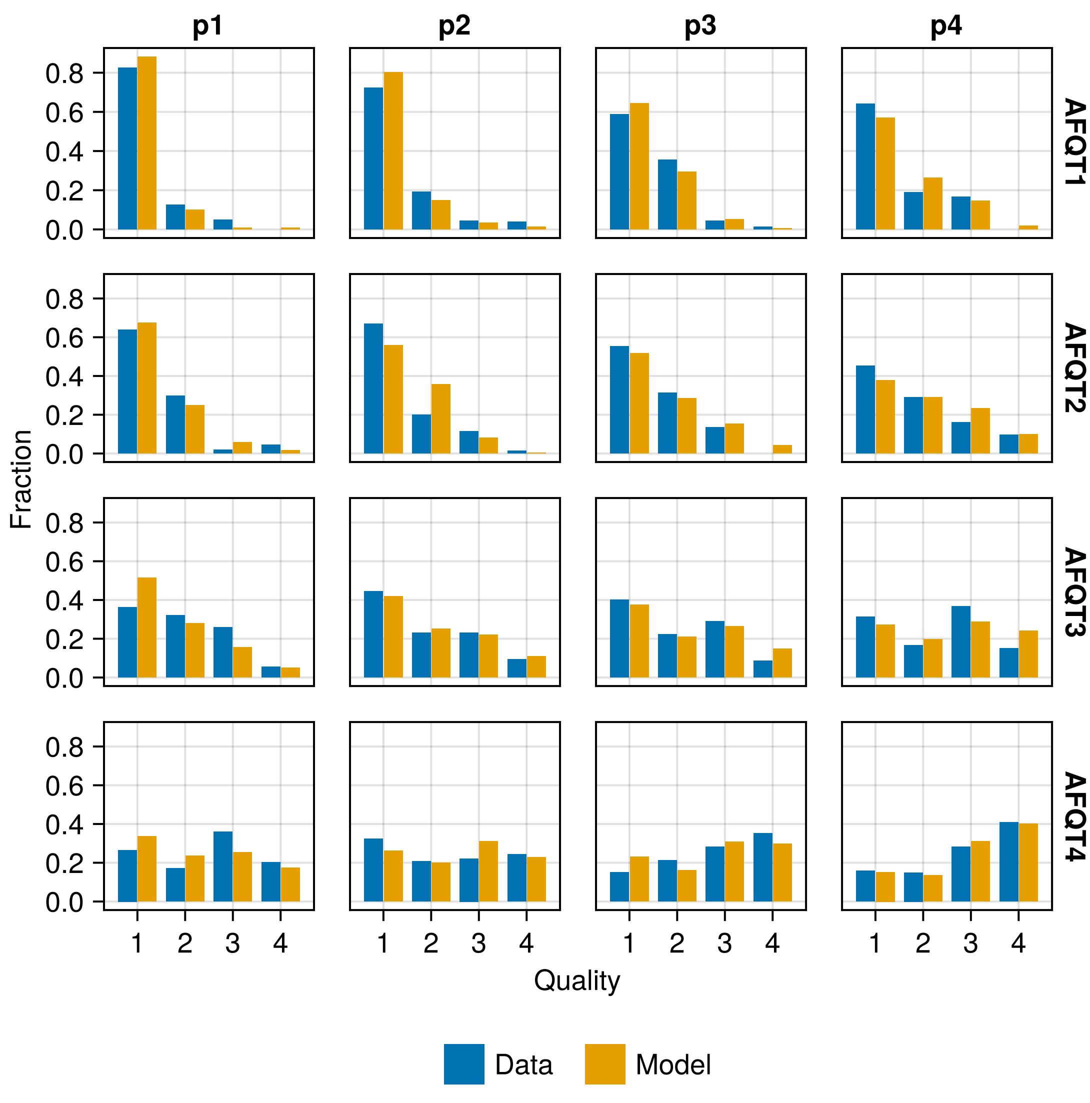
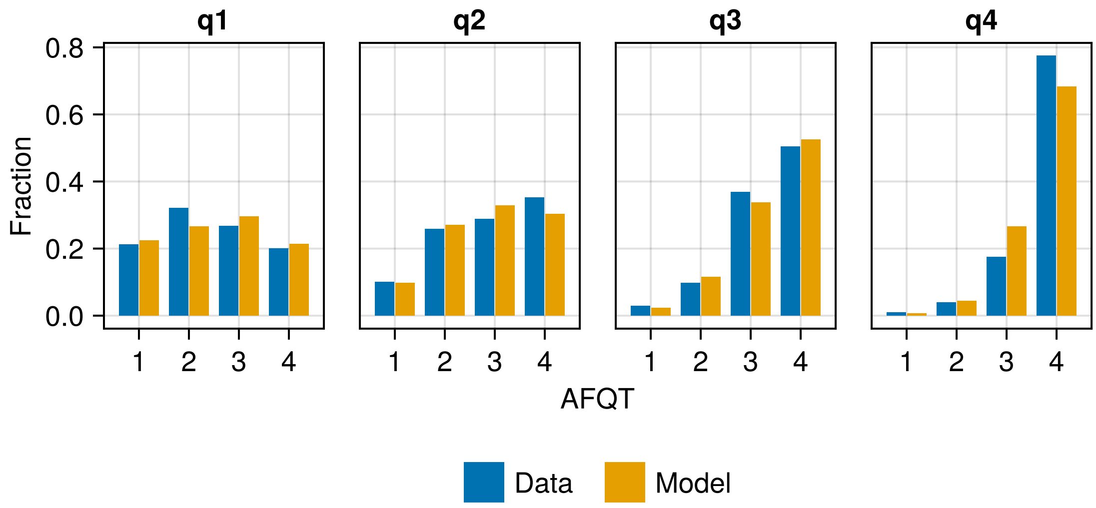


Figure 6: AFQT Distribution by College Quality



Note: For each college, the figure shows the fraction of freshmen in each AFQT quartile.

Figure 7: Mean AFQT Percentiles

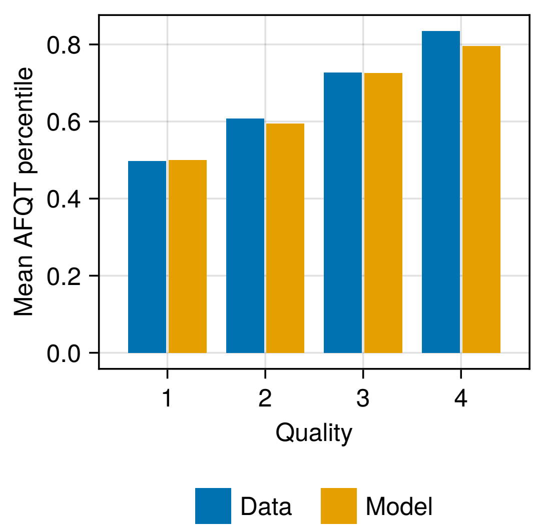
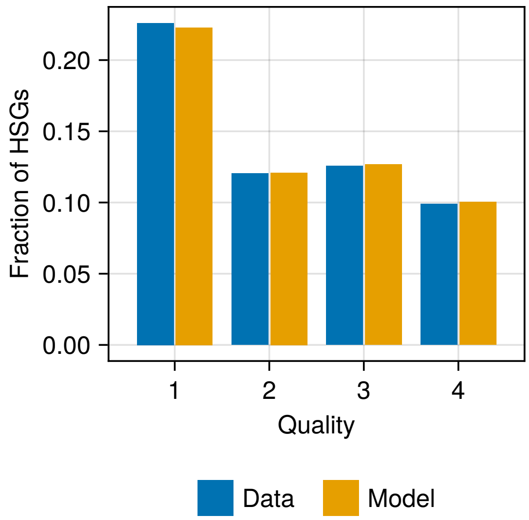


Figure 8: College Quality Choice



Note: The figure shows the fraction of high school graduates who choose each college quality. The columns add up to the college entry rate.

Figure 9: Graduation Rates

(a) By AFQT

(b) By College Quality

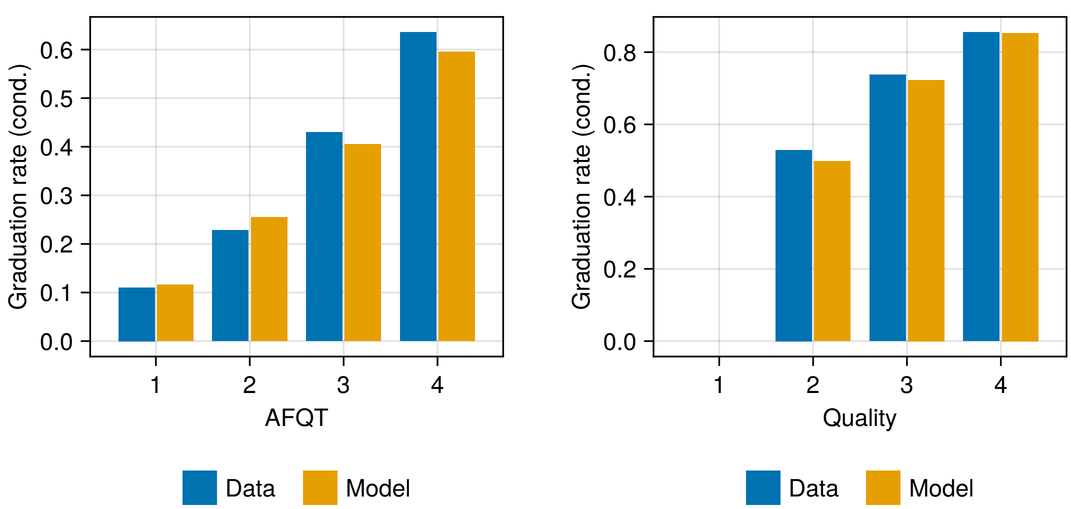
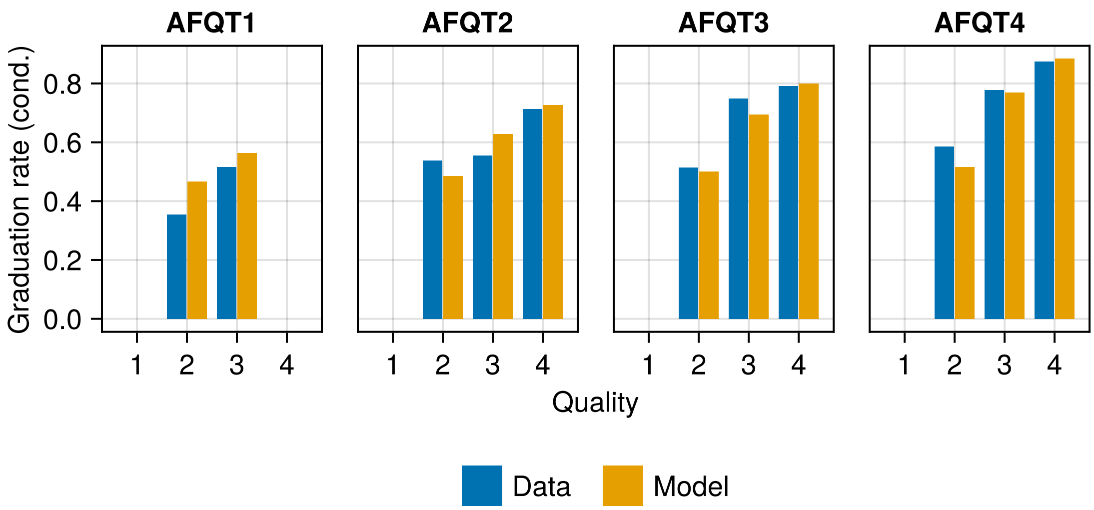


Figure 10: Graduation Rates by Quality and AFQT



Note: The figure shows the fraction of freshmen who later graduate from college for each college quality and AFQT quartile. The data do not contain enough $g4$ freshmen in $q4$ to compute an estimate of their graduation rate.

Figure 11: Graduation Rates by Quality and Parental Income

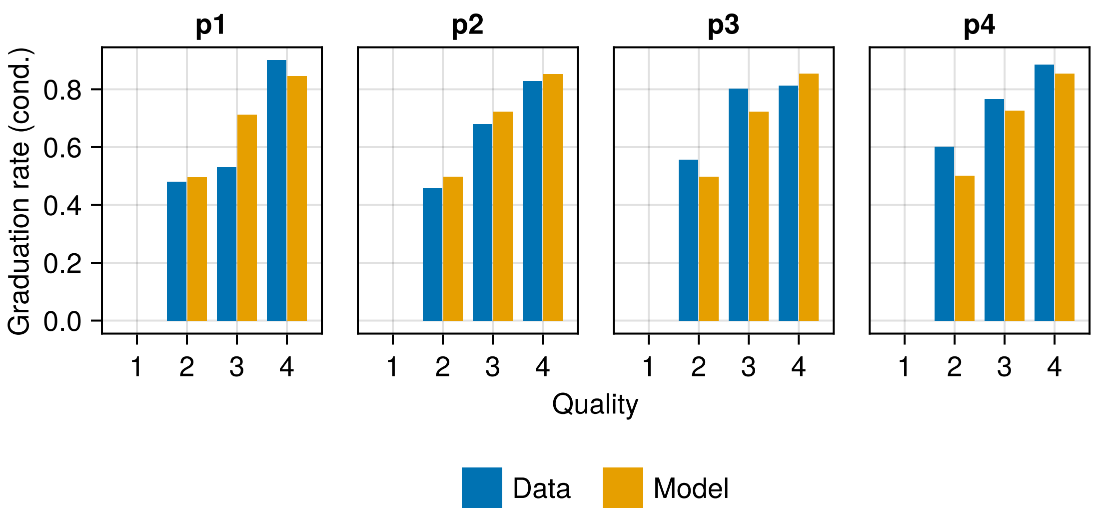


Figure 12: Cumulative Dropout Rates at End of Year 2

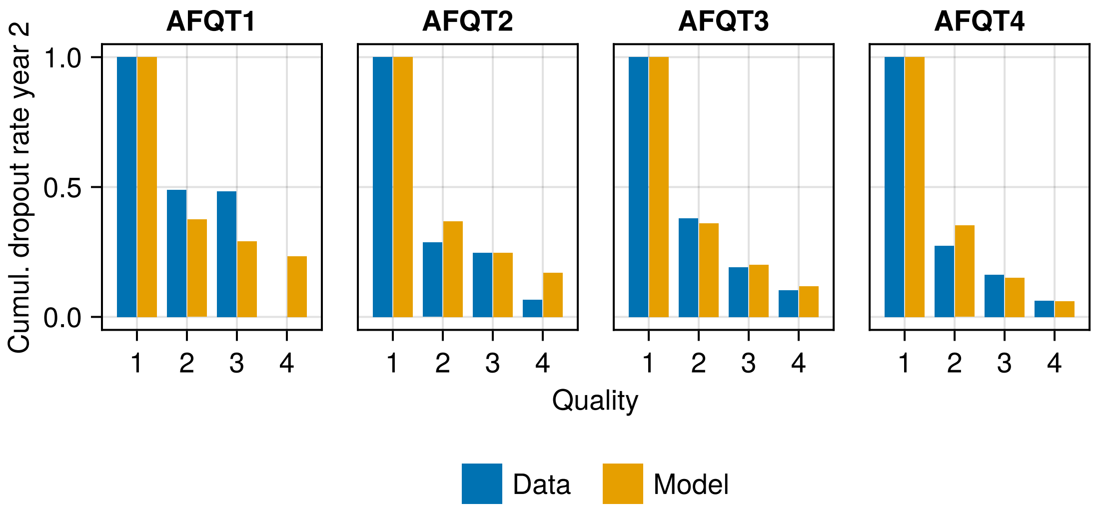
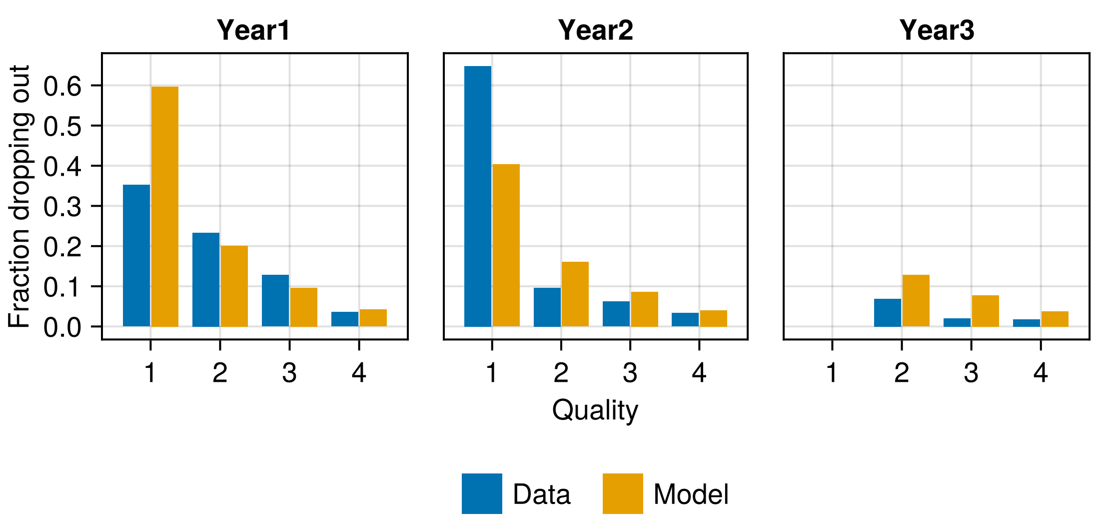


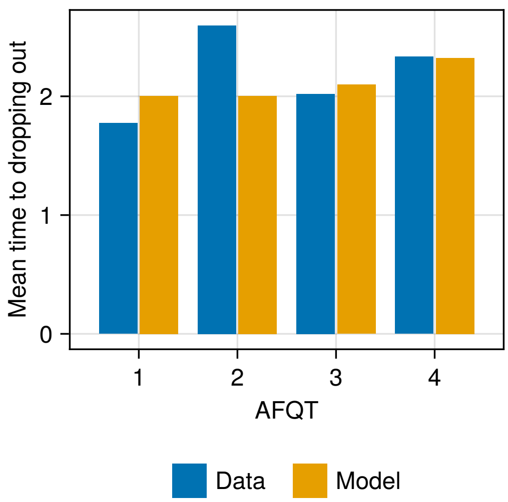
Figure 13: Fraction of Entrants that Drop Out by Year



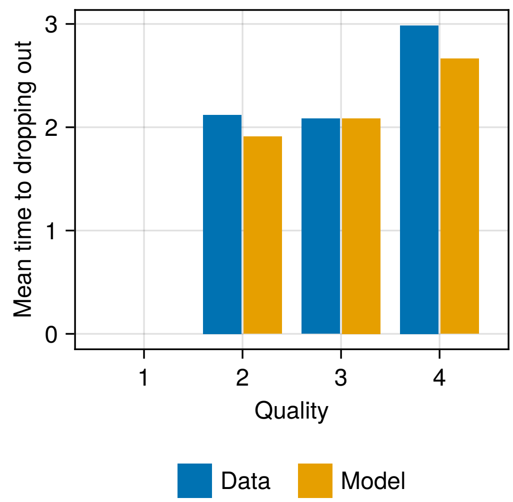
Note: The figure shows the fraction of initial entrants who drop out at the end of each year. In the data, many students attending $q1$ enroll for more than two years. We treat these students as if they dropped out at the end of year two. This creates the appearance of the dropout rate increasing with time. Our model cannot replicate this pattern, but it precisely matches the cumulative dropout rate at the end of year two.

Figure 14: Mean Time to Dropout and Graduation

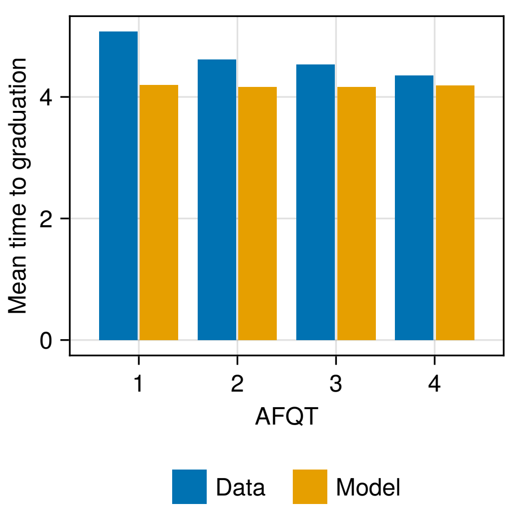
(a) Mean Time to Dropping Out



(b) Mean Time to Dropping Out



(c) Mean Time to Graduation



(d) Mean Time to Graduation

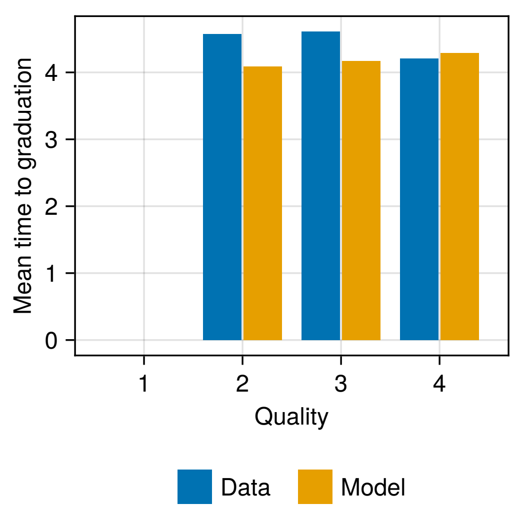


Table 8: Earnings Regressions. All Workers.

Regressor	Data	Model
AFQT 2	0.102 (0.0198)	0.0213
AFQT 3	0.121 (0.0208)	0.0456
AFQT 4	0.187 (0.0232)	0.122
SC	0.147 (0.0193)	0.124
CG	0.583 (0.0182)	0.584
Constant	2.34 (0.0145)	2.40

Table 9: Scalar Target Moments

Description	Data	Model
Graduation rate (cond.)	0.44 (0.01)	0.42
Fraction entering	0.57 (0.01)	0.57
Δ enrollment; tuition $\downarrow$ by \$5,000	17.5	17.5
Δ enrollment; full information	5.3	5.31

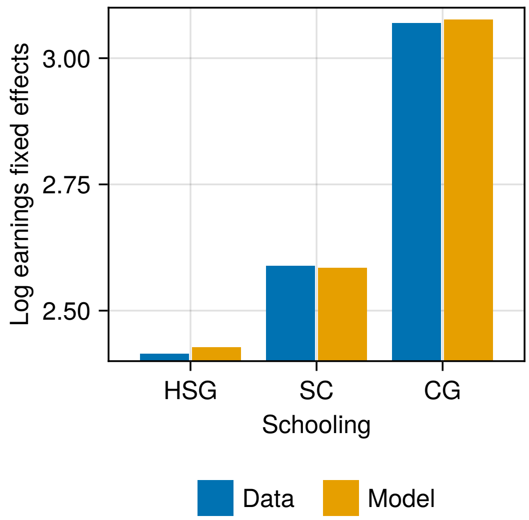
Note: The table shows the model fit for scalar target moments. Row 3 shows the change in enrollment when tuition is decreased by \$5,000. The data target is based on Dynarski et al. (2023). Row 4 shows the change in enrollment when full information is provided to students in the lowest half of the parental income distribution with test scores in the top quintile. The data target is based on Hoxby and Turner (2013). Standard errors for data moments are shown in parentheses where applicable.

2.4 Scaling up IAA Policies

In Table 10, we show how selected outcomes vary as the IAA boost value is increased from zero (baseline case) to 30 percentage points. As the boost value rises continuously, the pool of high-ability students constrained by admissions gets smaller and therefore the mean ability of the new selective-college entrants declines. At the same time, the mean ability of the displaced higher-income students rises. Thus, while the average ability of selective college students rises slightly at first (peaking at $\Delta z = 5$), it declines with further scaling.

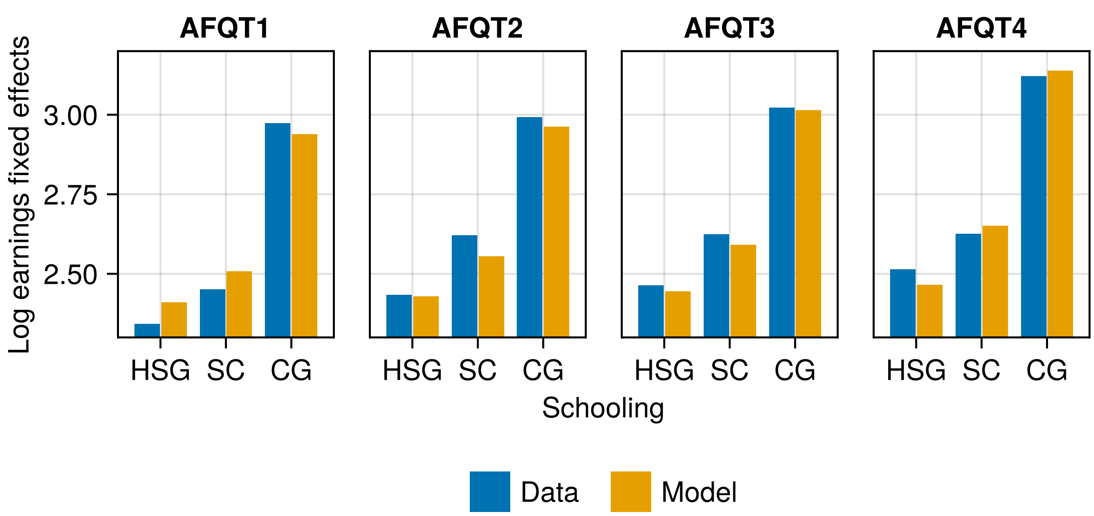
However, these changes do not translate into meaningful changes in aggregate earnings. The mean log lifetime earnings of students attending each college and in the aggregate are essentially flat (Figure 18, panel a). Even for the more aggressively scaled IAA policy ($\Delta z = 30$), the mean ability of $q4$ students is not substantially compromised and aggregate earnings decline by only 0.04 percent. By contrast, intergenerational mobility (measured by the inverse of intergenerational correlation ρ_Y) increases substantially with the boost value (bottom panel).

Figure 15: Earnings Fixed Effects by Schooling



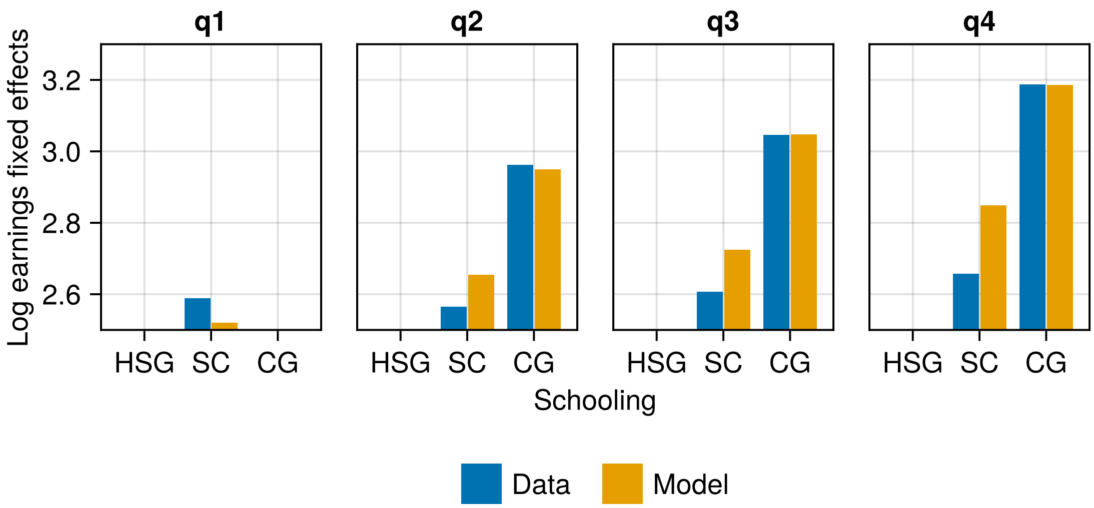
Note: In the data, fixed effects are estimated by regressing log earnings on a quartic polynomial in potential experience. The regressions use panel data and are estimated separately by education group. See Leukhina (2023) for details. In the model, individual log earnings are given by log earnings in the first year of work plus an experience profile that is common to all workers of a given education group. The fixed effect is then simply the level of initial earnings.

Figure 16: Earnings Fixed Effects by Schooling and AFQT



Note: See Figure 15 for the definition of earnings fixed effects.

Figure 17: Earnings Fixed Effects by Schooling and College



Note: See Figure 15 for the definition of earnings fixed effects.

Table 10: Scaling Up IAA Policies

		Boost					
	Baseline	5pp	10pp	15pp	20pp	25pp	30pp
Quality				Mean ability percentile			
1	50.18	50.05	50.01	50.00	50.18	50.18	50.24
2	59.11	59.59	59.47	59.08	58.91	58.76	58.64
3	73.06	73.14	73.34	73.27	73.13	72.91	72.75
4	79.97	80.04	79.86	79.73	79.63	79.43	79.08
			Intergenerational persistence of Y				
ρ_Y	42	40	39	37	35	33	31

Note: The table shows selected statistics for IAA policies with various boost values. The top panel shows the mean freshman ability percentile for each college quality. The bottom panel shows the intergenerational correlation of lifetime earnings.

To understand why IAA policies change the mean ability levels (and thus the lifetime earnings) of students enrolling in each college quality so little, consider the main IAA experiment with a boost of 15 percentage points. The policy causes 5.6 percent of lower-income students to either enter college or upgrade to a higher-quality college. A similar fraction of higher-income students either exit or downgrade. Even though the lower-income students who benefit from IAA policies are of somewhat higher ability than the displaced higher-income students, the net change in mean student ability levels in each college is small.

The main reason is that the fraction of students who switch is simply too small to make much of a difference. The change in the mean ability of freshmen enrolled in a given college equals the fraction of students who switch (near 6 percent) times the mean ability gap between those who upgrade and those who downgrade (both groups are of equal mass). Increasing the mean ability level by a single percentage point would require an ability gap between those who switch up and those who switch down of about 20 percentage points ($0.01 \approx 0.05 \times 0.2$).

For a larger boost of 30 percentage points, the fraction of students switching is larger. As many as 11.3 percent of lower-income students upgrade (or enter college). But now the ability gap between those who upgrade and those who downgrade is very small. The larger boost allows students of lower ability to upgrade and forces students of higher ability to downgrade. The change in aggregate lifetime earnings is once again very small.

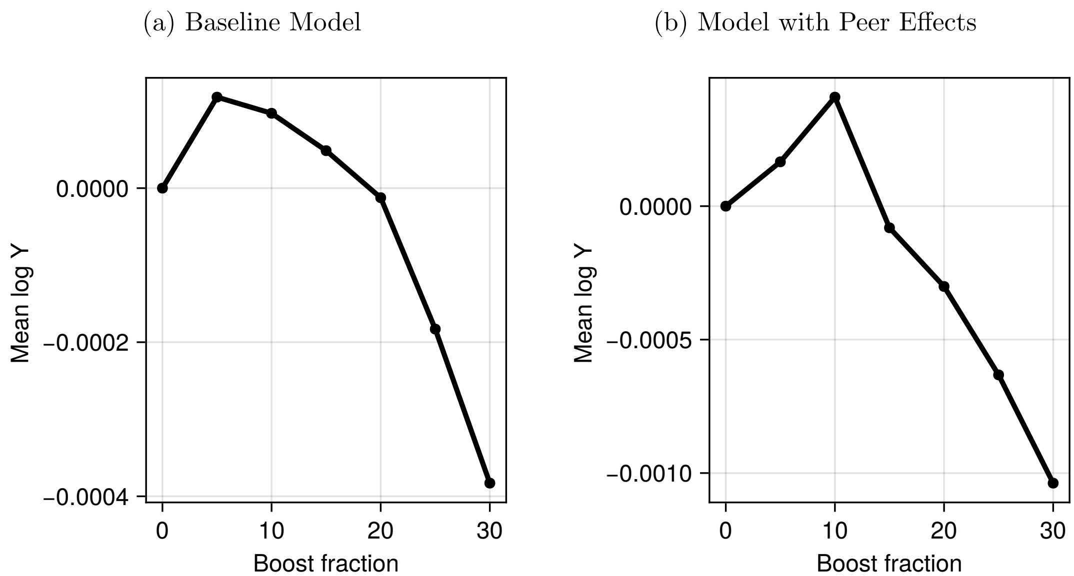
The presence of match effects is another important reason why the average ability of upgrading students remains relatively high even as IAA policies get scaled up: Students who upgrade to $q4$ when given the opportunity tend to positively self-select on ability. The overall message remains that there is essentially no trade-off between "equity" (intergenerational mobility) and "efficiency" (aggregate human capital or earnings).

3 Robustness

3.1 Peer Effects in College Productivity

It is possible that college productivity parameters $\{A_q\}$ are partly due to peer effects. College productivity may be high because the average student ability is high. In the paper, we showed that the average ability levels across colleges do not change significantly with IAA policy boost values, and therefore we should not expect our results

Figure 18: Effect of IAA Policies on Mean log Y



Note: The graphs show (absolute) changes in mean log lifetime earnings associated with different boost values in the baseline model and in the model with peer effects.

to be sensitive to the strength of peer effects. Here, we explicitly show implications for aggregate lifetime earnings under the extreme assumption that half of college productivity differences are due to peer effects. While the negative impact on aggregate earnings is amplified in panel b compared to panel a in Figure 18, the impact on earnings is very small.

3.2 Parental Transfer Heterogeneity

In the baseline model, parental transfers only depend on observable student and college characteristics. The model implies that financial constraints prevent few students from choosing high-quality colleges. In this robustness analysis, we explore a specification where financial constraints may be tighter for low-income students, which would then mute their response to IAA policies.

In the extended model, parental transfers are the product of two terms. The first term is a calibrated function that is linear in ability percentile and parental percentile with college-specific intercepts. The second term is a "parental generosity" endowment that is drawn from a uniform distribution with a mean of unity and a calibrated dispersion. The endowment is correlated with student ability and parental background. The calibration targets two additional sets of moments: mean transfers by q and p quartile,

Table 11: Effects of IAA Policies on College Access and Enrollment

Boost fraction	**0.0**	**15.0**	**30.0**
All HS graduates			
Fraction admitted to $q4$			
- lower-income	19.3	29.3	42.9
- higher-income	53.6	49.9	47.5
Fraction entering $q4$			
- lower-income	3.7	4.5	5.0
- higher-income	16.3	15.5	14.9
Top ability quartile			
Fraction admitted to $q4$			
- lower-income	78.0	92.2	98.4
- higher-income	97.0	94.7	93.4
Fraction entering $q4$			
- lower-income	17.3	19.2	20.1
- higher-income	31.4	30.8	30.6

Note: The table shows the effects of IAA policies for the model with parental transfer heterogeneity. Table columns represent IAA policies with different boost percentiles. A boost of zero is the baseline case. "Higher-income" ("lower-income") students have parental incomes above (below) the median.

and mean transfers by q and g quartile.

Compared with the baseline model, we find that financial constraints are now binding for more students, especially for those of low incomes and ability levels. Therefore, a smaller fraction of the admitted students can afford to enroll. As a result, colleges can admit a larger fraction of lower-income students without exceeding their capacities (see the first column of Table 11).

The same table reveals that the effect of IAA policies on admissions of lower-income students is comparable to the baseline model. When the IAA boost value Δz is set to 15 percentage points, for example, the fraction of lower-income students admitted to $q4$ colleges increases by 51.8 percent, which is similar to the 54.3 percent obtained in the baseline model. It is, however, harder to entice the admitted students to enroll in $q4$ as they are more financially constrained relative to the baseline. Thus, the effect on their enrollment in $q4$ is weakened.

As a result, the effects of IAA policies on intergenerational mobility are reduced by about one-third relative to the baseline case. When the IAA boost value Δz is set to 15 percentage points, the intergenerational persistence of lifetime earnings declines by 7.7 percent, compared with 13 percent in the baseline model. Nonetheless, our main result

Table 12: Effects of IAA Policies on Upward Mobility and Aggregate Outcomes

	0.0	**15.0**	**30.0**
	Level	Change relative to baseline	
Intergenerational mobility			
ρ_Y	46.5	−3.6	−7.5
Probability $p1 \to \mathcal{Y}4$	10.9	1.5	3.3
Probability $\mathcal{Y}4$, high vs low income	30.9	−3.2	−6.9
$\mathcal{Y}$ gap by parental income	26.6	−2.2	−4.7
Fraction $p1$ with $p4$ peers	25.5	0.2	0.1
Aggregate outcomes			
Mean log $\mathcal{Y}$	6.299	0.000	0.001
$\mathcal{Y}$ gap (90/10)	100.8	0.1	−0.2
Fraction entering	57.0	−0.0	−0.0
Graduation rate (cond.)	41.2	0.1	0.1

Note: The table shows the effects of IAA policies for the model with parental transfer heterogeneity. This table reports baseline-model outcomes and the changes implied by IAA policies with different boost values. Y denotes lifetime earnings in thousands of dollars, discounted to the age of labor market entry. "Probability p1 to Y4" is the probability that a student from the lowest parental income quartile reaches the highest lifetime earnings quartile. "Y gap by parental income" denotes the difference in mean log lifetime earnings between students from the top and bottom parental income quartiles. "Fraction p1 students with p4 peers" denotes the average share of peers from the top income quartile faced by students from the lowest parental income quartile. Changes are absolute changes relative to baseline values, except that changes in "Mean log Y" are reported as percent changes in Y.

is upheld. As in the baseline case, IAA policies substantially increase intergenerational mobility without significantly reducing aggregate earnings (see Table 12).

3.3 Parental Background Affects Graduation

Another potential concern about IAA policies is that the "pulled-in" lower-income students graduate at lower rates than the "pushed-out" higher-income students they displace. To address this concern, we study a version of the model in which graduation and dropout probabilities depend not only on student abilities but also on parental background.

For graduation rates, we assume that $\Pr_g(s) = (\gamma_{1,q} + \gamma_{2,q}\hat{a}) \times (1 - \gamma_{3,q} \times (1-p))$, where $\gamma_{1,q}, \gamma_{2,q} \geq 0$ and $0 \leq \gamma_{3,q} \leq 1$. For a given level of parental income, the probability of graduating is a linear function of students' ability percentiles. Students with higher parental incomes are more likely to graduate. Similarly, for dropout rates, we assume that $\Pr_d(s) = (\gamma_{4,q} - \gamma_{5,q}\hat{a}) \times (1 - \gamma_{6,q} \times p)$, where $\gamma_{4,q}, \gamma_{5,q} \geq 0$ and $0 \leq \gamma_{6,q} \leq 1$. Students with higher levels of ability or parental income are less likely to drop out. All probabilities are truncated into the unit interval.

Overall, we find that the baseline results are quite robust. The effects of IAA policies on college access and enrollment are similar to those found in the baseline model (Table 13). When the IAA boost value Δz is set to 15 percentage points, for example, the fraction of lower-income students admitted to $q4$ colleges increases by 49.7 percent while the fraction of lower-income students entering $q4$ increases by 37.8 percent. Compare these to 54.3 percent and 47.6 percent obtained in the baseline model.

Intergenerational persistence of lifetime earnings declines by 11 percent, which is only slightly smaller than the 13 percent obtained in the baseline model. The effects on intergenerational mobility are slightly smaller, while the changes in aggregate outcomes are similar (Table 14). As expected, IAA policies slightly reduce graduation rates as they reduce the mean parental income of four-year college entrants, but the changes in aggregate earnings and the earnings distribution remain small.

Our main message goes through: IAA policies substantially improve intergenerational mobility without a significant change in aggregate earnings.

Table 13: Effects of IAA Policies on College Access and Enrollment

Boost fraction	**0.0**	**15.0**	**30.0**
All HS graduates			
Fraction admitted to $q4$			
- lower-income	17.9	26.7	36.1
- higher-income	44.5	39.2	33.1
Fraction entering $q4$			
- lower-income	4.5	6.2	8.2
- higher-income	15.5	13.8	11.8
Top ability quartile			
Fraction admitted to $q4$			
- lower-income	67.5	82.0	90.8
- higher-income	87.0	81.2	74.8
Fraction entering $q4$			
- lower-income	17.0	20.3	22.3
- higher-income	30.3	28.3	26.1

Note: The table shows the effects of IAA policies for the model in which parental background affects dropout and graduation rates. Table columns represent IAA policies with different boost percentiles. A boost of zero is the baseline case. "Higher-income" ("lower-income") students have parental incomes above (below) the median.

Table 14: Effects of IAA Policies on Upward Mobility and Aggregate Outcomes

	0.0	**15.0**	**30.0**
	Level	Change relative to baseline	
Intergenerational mobility			
ρ_Y	43.8	−4.9	−10.6
Probability $p1 \to \mathcal{Y}4$	9.4	2.3	5.4
Probability $\mathcal{Y}4$, high vs low income	34.7	−5.5	−12.1
$\mathcal{Y}$ gap by parental income	26.4	−3.6	−8.1
Fraction $p1$ with $p4$ peers	27.6	1.0	1.4
Aggregate outcomes			
Mean log $\mathcal{Y}$	6.301	0.0	−0.0
$\mathcal{Y}$ gap (90/10)	98.7	0.2	−0.1
Fraction entering	57.1	0.1	0.3
Graduation rate (cond.)	42.8	−0.3	−0.8

Note: The table shows the effects of IAA policies for the model in which parental background affects dropout and graduation rates. This table reports baseline-model outcomes and the changes implied by IAA policies with different boost values. Y denotes lifetime earnings in thousands of dollars, discounted to the age of labor market entry. "Probability p1 to Y4" is the probability that a student from the lowest parental income quartile reaches the highest lifetime earnings quartile. "Y gap by parental income" denotes the difference in mean log lifetime earnings between students from the top and bottom parental income quartiles. "Fraction p1 students with p4 peers" denotes the average share of peers from the top income quartile faced by students from the lowest parental income quartile. Changes are absolute changes relative to baseline values, except that changes in "Mean log Y" are reported as percent changes in Y.

3.4 Noise in Admissions

When we allow for noise in the admission score and recalibrate the modified model, the admissions constraint actually becomes a more important reason for the undermatch of the lower-income students while preference heterogeneity becomes less important. More of the high-ability lower-income students are constrained by admissions.

As a result, the effects of IAA policies on college access and enrollment are strengthened relative to the baseline model (Table 15). For example, the fraction of high-ability lower-income students in $q4$ increases by 53 percent, compared to the 28 percent in the baseline model. Despite the stronger response among the targeted students, the impact on intergenerational mobility is slightly weaker. This is because lower-income students are ranked somewhat lower in terms of their admission score in this calibration, so fewer gain access to high-quality colleges under the baseline IAA policy (Table 16). As in the baseline model, IAA policies have little effect on aggregate earnings – the pulled-in students are similar to the pushed-out students in terms of their returns.

Table 15: Effects of IAA Policies on College Access and Enrollment

Boost fraction	**0.0**	**15.0**	**30.0**
All HS graduates			
Fraction admitted to $q4$			
- lower-income	9.6	17.2	26.9
- higher-income	49.4	43.1	37.1
Fraction entering $q4$			
- lower-income	2.6	4.6	6.8
- higher-income	17.4	15.4	13.2
Top ability quartile			
Fraction admitted to $q4$			
- lower-income	50.5	76.4	90.6
- higher-income	96.2	91.3	85.4
Fraction entering $q4$			
- lower-income	13.2	20.2	23.6
- higher-income	34.2	32.6	31.0

Note: The table shows the effects of IAA policies for the model with noise in admissions ranking. Table columns represent IAA policies with different boost percentiles. A boost of zero is the baseline case. "Higher-income" ("lower-income") students have parental incomes above (below) the median.

Table 16: Effects of IAA Policies on Upward Mobility and Aggregate Outcomes

	0.0	**15.0**	**30.0**
	Level	Change relative to baseline	
Intergenerational mobility			
ρ_Y	54.2	−4.8	−11.0
Probability $p1 \to \mathcal{Y}4$	7.1	2.5	5.9
Probability $\mathcal{Y}4$, high vs low income	40.0	−5.2	−12.4
$\mathcal{Y}$ gap by parental income	31.5	−3.2	−7.9
Fraction $p1$ with $p4$ peers	22.4	2.3	4.0
Aggregate outcomes			
Mean log $\mathcal{Y}$	6.300	0.1	0.1
$\mathcal{Y}$ gap (90/10)	97.0	0.5	0.2
Fraction entering	57.3	−0.0	−0.0
Graduation rate (cond.)	42.1	0.3	0.3

Note: The table shows the effects of IAA policies for the model with noise in admissions ranking. This table reports baseline-model outcomes and the changes implied by IAA policies with different boost values. Y denotes lifetime earnings in thousands of dollars, discounted to the age of labor market entry. “Probability p1 to Y4” is the probability that a student from the lowest parental income quartile reaches the highest lifetime earnings quartile. “Y gap by parental income” denotes the difference in mean log lifetime earnings between students from the top and bottom parental income quartiles. “Fraction p1 students with p4 peers” denotes the average share of peers from the top income quartile faced by students from the lowest parental income quartile. Changes are absolute changes relative to baseline values, except that changes in “Mean log Y” are reported as percent changes in Y.

3.5 Stronger Learning Complementarities for High-Ability Students

One concern may be that our baseline model slightly understates the degree of complementarity between ability and $q4$ colleges. This concern may arise because the model coefficient on the interaction term between the top test score quartile and $q4$ colleges in the college graduates’ earnings regression falls slightly short of its empirical counterpart – the target meant to identify the degree of complementarity. (See Table 2 in the main text.)

To address this concern, we study a version of the model in which the assumed form of complementarity in $q4$ is more flexible and therefore allows for a closer match of the identifying target. To be precise, we allow for the possibility that high-ability students enjoy additional productivity gains from attending a $q4$ college by introducing a quadratic term in the learning productivity equation:

$$\ln \mathcal{A}(q, a) = A_q + \phi_q a + \phi \max(0, a)^2 \mathbb{I}_{q=4}.$$

With the added flexibility, the calibration procedure indeed delivers a closer match of the college graduates' earnings regression (Table 17) and a slightly stronger complementarity between ability and $q4$ colleges.

Table 17: Earnings Regressions for College Graduates

Regressor	Data	Model
AFQT 2	0.0217 (0.0563)	0.0111
AFQT 3	0.0365 (0.0561)	0.0336
AFQT 4	0.004266 (0.0710)	0.0348
AFQT4-Qual3	0.0641 (0.0709)	0.0641
AFQT4-Qual4	0.207 (0.0858)	0.203
Quality 3	0.0534 (0.0412)	0.0534
Quality 4	0.0793 (0.0548)	0.0857
Constant	2.94 (0.0528)	2.91

Note: The table shows the coefficients and standard errors (in parentheses) of an earnings regression for college graduates in the model with stronger learning complementarities. The dependent variable is log earnings net of experience effects. The regressors include dummies for AFQT quartiles, college quality groups, and selected interactions.

The baseline results, however, are largely unchanged. The effects of IAA policies on college access and enrollment are similar to those found in the baseline model (Table 18). This is because the relative ranking of colleges, for a given type of student, is not significantly altered by the degree of learning complementarity. The effects on intergenerational mobility and aggregate outcomes are also nearly identical to those found in the baseline model (Table 19). The reason for this is that, as in the baseline model, students who are pulled into $q4$ colleges by an IAA policy are of similar learning ability to the pushed-out students. This implies that their earnings gains are also similar to the earnings losses of the pushed-out students. The stronger learning complementarity amplifies both gains and losses, but the effect on aggregate earnings washes out.

Table 18: Effects of IAA Policies on College Access and Enrollment

Boost fraction	**0.0**	**15.0**	**30.0**
All HS graduates			
Fraction admitted to $q4$			
- lower-income	15.1	23.4	32.0
- higher-income	42.6	37.2	30.8
Fraction entering $q4$			
- lower-income	4.3	6.3	8.5
- higher-income	15.7	13.8	11.6
Top ability quartile			
Fraction admitted to $q4$			
- lower-income	63.0	79.4	89.7
- higher-income	85.3	79.5	71.2
Fraction entering $q4$			
- lower-income	18.1	22.7	25.8
- higher-income	31.5	29.4	26.6

Note: The table shows the effects of IAA policies for the model with stronger learning complementarities. Table columns represent IAA policies with different boost percentiles. A boost of zero is the baseline case. "Higher-income" ("lower-income") students have parental incomes above (below) the median.

Table 19: Effects of IAA Policies on Upward Mobility and Aggregate Outcomes

	0.0	**15.0**	**30.0**
	Level	Change relative to baseline	
Intergenerational mobility			
ρ_Y	41.3	-5.4	-11.4
Probability $p1 \to \mathcal{Y}4$	11.3	2.8	6.2
Probability $\mathcal{Y}4$, high vs low income	30.6	-6.3	-13.0
$\mathcal{Y}$ gap by parental income	24.2	-3.9	-7.9
Fraction $p1$ with $p4$ peers	25.8	0.8	1.4
Aggregate outcomes			
Mean log $\mathcal{Y}$	6.305	0.0	-0.0
$\mathcal{Y}$ gap (90/10)	91.2	0.0	-0.6
Fraction entering	57.1	0.1	0.1
Graduation rate (cond.)	41.7	-0.1	-0.1

Note: The table shows the effects of IAA policies for the model with stronger learning complementarities. This table reports baseline-model outcomes and the changes implied by IAA policies with different boost values. Y denotes lifetime earnings in thousands of dollars, discounted to the age of labor market entry. "Probability p1 to Y4" is the probability that a student from the lowest parental income quartile reaches the highest lifetime earnings quartile. "Y gap by parental income" denotes the difference in mean log lifetime earnings between students from the top and bottom parental income quartiles. "Fraction p1 students with p4 peers" denotes the average share of peers from the top income quartile faced by students from the lowest parental income quartile. Changes are absolute changes relative to baseline values, except that changes in "Mean log Y" are reported as percent changes in Y.

3.6 No Learning Complementarities

Suppose that learning productivity in college q does not depend on student ability, so that everyone enjoys the same increment in learning productivity when they upgrade to a higher quality college. In such a setup, the concern that IAA policies reduce the average ability level in top colleges becomes less relevant. Even if it were true, the pulled-in students would enjoy the same increment in learning productivity that is lost by the pushed-out students. To the extent that the target group responds to the policy intervention, the policy-maker would be able to redistribute without the loss of aggregate earnings. Nonetheless, we explore this alternative formulation and its implications for the effects of IAA policies in the context of our model.

To be precise, we assume the following form of learning productivity:

$$\ln \mathcal{A}(q, a) = A_q + \phi a.$$

Without learning complementarities, the overall model fit is quite poor. In particular, the calibration delivers close-to-zero coefficients on the two interaction terms of the college graduates' earnings regression target (from Table 2 of the paper). The financial returns to choosing a more selective college are now more similar across the population, and the earnings distribution is less dispersed. Even lower ability students now enjoy earnings gains by upgrading to a more selective college.

We find that the effects of IAA policies on college access and enrollment are slightly stronger than in the baseline model (Table 20). For the IAA boost value Δz of 15 percentage points, the fraction of lower-income students admitted to $q4$ colleges increases by 62.5 percent while the fraction of lower-income students entering $q4$ increases by 57.1 percent. Compare these to 54.3 percent and 47.6 percent obtained in the baseline model.

The impact on intergenerational mobility is slightly weaker because the financial returns to $q4$ are substantially smaller for the high-ability students (Table 21). Indeed, intergenerational persistence of lifetime earnings declines by 10.7 percent, compared to the 13 percent obtained in the baseline model. As expected, the effect on aggregate earnings is close to zero, because earnings gains associated with college upgrading are more similar across the population.

Table 20: Effects of IAA Policies on College Access and Enrollment

Boost fraction	**0.0**	**15.0**	**30.0**
All HS graduates			
Fraction admitted to $q4$			
- lower-income	12.8	20.8	29.9
- higher-income	46.4	40.6	34.7
Fraction entering $q4$			
- lower-income	3.5	5.5	7.7
- higher-income	16.5	14.5	12.3
Top ability quartile			
Fraction admitted to $q4$			
- lower-income	60.3	79.1	90.4
- higher-income	91.3	86.0	79.5
Fraction entering $q4$			
- lower-income	16.0	21.4	24.4
- higher-income	32.5	30.5	28.2

Note: The table shows the effects of IAA policies for the model with no learning complementarities. Table columns represent IAA policies with different boost percentiles. A boost of zero is the baseline case. “Higher-income” (“lower-income”) students have parental incomes above (below) the median.

Table 21: Effects of IAA Policies on Upward Mobility and Aggregate Outcomes

	0.0	**15.0**	**30.0**
	Level	Change relative to baseline	
Intergenerational mobility			
ρ_Y	48.7	-5.2	-11.1
Probability $p1 \to \mathcal{Y}4$	9.5	2.8	5.8
Probability $\mathcal{Y}4$, high vs low income	34.6	-5.8	-12.6
$\mathcal{Y}$ gap by parental income	26.8	-3.6	-8.0
Fraction $p1$ with $p4$ peers	24.8	1.5	2.2
Aggregate outcomes			
Mean log $\mathcal{Y}$	6.299	0.0	0.0
$\mathcal{Y}$ gap (90/10)	96.2	-0.0	-0.1
Fraction entering	57.2	-0.1	-0.1
Graduation rate (cond.)	41.3	0.2	0.0

Note: The table shows the effects of IAA policies for the model with no learning complementarities. This table reports baseline-model outcomes and the changes implied by IAA policies with different boost values. Y denotes lifetime earnings in thousands of dollars, discounted to the age of labor market entry. "Probability p1 to Y4" is the probability that a student from the lowest parental income quartile reaches the highest lifetime earnings quartile. "Y gap by parental income" denotes the difference in mean log lifetime earnings between students from the top and bottom parental income quartiles. "Fraction p1 students with p4 peers" denotes the average share of peers from the top income quartile faced by students from the lowest parental income quartile. Changes are absolute changes relative to baseline values, except that changes in "Mean log Y" are reported as percent changes in Y.

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