# Grading Policies and College Major Choice with Ability Learning

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*Disclaimer: The conclusions of this research do not necessarily reflect the opinions or official position of the Texas Education Agency, the Texas Higher Education Coordinating Board, the Texas Workforce Commission or the State of Texas.

# Motivation

- College major is a determining factor of one's lifetime earnings (Altonji et al., 2014, Webber, 2013).
- What do students consider when choosing courses and majors in college?
  - Interest in the field, comparative advantage, labor market outcomes, on-time graduation (Arcidiacono, 2004, Wiswall and Zafar, 2015, Zafar, 2013, Andrews et al., 2024, Hsu, 2018)
  - Value a high GPA (Butcher et al., 2014, Ahn et al., 2024)
  - Exploring a field (Stinebrickner and Stinebrickner, 2012, Bordon and Fu, 2015, Aucejo et al., 2024)

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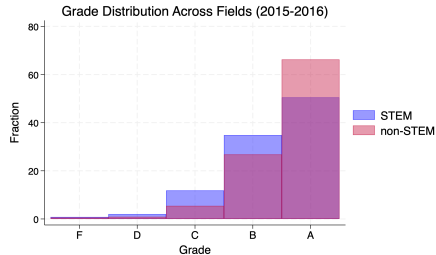
- The latter two mechanisms interact directly with departments' grading policies, which experienced significant uneven grade inflation across fields.



# Research Questions

- **Q:** How does uneven grade inflation in college across fields affect educational choices?
- **Q:** How does it affect sorting into majors based on comparative advantage?
- **Q:** How can alternative grading policies shape educational choices in college?

# What This Paper Does

- Build a structural individual decision model of college course and major choices.
  - Two main channels: taste for a high GPA & ability learning
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- Model is matched to the administrative education records of a flagship university in TX.
  - Complete history of course taking and grades $\Rightarrow$ rich modeling of latent ability and course grades.
- Simulate counterfactual grading policies and full-information benchmark to:
  - Understand the effect of uneven grade inflation on course & major choice and degree completion.
  - Quantify the uncertainty students face about their ability in college.
  - Two counterfactual grading policies: (1) equalized to non-STEM level; (2) equalized to Avg. B.

▸ Data ▸ Summary statistics

# Contribution to the Literature

- College major choice: Arcidiacono, 2004, Wiswall and Zafar, 2015, Wiswall and Zafar, 2018, Wiswall and Zafar, 2021, Zafar, 2013, Bordon and Fu, 2015, Lovenheim and Smith, 2023, Andrews et al., 2024
- How grades affect educational choices and outcomes: Bar et al., 2009, Butcher et al., 2014, Bleemer and Mehta, 2024, Denning et al., 2022, Jiang et al., 2021, Ahn et al., 2024, Denning et al., 2025
- Uncertainty and learning: Arcidiacono, 2004, Zafar, 2011, Stinebrickner and Stinebrickner, 2012, Bordon and Fu, 2015, Aucejo et al., 2024, Larroucau and Rios, 2020, Crawford and Shum, 2005, Hsu, 2018, Papageorgiou, 2014, Guvenen et al., 2020

- **Contribution**
  - Implication of grade inflation in college on major sorting by comparative advantage.
  - Novel modeling of latent ability and course grades: grade inflation $\Rightarrow$ less accurate signal.
  - The design of the signal can shape information acquisition through preferences (e.g. CEO's project choice and performance rating).

# Model: Overview

- Majors ($m$) are grouped into STEM ($m = 1$) and non-STEM ($m = 2$) (Andrews et al., 2024).
  - STEM: Biology, CS, Engineering, Math & Stat, Physical Sciences, Business & Econ
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  - Allow preference to be gender specific.
- **Individual decision model** with 7 periods (each period = semester).
  - Period 1-6: Students choose which course bundle to take or to dropout.
    - Accumulate GPA & course history, learn about comparative advantage.
  - Period 7: Students choose which major to graduate with $\Rightarrow$ Receive graduation payoff.

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3. Time to graduation
   - Extra time to stay in college after 6 semesters is stochastically determined by course taking history.
   - Staying longer in college is costly (tuition, foregone earnings).
   - Incentive to take enough courses in both fields *and* in a field you are graduating to graduate on time.

# Model: Overview

## Grading Policy and Belief Updating

- Gaussian models can underestimate the noise of top-coded grades. ▸ Gaussian
- Course Grades: $G_{imc} \sim Binomial(N = 4, a_{im}^{c_m})$ ▸ Mapping
  - $a_{im} \in [0, 1]$: ability to learn in major $m$.
  - $c_m < 1$: grading policy parameter for field $m$ (low $c_m \Rightarrow$ more grade inflation). ▸ $c_m$

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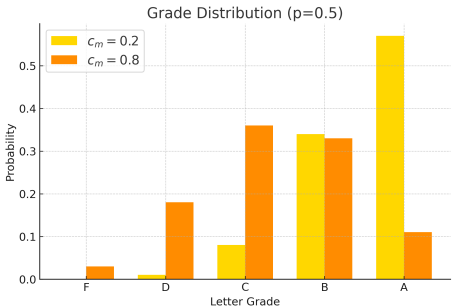


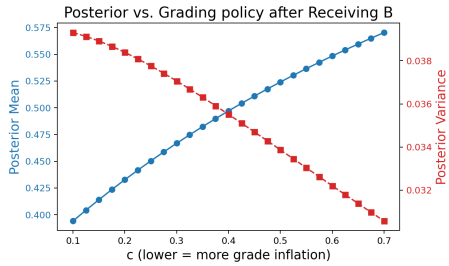

# Data: Texas Education Research Center Data

- Administrative educational records of all students who enroll in public institutions in Texas.
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- Complete course taking & grades history linked to major, graduation outcomes, SAT scores, and demographics.
- Sample: UT-Austin 2015-2016 Cohorts first-time full-time undergraduate students
  - Grade inflation is widespread, especially at more selective universities (Rojstaczer and Healy, 2012).
  - Harvard grade inflation report: 79% A in 2020-2021.
- Data facts
  1. GPA residuals are positively correlated with staying in the major.
  2. Isolating the preference for a high GPA: student's course choices react to grading policies.

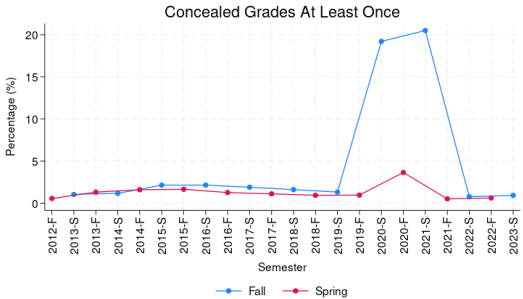
# Data: GPA residuals positively correlate with staying in the major

$$GPA_{imt} = \overbrace{\alpha_i}^{\text{Individual FE}} + \overbrace{\eta_{a(it)}}^{\text{Seniority FE}} + \overbrace{\rho_{q(imt)}}^{\text{Course portfolio FE}} + \varepsilon_{imt} \quad \text{for } m = 1, 2 \tag{1}$$

$$\underbrace{STEM_i}_{\substack{1 \text{ if major is } m=1 \\ \text{in semester } 7}} = \underbrace{\theta_1}_{\substack{0.2165 \\ (0.0024)}} \underbrace{\sum_t \left( \frac{\hat{\varepsilon}_{i1t}}{6} \right)}_{\substack{\text{Residual grade} \\ \text{average} \\ \text{in STEM}}} + \underbrace{\theta_2}_{\substack{-0.1378 \\ (0.0025)}} \underbrace{\sum_t \left( \frac{\hat{\varepsilon}_{i2t}}{6} \right)}_{\substack{\text{Residual grade} \\ \text{average} \\ \text{in non-STEM}}} + X_i'\Gamma + \nu_{it} \tag{2}$$

- $X_i$: Math & Reading SAT, initial major, gender, parental education level.
- 1 SD increase in STEM grade residual $\Rightarrow$ 31pp increase in STEM declaration.
- 1 SD increase in non-STEM grade residual $\Rightarrow$ 20pp decrease in STEM declaration.
- Consistent with ability learning through course grades story.

# Data: Isolating the Preference for a High GPA




| | Eligibility | Commitment | Course limit |
|---|---|---|---|
| Pre-pandemic | After 30 credits | Before grades | Two electives |
| Spring 2020 | Everyone | After grades | Unlimited |
| Fall 2020 – Spring 2021 | Everyone | After grades | Total three |

**Table:** UT-Austin Pass/Fail Grading Policy

# Data: Isolating the Preference for a High GPA

- Empirical strategy: Compare students across time + Placebo test on other universities.

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- Results

1. Probability of taking any STEM course increased 1.50-2.13%.
2. Share of courses enrolled in STEM increased 1.1-1.3%.
3. Female (3.67%, 1.4%) and Non-STEM (5.56%, 2.8%) more responsive.

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- Mapping to the model: indirect inference by simulating grade concealing in the model.

▸ Placebo ▸ Long-term ▸ Indirect Inference

# Data: Isolating the Preference for a High GPA

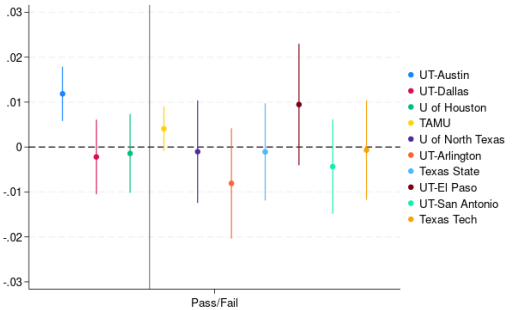


**Figure:** Probability of Taking Any STEM Course

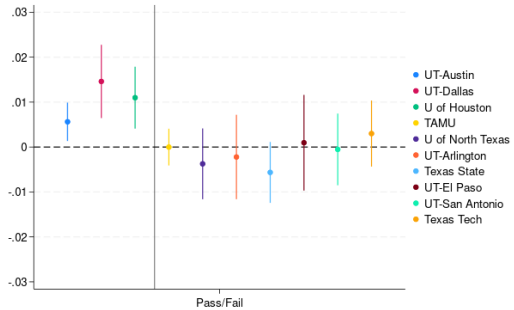


**Figure:** Share of STEM Courses Enrolled

# Estimation

- **Two-Stage Estimation**:
  - First Stage: Simulated Maximum Likelihood
    - Grading policies in each major.
    - Ability distribution in each major.
  - Second Stage: Indirect Inference
    - Per-period enrollment cost and graduation payoff parameters.
    - Time to graduation process.
    - Preference shock.
- **Rationale**
  - Initial beliefs = Population ability distribution (assumption)
  - Initial beliefs + Sequence of course grades $\Rightarrow$ Control selection into courses.

▸ Likelihood ▸ Indirect Inference ▸ Model Fit

# Graduation Payoff: Value of GPA and the Cost of Extra Semester

| | Male | Female |
|---|---|---|
| Marginal cost of extra semester to graduate | 1.70 | 2.60 |
| Marginal Value of GPA | 0.78 | 1.81 |
| in number of extra semesters | 0.49 | 0.69 |

- Female students value GPA 90% more than male students.
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- Female students value GPA 90% more than male students.
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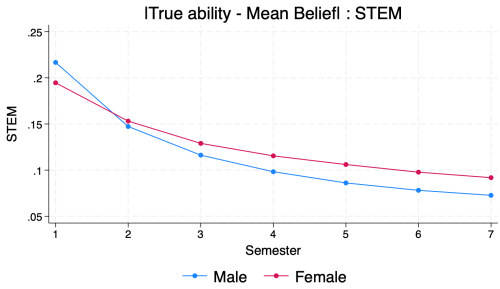
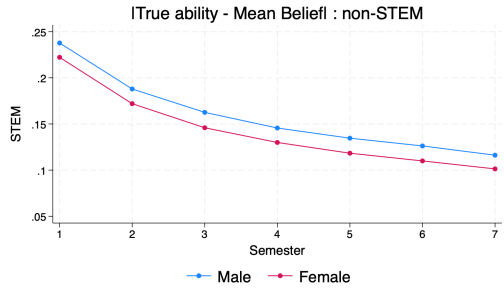
- Context
  - A semester is roughly about 16 weeks.
  - Per semester average tuition of in-state public university: $4,875.

# Convergence of Beliefs to True Ability

▸ Variance of belief




- Students' belief converge to their true ability but on average 0.27-0.43 SD gap left.
- Female students learn more about non-STEM ability, male students learn better about STEM ability.

# Counterfactual Grading Policies and Educational Outcomes

**Table:** Counterfactual Grading Policies and Educational Outcomes

| | Male | | | Female | | |
|---|---|---|---|---|---|---|
| | Status Quo | Uniform inflation | Uniform deflation | Status Quo | Uniform inflation | Uniform deflation |
| GPA | 3.36 | 3.49 | 2.90 | 3.47 | 3.56 | 3.01 |
| Major = STEM (%) | 72.68 | 74.18 | 70.64 | 42.16 | 46.22 | 41.47 |
| Dropout (%) | 6.10 | 5.51 | 9.24 | 2.99 | 2.34 | 7.62 |
| Time to graduation | 1.96 | 1.97 | 1.96 | 1.67 | 1.71 | 1.68 |

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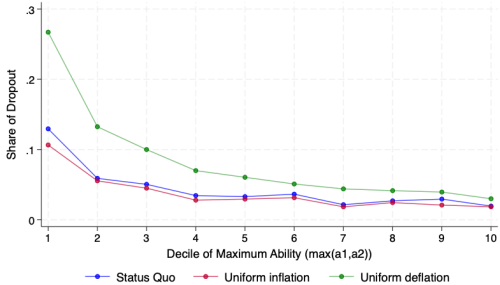
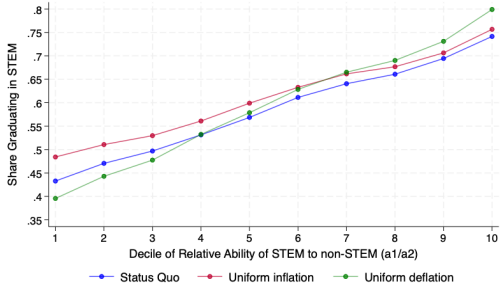
- Effect on time to graduation is minimal.

# Grade Inflation ⇒ Less Sorting

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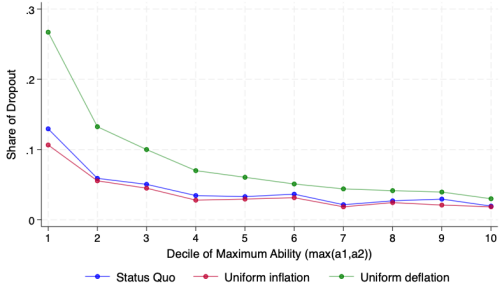


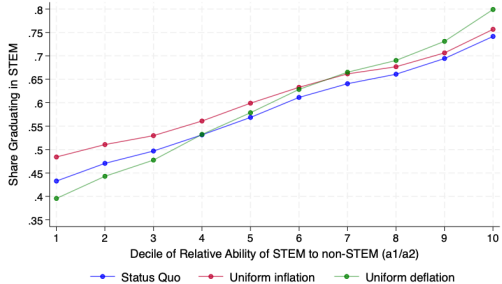


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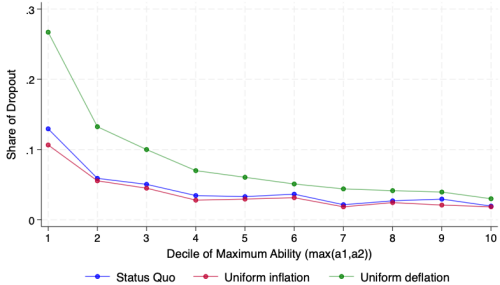


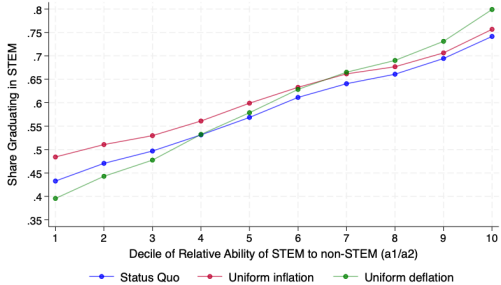


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- Two channels (in the paper):
  1. Grade inflation reduces incentive to sort more based on comparative advantage.
  2. More uncertain about comparative advantage due to noisier signals.
- Worst to best skill matched occupation improves wages by 11% per year (Guvenen et al., 2020).

# Conclusions

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- Grade inflation can "help" students on observables, such as degree completion and STEM representation. However, it can undermine information acquisition and decrease sorting by comparative advantage, likely hurting them in the labor market and lowering aggregate efficiency.

# Appendix: Summary Statistics of Pass/Fail Expansion Analysis

**Table:** Summary Statistics

| | Male | Female | | Male | Female |
|---|---|---|---|---|---|
| Math SAT | 1.205 (1.041) | 0.572 (1.031) | Graduation rate | 85.2% | 90.0% |
| Math SAT missing | 9.4 % | 8.80% | Initial major is STEM | 65.5% | 43.5% |
| Reading SAT | 1.037 (1.030) | 0.835 (1.027) | Final major is STEM | 60.6% | 37.3% |
| Reading SAT missing | 9.0% | 6.9% | non-STEM \| STEM | 5.6% | 14.6% |
| GPA | 3.273 (0.486) | 3.402 (0.425) | STEM \| non-STEM | 20.2% | 7.0% |
| GPA in STEM | 3.127 (0.626) | 3.153 (0.639) | Dropout \| STEM | 19.0% | 11.0% |
| GPA in non-STEM | 3.435 (0.506) | 3.557 (0.414) | Dropout \| non-STEM | 12.6% | 8.7% |
| Credit hours taken | 91.817 (20.857) | 93.671 (17.959) | | | |
| Share of STEM taken | 57.4% | 40.1% | N | 18,171 | 21,890 |

*Notes*: Standard deviations are in parentheses.

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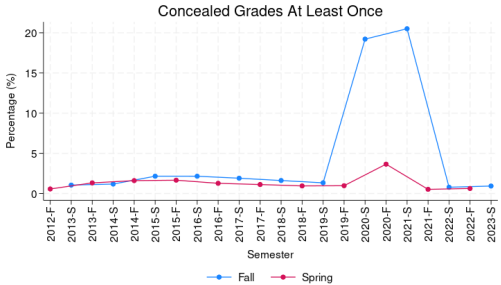
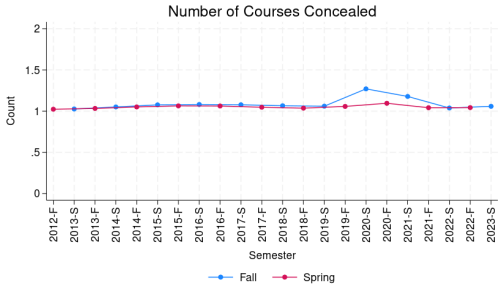
# Appendix: Concealing Decision




- Fraction of students concealing at least one grade rose from 1.4% to 19.2% in Spring 2020.
- After a dip in Fall 2020 to 3.7%, it rebounds to 20.5% in Spring 2021.
- Avg. N of courses concealed remained steady with a rise to 1.2 during the flexible pass/fail period.

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# Appendix: Empirical Strategy

$$Y_{it} = \alpha + \beta_0 \underbrace{\text{Expect}_{it}}_{\substack{\text{Fall 2020} \\ \text{dummy}}} + \beta_1 \underbrace{\text{PF}_{it}}_{\substack{\text{Spring 2021} \\ \text{dummy}}} + \underbrace{\delta_{am(it)}}_{\substack{\text{Academic} \\ \text{seniority} \\ \times \text{ major FEs}}} + \underbrace{\gamma_i}_{\text{Student FE}} + \underbrace{S'_{it}\Lambda}_{\substack{\text{Time-varying} \\ \text{controls}}} + \varepsilon_{iat}$$

- Exploit time variation in UT-Austin's pass/fail policy and compare students with similar seniority, prior grades, and course loads.
- Time-varying controls include cumulative credit hours taken in STEM and non-STEM, cumulative GPA in STEM and non-STEM, separately.
- Test if a more generous pass/fail policy encouraged risk-taking in course selection (i.e., taking harsher-graded STEM courses).

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# Appendix: Results - Extensive Margin

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Sample | All | Female | Male | non-STEM | STEM |
| $Expect$ | 0.017*** | 0.020*** | 0.013*** | 0.030*** | 0.007*** |
| | (0.003) | (0.005) | (0.004) | (0.007) | (0.002) |
| $PF$ | 0.012*** | 0.013*** | 0.010*** | 0.022*** | 0.004* |
| | (0.003) | (0.005) | (0.004) | (0.007) | (0.002) |
| Mean | 0.797 | 0.545 | 0.867 | 0.539 | 0.976 |
| SD | 0.402 | 0.441 | 0.340 | 0.498 | 0.154 |

*Notes*: Standard errors are clustered at the individual level. * p-value < 0.1, ** p-value < 0.05, and *** p-value < 0.001.

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# Appendix: Results - Intensive Margin

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Sample | All | Female | Male | non-STEM | STEM |
| $Expect$ | 0.007*** | 0.006** | 0.008** | 0.005 | 0.007*** |
| | (0.002) | (0.003) | (0.003) | (0.003) | (0.003) |
| $PF$ | 0.006*** | 0.004 | 0.007** | 0.006** | 0.003 |
| | (0.002) | (0.003) | (0.003) | (0.003) | (0.003) |
| Mean | 0.523 | 0.437 | 0.620 | 0.213 | 0.737 |
| SD | 0.357 | 0.349 | 0.341 | 0.245 | 0.250 |

*Notes*: Standard errors are clustered at the individual level. * p-value < 0.1, ** p-value < 0.05, and *** p-value < 0.001.

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# Appendix: Long-term Effect of COVID Pass/Fail Grading Policy

$$Y_i = \sum_{k \neq -1} \beta_k \cdot (\mathbf{1}\{t(i) - 2019 = k\} \cdot D_i) + \alpha_{s(i)} + \lambda_{t(i)} + X_i'\Gamma + \varepsilon_{it} \tag{3}$$

- $Y_i$: Whether $i$ graduated in STEM in 5 years.
- $D_i$ is a dummy that takes 1 if $i$'s school continued Pass/Fail expansion after Spring 2020.
- $\beta_k$ identifies the treatment effect $k$ periods away from the event.
- $\alpha_{s(i)}$: School fixed effect.
- $\lambda_t$: Cohort fixed effect.
- $X_i$: Subject SAT scores, gender, parental education level, initial intended major.

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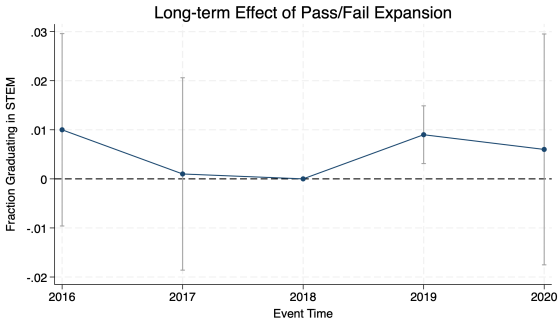
# Appendix: Long-term Effect of COVID Pass/Fail Grading Policy

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# Identifying Taste for High GPA

## Placebo Test

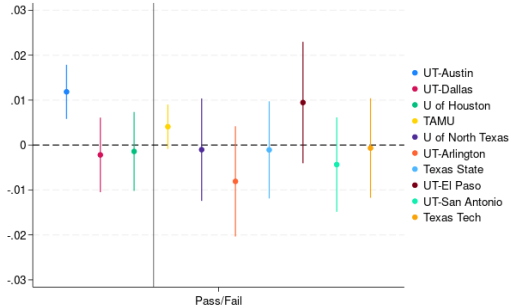


**Figure:** Probability of Taking Any STEM Course

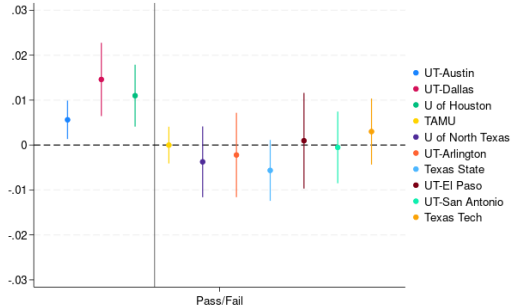


**Figure:** Share of STEM Courses Taken

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# Identifying Taste for High GPA

## Placebo Test

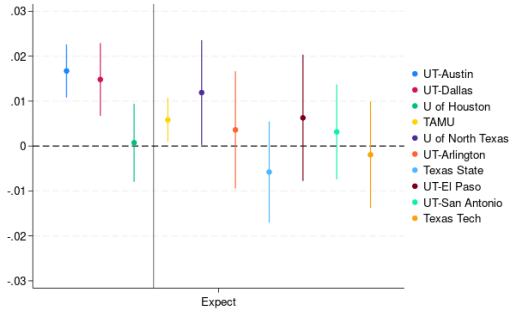


**Figure:** Probability of Taking Any STEM Course

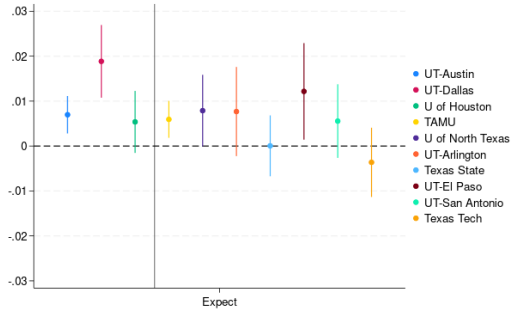


**Figure:** Share of STEM Courses Taken

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# Model: Optimization Problem

$$\max\{\{\max_{\vec{q}} \overbrace{U_t(\vec{q},\Omega_{it})}^{\text{Flow cost of taking bundle } \vec{q}} + 0.95 \cdot \overbrace{\mathbb{E}_{\Omega'_{i,t+1}}[V_{t+1}(\Omega'_{i,t+1})|\Omega_{it},\vec{q}]}^{\text{Continuation value}} + \eta_{i\vec{q}t}\},\ \eta_{iDt}\} \text{ for } t = 1,...,6$$

$$\max\{\max_{m\in\{1,2\}} \mathbb{E}_{\Omega_{iT}}[\underbrace{V_{im}(\Omega_{iT})}_{\text{Graduation payoff}}] - C(X_i)\cdot\mathbb{E}_{\Omega_{iT}}[\underbrace{T_{im}}_{\text{Extra time}}] + \xi_{im}\},\ \xi_{iD}\} \text{ in } T = 7$$

$$F_{\boldsymbol{\eta}_t}(\eta_{Dt},\{\eta_{\vec{q}t}\}_{\vec{q}\in\boldsymbol{Q}}) = \exp\left(-e^{-\eta_{Dt}/\nu} - \left(\sum_{\vec{q}\in\boldsymbol{Q}} e^{-\eta_{\vec{q}t}/(\nu\lambda_Q)}\right)^{\lambda_Q}\right) \text{ for } t = 1,\cdots,6$$

$$F_{\boldsymbol{\xi}}(\xi_D,\{\xi_m\}_{m\in\{1,2\}}) = \exp\left(-e^{-\xi_D} - \left(\sum_{m\in\{1,2\}} e^{-\xi_m/\lambda_M}\right)^{\lambda_M}\right)$$

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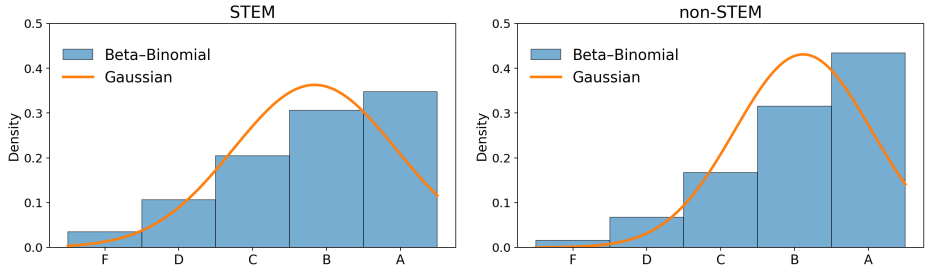
# Model: Ability, Beliefs, and Grading Policy

- Gaussian models can underestimate the noise of top-coded grades.
  - Suppose $a_{im} \sim \text{Normal}(\mu_{im}, \sigma^2_{im})$ and $G_{im} = \overline{g}_m + a_{im} + \varepsilon_{im}$ where $\varepsilon_{im} \sim \text{Normal}(0, \nu^2_m)$
  - Gasussian predicts non-STEM sends more accurate signal: $\nu_1 = 1.07 > \nu_2 = 0.89$

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# Appendix: Graduation Payoff

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$$\max\{\max_{m\in\{1,2\}}\{\underbrace{\mathbb{E}[V_{im}]}_{\substack{\text{Terminal payoff}\\ \text{from choosing}\\ \text{major } m}} - \underbrace{C\cdot\mathbb{E}[T_{im}]}_{\substack{\text{Cost associated}\\ \text{with extra time}\\ \text{to graduate}}} + \xi_{im}\},\ \xi_{iD}\} \tag{4}$$

# Appendix: Graduation Payoff

▸ Back to main

$$\max\{\max_{m\in\{1,2\}}\{\underbrace{\mathbb{E}[V_{im}]}_{\text{Terminal payoff from choosing major } m} - \underbrace{C\cdot\mathbb{E}[T_{im}]}_{\text{Cost associated with extra time to graduate}} + \xi_{im}\},\ \xi_{iD}\} \tag{4}$$

$$V_{im} = \beta_{0m} + \beta_1 \underbrace{GPA_i}_{\text{Final GPA}} + \beta_{2m} \underbrace{a_{im}}_{\text{Ability in field } m} + \beta_{3m} \underbrace{a_{i,-m}}_{\text{Ability in the other field}} + \beta_{4m} \underbrace{S_{im}}_{\text{Share of course in field } m} + \beta_{5m}\left(p_{im}\cdot S_{im}\right),\quad V_0 = 0 \tag{5}$$

# Appendix: Graduation Payoff

▸ Back to main

$$\max\{\max_{m\in\{1,2\}}\{\underbrace{\mathbb{E}[V_{im}]}_{\substack{\text{Terminal payoff}\\ \text{from choosing}\\ \text{major } m}} - \underbrace{C\cdot\mathbb{E}[T_{im}]}_{\substack{\text{Cost associated}\\ \text{with extra time}\\ \text{to graduate}}} + \xi_{im}\},\ \xi_{iD}\} \tag{4}$$

$$T_{im}(\Omega_{i9}) \sim \text{Poisson}(\lambda_{im})$$

$$\text{s.t. } \log(\lambda_{im}) = \tau_{0m} + \tau_{1m}\underbrace{Q_{i9m}}_{\substack{\text{Cumulative}\\ \text{N of courses}\\ \text{taken in } m}} + \sum_{k\neq m}\tau_{2k}Q_{i9k} + \sum_{k\neq m}\tau_{3k}Q_{i9m}Q_{i9k} \tag{5}$$

# Model Mechanism

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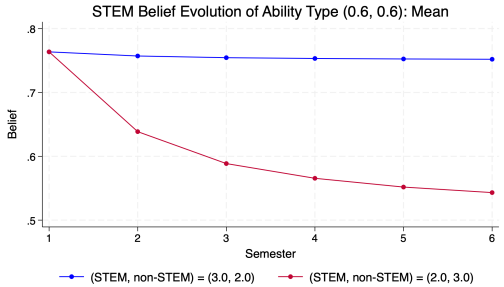
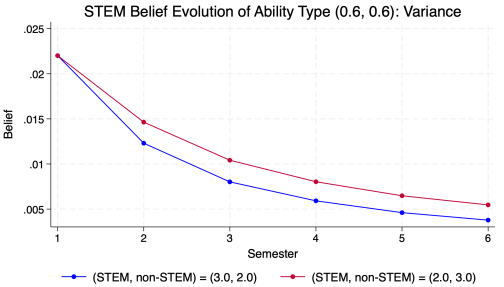
- Fix ability, always give the same grades ⇒ How do beliefs and choices evolve?



# Model Mechanism

▸ Back to Main

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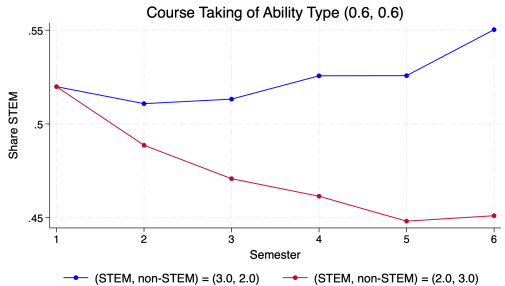


- Graduation in STEM: 46.50% vs. 36.74%

# Appendix: Grading Policy

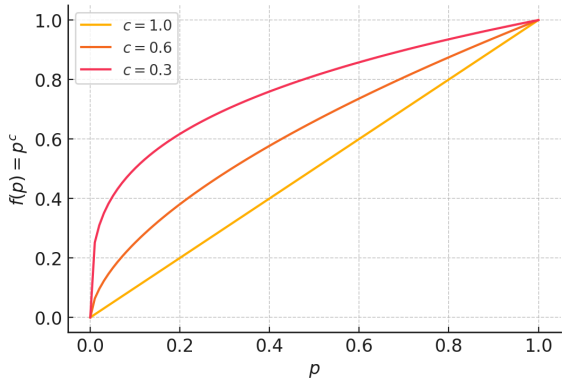


**Figure:** How $c_f$ Distorts the Relationship Between $p_{if}$ and $g_{ifc}$

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# Appendix: Grading Scheme

**Table:** Mapping of Letter Grade - $g_{ifc}$ - Grade Points

| Letter Grade | $g_{ifc}$ | Grade Points |
|---|---|---|
| A | 4 | 4.0 |
| B | 3 | 3.0 |
| C | 2 | 2.0 |
| D | 1 | 1.0 |
| F | 0 | 0.0 |

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# Appendix: Belief Updating Rule

- Prior beliefs start from the population distribution of ability.
- Upon receiving a stream of grades $\{g_{imc}\}_{c \in \mathcal{C}_m}$, update beliefs by updating $\alpha'_{im}$ and $\beta'_{im}$.

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$$f_{im}^{Posterior}(a) \propto \overbrace{a^{\alpha_{im}-1} \times (1-a)^{\beta_{im}-1}}^{\text{Contribution from the prior}} \times \overbrace{\{(a^{c_m})^{g_{imc}} \times (1-a^{c_m})^{N-g_{imc}})\}}^{\text{Contribution from the likelihood}} \tag{6}$$

$$\mathbb{E}(a_{im}) = \int a \cdot f_{im}^{Posterior}(a) da, \quad \mathbb{V}(a) = \int (a - \mathbb{E}(a))^2 \cdot f_{im}^{Posterior}(a) dp$$

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$$\mathbb{E}(a_{im}) = \int a \cdot f_{im}^{Posterior}(a)da, \quad \mathbb{V}(a) = \int (a - \mathbb{E}(a))^2 \cdot f_{im}^{Posterior}(a)dp$$

- Updating rule:

$$\alpha'_{im} = \mathbb{E}(a_{im}) \cdot \left( \frac{\mathbb{E}(a_{im}) \cdot (1 - \mathbb{E}(a_{im}))}{\mathbb{V}(a_{im})} - 1 \right), \quad \beta'_{im} = (1 - \mathbb{E}(a_{im})) \cdot \left( \frac{\mathbb{E}(a_{im}) \cdot (1 - \mathbb{E}(a_{im}))}{\mathbb{V}(a_{im})} - 1 \right) \tag{7}$$

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# Appendix: First Stage - Grade Equation & Ability Distribution

- Parameters: $\Theta_a = \{\pi_{1f}, \overline{\alpha}_f, \pi_{2f}, \overline{\beta}_f, c_f\}_f$.
- Individual's Likelihood Contribution:

$$L(\{g_{ifct}\}_{f,c,t}|\Theta_a) = \int L(\{g_{ifc1}\}_{f,c}|\Theta_a, A) \times L(\{g_{ifc2}\}_{f,c}|\{g_{ifc1}\}_{f,c}, \Theta_a, A) \cdots \times L(\{g_{ifc8}\}_{f,c}|\{g_{ifc1}\}_{f,c}, \cdots, \{g_{ifc8}\}_{f,c}, \Theta_a, A)\, dF_A. \tag{8}$$

- Conditional on ability, grade shocks are idiosyncratic.
- Grade likelihood conditional on ability $\Longrightarrow$ Binomial distribution
- Ability likelihood $\Longrightarrow$ Beta distribution given SAT scores
- Simulate each individual's ability 30 times and maximize the log-likelihood.

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# Appendix: Second Stage - Rest of the Parameters

- Parameters: $\Theta_d = \{\gamma_{1f}, \gamma_{2f}, \beta_{0m}, \beta_{2m}, C, \tau_{0m}, \tau_{1m}, \tau_{2k}, \tau_{3k}, \delta, \beta_1\}$.
- Indirect inference

$$\hat{\Theta}_d = \arg\min_{\Theta_d \in \Theta} \left(\hat{\beta}^{\text{data}} - \hat{\beta}^{\text{sim}}(\Theta_d)\right)^\top W \left(\hat{\beta}^{\text{data}} - \hat{\beta}^{\text{sim}}(\Theta_d)\right) \tag{9}$$

- Moments matched
  1. Coefficients from regression of major choice using individuals who did not drop out until $t = 7$.
  2. Coefficients from regressions of extra time to graduate on number of courses taken in each field.
  3. Share choosing each major and average extra time to graduate by one's major.
  4. Share of students dropping out in period 2-6.
  5. Average number of courses taken in one's own major chosen in $t = 7$ during $t = 1 - 6$.
  6. $\Delta$(fraction of students who take any STEM course) and $\Delta$(N of STEM courses taken)
  7. Fraction of students who choose to conceal the lowest grade when concealing is available.

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# Appendix: Grade concealing in the second stage estimation

- Assumption: Each period, conceal the lowest grade when it's profitable.
- Let $PF_{i,t}$ be the number of concealed grades for $i$ at the beginning of $t$.

$$\max_{\vec{q}} \overbrace{U_t(\vec{q}, \Omega_{it})}^{\text{Flow cost of taking bundle } \vec{q}} + 0.95 \cdot \overbrace{\mathbb{E}_{\Omega'_{i,t+1}|\Omega_{it}}[V_{t+1}(\Omega'_{i,t+1}, PF_{i,t+1}|\Omega_{it}, PF_{it})|\vec{q}]}^{\text{Continuation value}} + \overbrace{\sigma\,(\eta_{idt} + \lambda^q\ \eta_{i\vec{q}t})}^{\text{preference shock}} \tag{10}$$

- For a drawn grade shock and thus $\Omega'_{i,t+1}$,

$$V_{t+1}(\Omega'_{i,t+1}, PF_{i,t+1}) = \begin{cases} V_{t+1}(\Omega'_{i,t+1}, PF_{it}+1) & \text{if } V_{t+1}(\Omega'_{i,t+1}, PF_{it}+1) > V_{t+1}(\Omega'_{i,t+1}, PF_{it}) \\ V_{t+1}(\Omega'_{i,t+1}, PF_{it}) & \text{otherwise} \end{cases} \tag{11}$$

# Appendix: Grade concealing in the second stage estimation

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$$\max_{\vec{q}} \overbrace{U_t(\vec{q}, \Omega_{it})}^{\text{Flow cost of taking bundle } \vec{q}} + 0.95 \cdot \overbrace{\mathbb{E}_{\Omega'_{i,t+1}|\Omega_{it}}[V_{t+1}(\Omega'_{i,t+1}, PF_{i,t+1}|\Omega_{it}, PF_{it})|\vec{q}]}^{\text{Continuation value}} + \overbrace{\sigma\left(\eta_{idt} + \lambda^q \eta_{i\vec{q}t}\right)}^{\text{preference shock}} \tag{10}$$

- For a drawn grade shock and thus $\Omega'_{i,t+1}$,

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$$\text{where } V_{im} = \beta_{0m} + \beta_1 GPA_i + \beta_{2m} p_{im} + \beta_{3m} S_{im} + \beta_{4m}\left(p_{im} \cdot S_{im}\right) - \overbrace{\beta_5 PF_{i7}}^{\text{Cost of Concealing}}, \quad V_0 = 0 \tag{12}$$

▸ Back to main (data) ▸ Back to main (estimation)

# Appendix: Estimation Results

**Table:** Estimates: Flow Utility and Graduation Payoff

| | Male | | Female | |
|---|---|---|---|---|
| | STEM | non-STEM | STEM | non-STEM |
| **Flow utility** | | | | |
| Enrollment ($\gamma_0$) | -1.67 | | -1.71 | |
| | (0.036) | | (0.017) | |
| per 1 course ($\gamma_m$) | -0.11 | -0.07 | -0.13 | -0.12 |
| | (0.023) | (0.001) | (0.075) | (0.001) |
| **Graduation payoff** | | | | |
| Mean utility ($\beta_{0m}$) | 0.77 | 1.03 | 0.44 | 0.94 |
| | (0.011) | (0.029) | (0.035) | (0.011) |
| Taste for GPA ($\beta_1$) | 0.78 | | 1.81 | |
| | (0.019) | | (0.024) | |
| Ability in my major ($\beta_{2m}$) | -1.97 | -2.03 | -2.05 | -2.29 |
| | (0.012) | (0.004) | (0.042) | (0.040) |
| Share of courses ($\beta_{3m}$) | 3.57 | 3.30 | 3.79 | 3.22 |
| | (0.024) | (0.031) | (0.027) | (0.060) |
| Ability × Share of courses ($\beta_{4m}$) | 13.85 | 7.44 | 10.72 | 7.94 |
| | (0.013) | (0.015) | (0.081) | (0.032) |
| **Cost of extra semester** ($C$) | 1.70 | | 2.60 | |
| | (0.048) | | (0.012) | |
| **Cost of concealing 1 grade** | 0.06 | | 0.15 | |
| | (0.0002) | | (0.005) | |

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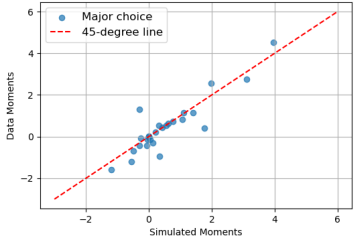
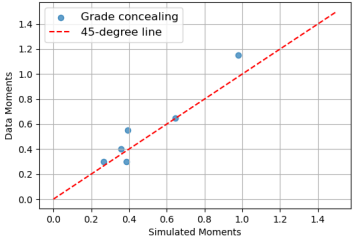
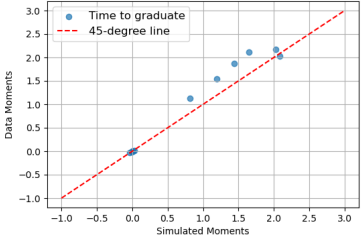
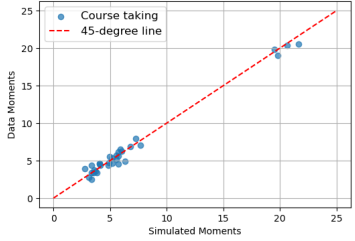
# Model Fit

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# Appendix: Other Parameter Estimates I

**Table:** Estimates: Ability Distribution and Grading Policies

| | STEM | | non-STEM | |
|---|---|---|---|---|
| | Coeff | SE | Coeff | SE |
| **Ability parameters** | | | | |
| $\alpha$: mean | 0.635 | (0.075) | 0.682 | (0.067) |
| $\alpha$: H parental edu. | 0.289 | (0.038) | 0.229 | (0.038) |
| $\alpha$: female | 0.174 | (0.046) | 0.319 | (0.039) |
| $\beta$: mean | 1.537 | (0.076) | 1.315 | (0.074) |
| $\beta$: H parental edu. | -0.287 | (0.081) | -0.399 | (0.073) |
| $\beta$: female | 0.446 | (0.056) | 0.093 | (0.044) |
| SAT: intercept | 0.884 | (0.032) | 0.692 | (0.022) |
| SAT: slope | 1.295 | (0.057) | 0.765 | (0.033) |
| SAT: scale | 4.338 | (0.012) | 4.301 | (0.011) |
| **Grading policy** | | | | |
| Year 1 | 0.166 | (0.015) | 0.120 | (0.007) |
| Year 2 | 0.178 | (0.016) | 0.120 | (0.007) |
| Year 3 | 0.166 | (0.015) | 0.103 | (0.006) |

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# Appendix: Other Parameter Estimates II

**Table:** Estimates: Extra Time to Graduation

| | STEM | | non-STEM | |
|---|---|---|---|---|
| | Coeff | SE | Coeff | SE |
| $\tau_0$ | 0.368 | (0.007) | 1.490 | (0.002) |
| $\tau_1$ | 0.017 | (0.0002) | -0.066 | (0.0006) |
| $\tau_2$ | 0.039 | (0.0004) | -0.074 | (0.0002) |
| $\tau_3$ | -0.002 | (0.00001) | 0.007 | (0.00004) |

**Table:** Estimates: Preference Shock

| | Coeff | SE |
|---|---|---|
| $\nu_1$ | 1.13 | (0.006) |
| $\nu_2$ | 0.87 | (0.003) |
| $\nu_3$ | 0.96 | (0.007) |
| $\lambda_Q$ | 0.77 | (0.002) |
| $\lambda_M$ | 0.29 | (0.015) |

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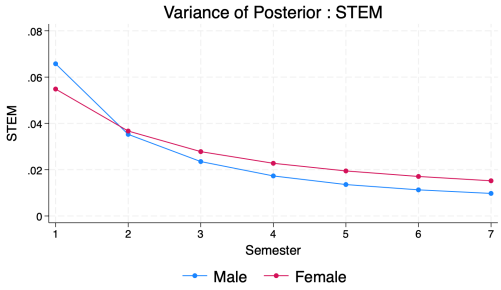
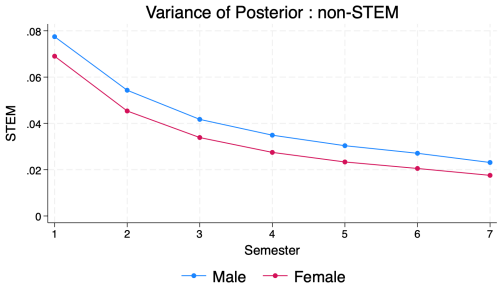
# Appendix: Grading Policies and Learning

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