Parental Investment and Intergenerational mobility:

An Estimable Dynamic Tournament Model of College Admission

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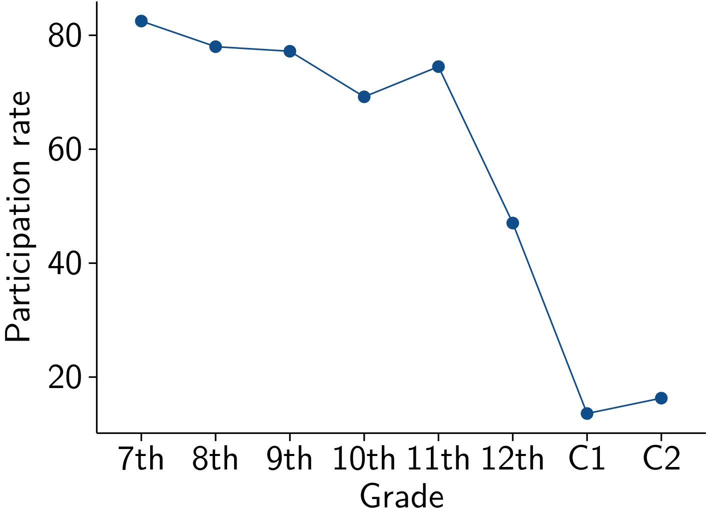
Summary of Motivation

- The competition aspects of parental investment
  - Private tutoring expenditure accounts for about 10% of household income in many countries
  - Seats for elite/good colleges are finite
  - Parental investment participation drops once the child graduates from high school
- College as the predictor of your lifetime income
  - Evidence shows that getting above the cutoff for elite college makes big difference (Zimmerman 2019, Sekhri 2019, Jia and Li 2019)
  - *The elite college premium grows over time*
  - Parental Investment increases the probability of getting into elite colleges $\Longrightarrow$ Implications for intergenerational mobility
- You have to beat your competitors to go to better colleges (for better lifetime income)
  - How?: parental investment, self-study, good initial conditions
  - Dynamic incentives: marginal effects of the modes might change over time

Motivation : Tutoring Participation after high school



Korea Education Longitudinal Study (2005) back

College Wage Differentials grow over time

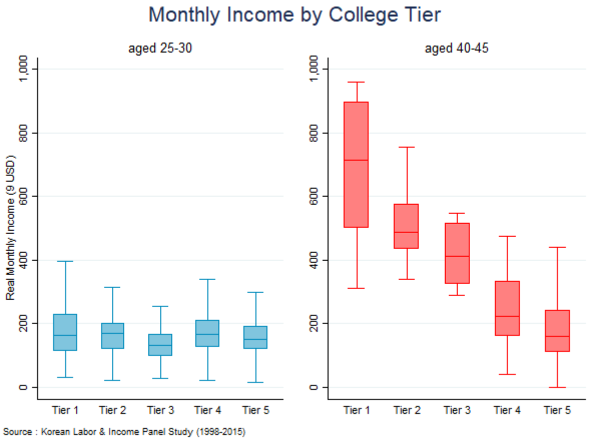


Figure: Average Income by Graduated College Tier

back Source: Author's Calculation using KLIPS Dataset (Unit :10,000 KRW= 9 USD)

Motivation : Dynamics of Parental Investment and Students' efforts

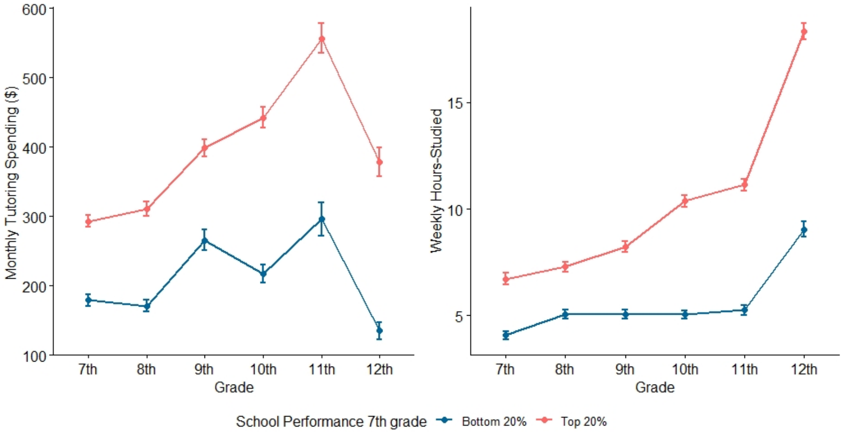


Figure: Dynamics of Tutoring and Hours-Studied

Research Questions

1. How much does parental investment (private tutoring expenditure) affect intergenerational mobility?
   - Simulate the world without parental investment controlling for students' self-efforts and parental education
2. How do the effects of tutoring expenditure and hours studied change with age?
   - Dynamic substitutability and complementarity
3. How would households react if there are fewer people to compete for elite college?
   - How would households respond to the low fertility regime?
4. *How productive is the parental investment?*
   - *Is it mostly for winning the competition rather than to enhance human capital? (simulate the world colleges provide equal outcome)*

What this paper does

1. Develop a dynamic tournament model incorporating competition between households
   - Model builds on Lazear and Rosen to incorporate the competition
   - Each household chooses (i) quantity and (ii) quality of parental investment and (iii) hours of self-study (efforts) to get its children into the better colleges
   - Colleges differ in income prospects (prizes) of graduates
2. Estimate the structural model using maximum simulated likelihood
   - Requiring tutoring expenditure, tutoring hours, hours self-studied, test scores over time $\Longrightarrow$ Korea Educational Longitudinal Studies
3. Quantification and policy experiments using the estimated model
   - Quantify the effects of tutoring expenditure on intergenerational mobility
     - ★ China's tutoring ban policy
   - Tutoring subsidy for the low income households
   - Cohort shrinking $\rightarrow$ Response of the households

Where I am

1. I started with the model with one choice variable (parental investment), estimated the model, and conducted counterfactuals
   - Stronger marginal effects of tutoring expenditure in earlier age (the effects decrease as students get older)
   - Intergenerational elasticity of earnings about 6 times higher with the existence of private tutoring
     - ★ Tutoring expenditure leads to less intergenerational mobility
2. Extension: adding hours of self-study and parental education to elicit more rich implications
   - Stronger marginal effects of tutoring expenditure in earlier age. The effects of self-study stays stable over time.
   - Parental education increases the effects of self-study, not so much for parental investment
3. Currently finishing up with the estimation of the extended model and writing code for the counterfactuals

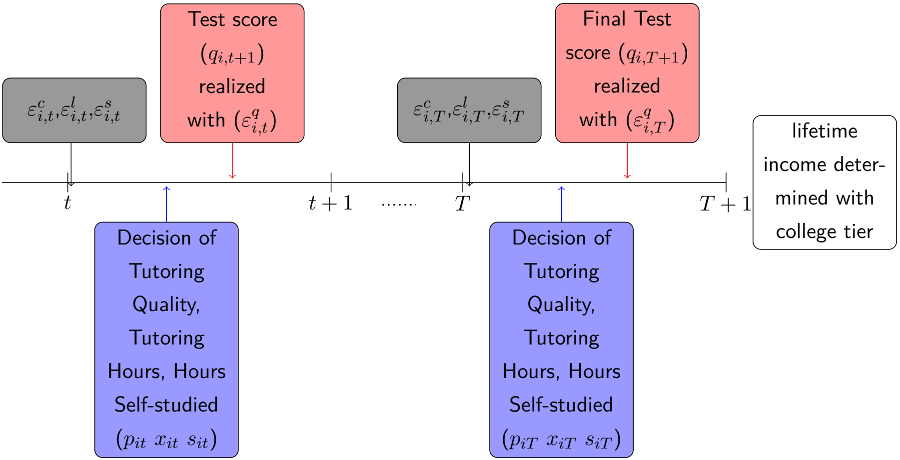
Difficulties I am facing/faced

- Missing test scores
  - The model period is from 7th to 12th grade, but the test scores of 10th and 11th grade are missing
  - I simulate those test scores, but the searching algorithm produced unreasonably large numbers
- Heavy computation in terms of model solving
  - Three continuous choice variables. Six continuous state variables.
- Efforts to find the "best" interpolation routine
  - I need to interpolate 6 dimension value function and to get first/second order partial derivatives, allowing for extrapolation
  - Options on the table: Bspline, Keane-Wolpin Interpolation, Habermann-Kinderman fast spline, and variation diminishing spline

Summary of the dynamic tournament model

1. Household i starts with initial academic performance q_{i1}
2. As soon as the household enters into time t, the consumption shock (ε^c_{it}), the leisure shock (ε^l_{it}), and the self-study productivity shock (ε^s_{it}) are realized.
3. Each household chooses quality of tutoring (p_{it}), hours of tutoring (x_{it}), and hours self-studied (s_{it}) to maximize its value function
4. The future lifetime income of its child is determined by the final test score ($q_{i,T+1}$), and the tournament structure
5. To get into college tier j, the child's score ($q_{i,T+1}$) should be greater than the cutoff of college tier j ($\bar{Q}_j$)
6. The test score is a function of previous year's test score (q_{it}), parental investment, and students' efforts.

The structure of the dynamic model : Timing of the decision



Expected Lifetime income (Terminal Value)

Expected lifetime income is defined as,

$$\sum_{j=1}^{J}\left[\underbrace{\ln(v_j)}_{\text{Prize of going to the } j^{th} \text{ tier college}} \times \underbrace{Prob(\bar{Q}_{j-1} \geq q_{i,T+1} \geq \bar{Q}_j)}_{\text{Probability of going to the } j^{th} \text{ tier college}}\right]$$

v_j: Average lifetime income of graduates of j^{th} tier colleges

q_{iT+1} : $i's$ CSAT score which determines the college to attend

$\bar{Q}_j$: Threshold to be admitted into j^{th} tier colleges

- Then how is $q_{i,T+1}$ generated?

Test score function

$$\ln q_{i,t+1} = \delta_{0t} + \delta_{1t} \ln q_{it} + \delta_{2t} \ln(1 + {p_{it}}^{\kappa} {x_{it}}^{1-\kappa}) + \varepsilon^s_{it} \delta_{3t} \ln(1 + s_{it}) + \delta_{4t} \ln pedu_i + \lambda_i + \eta^q_{it};$$

q_{it} : Test score at time t

p_{it} : tutoring quality

x_{it} : time spent for tutoring

s_{it} : time spent for self-study

η^q_{it} : Random shock of the test at time t

I also let δ_{2t} and δ_{3t} depend on the years of parental education

Issue #1 Missing test scores and weak identification

- Test score for $t = 4, 5$ are missing (but other input data is available)
- I simulate them:
  - Draw R random shocks ε_{it}^{qr}, $R = 1, 2, ...R$
  - Each random draw has corresponding simulated test score $q_{i,t+1}^{r}$
- Problem: the parameter searching algorithms pick unrealistically big parameters. (Weakly Identified)
  - For other periods, test score $q_{it} \in [250, 550]$
  - The searching algorithms pick parameters so that q_5 and q_6 be something like 8000

Simple but drastic solution

- I linearly interpolate δ_{0t} and δ_{1t} for $t = 4, 5$ using the coefficients of periods $t = 3$ and $t = 6$.
- So

$$
\begin{aligned}
\delta_{04} =& \delta_{03} + \frac{1}{3}(\delta_{06} - \delta_{03}) \\
\delta_{05} =& \delta_{03} + \frac{2}{3}(\delta_{06} - \delta_{03})
\end{aligned}
$$

- With this assumption the test score level becomes stable
- But this is probably drastic solution

The recursive representation

$$
\begin{aligned}
V_{it}(Z_{it}, \bar{\varepsilon}_{it}) = & \max_{x_{it}, p_{it}, s_{it}} \Big\{ \varepsilon^c_{it} \ln(c_{it}) + \alpha_1 \varepsilon^l_{it} \ln(l_{it}) \\
& + \beta \underset{\varepsilon^q_{it,}\, \bar{\varepsilon}_{i,t+1}}{E} \Big[V_{i,t+1}(Z_{it+1}, \bar{\varepsilon}_{i,t+1} \Big| \Gamma_{it}) \Big] \Big\}, \\
& \text{for } t < T; \\
V_{iT}(Z_{iT}, \bar{\varepsilon}_{iT}) = & \max_{x_{iT}, p_{iT}, s_{iT}} \Big\{ \varepsilon^c_{iT} \ln(c_{iT}) + \alpha_1 \varepsilon^l_{iT} \ln(l_{iT}) \\
& + \alpha_2 \sum_{j=1}^{J} \ln(v_j) \times Prob(\ln \bar{q}_{j-1} \geq \ln q_{i,T+1} \geq \ln \bar{q}_j \Big| \Gamma_{iT}) \Big\}, \\
s.t.\ & c_{it} + e_{it} \leq w_{it}; \\
& e_{it} = p_{it} x_{it} \\
& s_{it} + l_{it} + x_{it} \leq h; \\
& \bar{\varepsilon}_{it} = \{\varepsilon^c_{it}, \varepsilon^l_{it}, \varepsilon^s_{it}\},\ Z_{it} = \{w_{it}, \ln q_{it}, pedu_i\}. \\
& \Gamma_{it} = \{q_{it,}, \{\bar{q}_j\}_{j=1}^J, \{w_{it}\}_{t=1}^T, x_{it}, s_{it}, p_{it}\};
\end{aligned}
$$

Error term specifications

$$\begin{pmatrix} \ln \varepsilon_{it}^{c} \\ \ln \varepsilon_{it}^{l} \\ \ln \varepsilon_{it}^{q} \\ \ln \varepsilon_{it}^{s} \end{pmatrix} = \begin{pmatrix} \lambda_i^c \\ \lambda_i^l \\ \lambda_i^q \\ \lambda_i^s \end{pmatrix} + \begin{pmatrix} \eta_{it}^c \\ \eta_{it}^l \\ \eta_{it}^q \\ \eta_{it}^s \end{pmatrix}$$

$$\begin{pmatrix} \lambda_i^c \\ \lambda_i^l \\ \lambda_i^q \\ \lambda_i^s \end{pmatrix} \sim N\left(0, \Omega_{4\times 4}^{\lambda}\right);$$

$$\begin{pmatrix} \eta_{it}^c \\ \eta_{it}^l \\ \eta_{it}^q \\ \eta_{it}^s \end{pmatrix} \sim N\left(0, \Omega_{4\times 4}^{\eta}\right);$$

Issue #2 Model solution

There are six state variables. For observed part,

$$Z_{it} = \{w_{it}, \ln q_{it}, pedu_i\}.$$

For the unobserved part,

$$\bar{\varepsilon}_{it} = \{\varepsilon^c_{it}, \varepsilon^l_{it}, \varepsilon^s_{it}\}.$$

- It takes a long time to solve the dynamic model.
- With OpenMP (40 cores), it still takes about 40 seconds to evaluate the likelihood function once *using Fortran*
- My solution is adopting MPI for the model solving routine. Still work in progress.
- EGM maybe? $\Longrightarrow$ (i) concave utility (ii) state variables can be analytically expressed (iii) realization of shocks?

The advantage of using the Korean Data

- Richness of private tutoring data (Korean Education Longitudinal Studies, Korean Labor & Income Panel)
  - Average monthly tutoring expenditure, hours of tutoring, self-study data from 7th grade
  - Administrative exam score data available for 7-9th grade, and 12th grade

- Straightforward system to understand the effects of competition on tutoring investment
  - National standardized exam (College Scholastic Ability Test) determines the college to attend
  - Fixed seats for each college
  - A commonality of college admission competition (China, Turkey, Japan, Singapore etc)

Likelihood function

I denote θ as the set of parameters, S_{it} as the set of state variables, and Λ_i as the set of person-specific shocks. The likelihood contribution of household i is

$$\mathcal{L}_i(\theta|q_{i0},\{w_{it}\}_{t=1}^{T}) = \int\limits_{\Lambda_i} \left(\Pi_{t=1}^{T_i}\mathcal{L}_{it}(\theta|S_{it},\Lambda_i)\right)\cdot f_{\Lambda_i}(\Lambda_i)d\Lambda_i;$$

where

$$\begin{aligned}\mathcal{L}_{it}(\theta|S_{it},\Lambda_i) = & \Big[f_{p_{it}}(p_{it})\cdot f_{x_{it}}(x_{it}|p_{it})\cdot f_{s_{it}}(s_{it}|p_{it},x_{it})\cdot f_{q_{it}}(q_{it}|p_{it},x_{it},s_{it})\Big]^{d_{it}^e d_{it}^s} \\ & \times\Big[f_{p_{it}}(p_{it})\cdot f_{x_{it}}(x_{it}|p_{it})\cdot \Pr(s_{it}=0|p_{it},x_{it})\cdot f_{q_{it}}(q_{it}|p_{it},x_{it},s_{it})\Big]^{d_{it}^e(1-} \\ & \times\Big[\Pr(p_{it}x_{it}=0)\cdot f_{s_{it}}(s_{it}|p_{it}x_{it}=0)\cdot f_{q_{it}}(q_{it}|p_{it},x_{it},s_{it})\Big]^{(1-d_{it}^e)d_{it}^s} \\ & \times\Big[\Pr(p_{it}x_{it}=0)\cdot \Pr(s_{it}=0|p_{it}x_{it}=0)\cdot f_{q_{it}}(q_{it}|p_{it},x_{it},s_{it})\Big]^{(1-d_{it}^e)(1-}\end{aligned}$$

Conclusion

1. Preliminary Results
    - Stronger marginal effects of tutoring expenditure in younger periods.
    - The effects of self-study are stable over time.
    - Parental education increases the effects of self-study, not so much for parental investment
2. ..writing code for the counterfactuals
    - Intergenerational mobility where: (i) Tutoring is not an option (ii) Tutoring and self-study are not options
    - Subsidy for low income households
    - Response of the households in the ultra-low fertiltiy regime

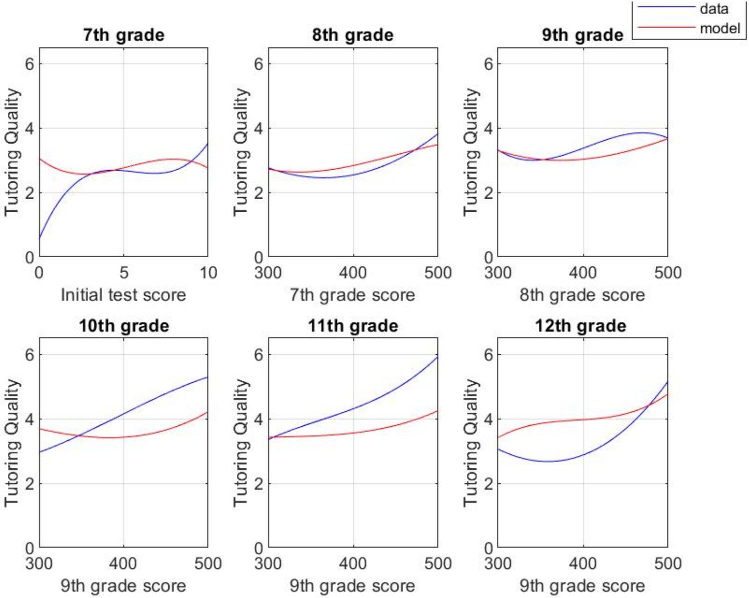
- Thank you!!!

Sample fit: Test Scores

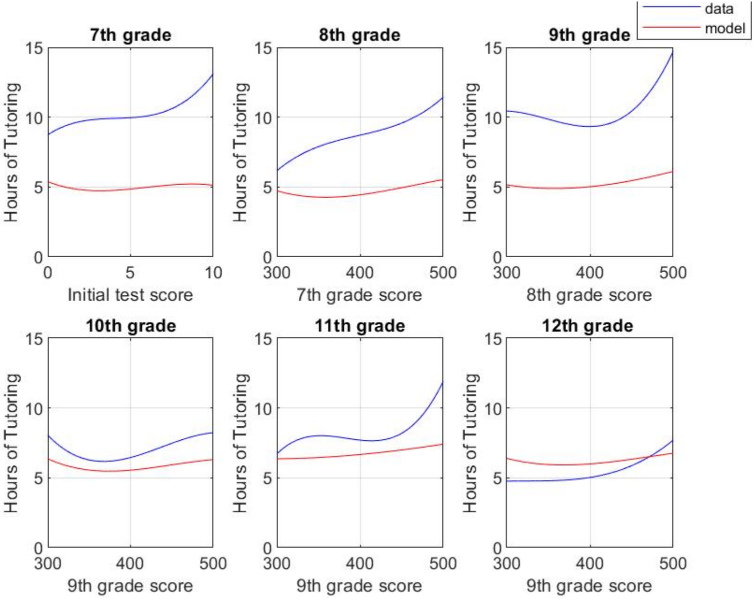
	7th	8th	9th	10th	11th	12th
Log Test-Score ($\log q$)						
Data						
mean	6.042	6.037	6.040	-	-	6.016
std	(0.111)	(0.117)	(0.118)	-	-	(0.155)
Model						
mean	5.942	5.915	5.930	5.920	5.892	5.851
std	(0.069)	(0.044)	(0.035)	(0.027)	(0.020)	(0.015)

Table: Log Test Scores Sample Fit

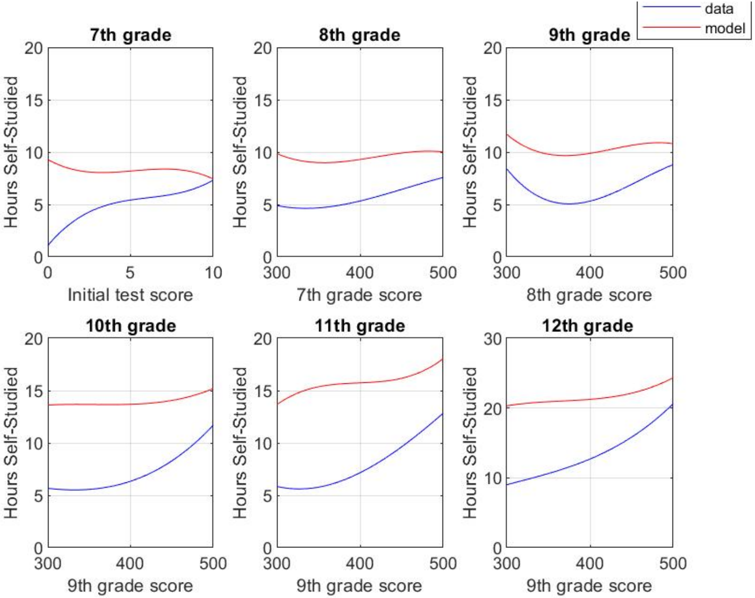
Sample fit: Tutoring Quality



Sample fit: Hours spent in tutoring



Sample fit: Hours spent in self-study



Motivation

1. Parental Investment (private tutoring) and its potential effects on lifetime income

- Tutoring has a positive association with subsequent test score
- The effects of elite college on earnings exist and grow over the life-cycle
  - *The elite university cutoff effects*: China (Jia and Li 2020), India (Sekhri 2019) Chile (Zimmerman 2019)
  - *The premium grows over time*: Ko 2011, Koh and Lee 2019
- China's tutoring ban policy
  - *"China is barring tutoring for profit in core school subjects... to ease financial pressures on families that have contributed to low birth rates,..."*

Motivation : Competition and Dynamics

2. The competitive nature of parental Investment (private tutoring)

- Tutoring as a means to get finite seats for better colleges
- The strategic interaction through such competition not formally implemented and estimated in the literature
- Rapid cohort changes in the countries where private tutoring is popular

3. Complementarity and substitutability of parental Investment and the child effort

- The child effort variable is often ignored in the literature
- The average self-study hours soars up at the end while many students reduce or quit tutoring
- The effects of tutoring and self-study might change over time in a different way

The Prize Structure

Ranking	Average lifetime Earnings of Graduates of each tier
$1st$	$\$v_1$
$2nd$	$\$v_2$
$\vdots$	$\vdots$
$(J-1)^{th}$	$\$v_{J-1}$
J^{th}	$\$v_J$

- There are J tiers ($J-1$ college tiers, the high school graduate tier)
- There are N households
- Each tier j has S_j seats such that $\sum_{j=1}^{J-1} S_j = M < N$
- $v_j = \sum_{t=1}^{T^*} \delta^t E(y^j)$

Probabilities of going to the tiers

Ranking	Probabilities of going to the tier
$1st$	$Prob_i(\infty \geq q_{i,T+1} \geq \bar{Q}_1)$
$2nd$	$Prob_i(\bar{Q}_1 \geq q_{i,T+1} \geq \bar{Q}_2)$
$\vdots$	$\vdots$
$(J-1)^{th}$	$Prob_i(\bar{Q}_J \geq q_{i,T+1} \geq \bar{Q}_{J-1})$
J^{th}	$Prob_i(\bar{Q}_{J-1} \geq q_{i,T+1} \geq 0)$

- $q_{i,T+1}$ is the final test score of person i
- $\bar{Q}_j$ is the cutoff for j^{th} college tier (The lower bound of q_{T+1} of j^{th})
- $\bar{Q}_j$ changes with the distribution of the final test score
- $\bar{Q}_j$ changes with the tutoring choices of individuals

Estimation procedure

1. Generate average lifetime income of each tier using Korean Labor & Income Panel Study Data Details

- Using Korean Labor & Income Panel Study, I estimate the wage equation and predict the average income of college tiers

  - ★ I sum the discounted tier-specific income for different ages, and define it as tier-specific lifetime income (v_j)

1. Main analysis: estimate the dynamic tournament model

  - ★ Using Korean Educational Longitudinal Studies, I estimate the dynamic tournament model by maximum simulated likelihood

Lifetime income

Using KLIPS, the income equation estimated is

$$\ln y_{it} = \sum_{Tier=1}^{5} \left\{ \beta_{tier}(D_{it}^{Tier} \cdot Age_{it}) + \alpha_{tier} D_{it}^{Tier} \right\} + Z\gamma,$$

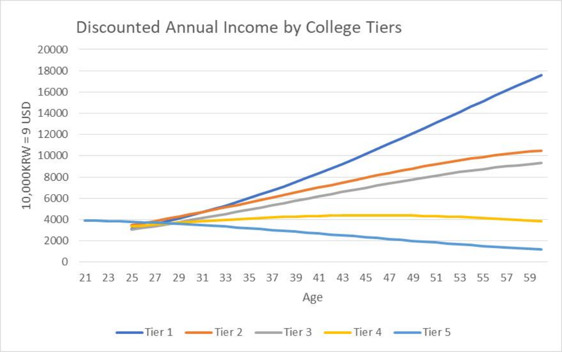


Figure: Predicted Annual income of Graduates by College Tiers

more

Literature review and Contribution

- Studies of Income Inequality and Intergenerational Mobility
  - Becker et al. (2018) Chetty et al. (2014) Becker and Tomes (1979, 1986)
  - ***The impact of parental investment on intergenerational mobility*** controlling for child's self efforts and parental education

- Structural model of parental Investment and the child outcome
  - Del Boca, Flinn, Wiswal (2014 Restud): Estimating the effects of time and monetary parental investment using a dynamic model
  - Agostinelli (2018 *working paper*) : Social Interactions and Parental Investment
  - Bodoh-creed and Hickman (2019 *working paper*) : Pre-college HC investment on college quality & labor market outcome using empirical auction framework
  - ***The introduction of the child effort variable and estimation with student competition***

Literature review and Contribution continued

- Application of Rank-Order Tournament Model
  - Lazear and Rosen (1979) Rosen (1982)
  - Structural estimation of tournament model: Ferrall (1996, 1997) Chen and Shum (2010) Zheng and Vukina (2007)
  - ***Dynamic tournament with the selection process of heterogeneous agents***
  - ***Reasonable measures of efforts and resources***

- Private tutoring literature in economics
  - Few papers on welfare implications (Kim Tertilt Yum 2018)
  - Papers tend to focus on the effects of private tutoring on academic performance only
  - ***First paper to estimate the effects of tutoring on intergenerational mobility***

Data

- Korean Education Longitudinal Studies 2005
  - Tracking 6,908 7th grade students for 15 years
  - Household's tutoring expenditure, income, administrative national standardized exam score and CSAT score
  - Relatively more detailed information on tutoring expenditure
- Korean Labor & Income Panel Study
  - Information on income, college they graduated from,
  - To predict lifetime income of each individual proceduremain

Standard errors

For parameter set θ, I computed

$$S_{n\times k} = \frac{\mathcal{L}(\boldsymbol{\theta}+\triangle)-\mathcal{L}(\boldsymbol{\theta})}{\triangle};$$

$$V_{k\times k} = (\frac{S'S}{N})^{-1};$$

$$\text{Standard error of } \boldsymbol{\theta} = diag\left(\sqrt{\frac{V}{N}}\right)$$

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Auxiliary regression A

Table:

	Dependent variable:
	log(CSAT)
ln(Performance 6th)	0.266***
	(0.007)
ln(Tutoring-Middle)	0.019***
	(0.002)
intercept	4.557***
	(0.034)
Observations	3,482
R^2	0.378
Residual Std. Error	0.151 (df = 3479)
Note:	*p<0.1; **p<0.05; ***p<0.01

Auxiliary regression B

Table:

	Dependent variable:
	log(CSAT)
ln(Performance 9th)	0.416***
	(0.014)
ln(Tutoring-High)	0.078***
	(0.004)
intercept	4.082***
	(0.023)
Observations	5,864
R^2	0.237
Residual Std. Error	0.389 (df = 5861)
Note:	*p<0.1; **p<0.05; ***p<0.01

back

Income-Tutoring Regression

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Table:

	Dependent variable:
	log(Initial Income)
log(Private tutoring)	0.003
	(0.008)
log(CSAT Score)	0.283***
	(0.047)
intercept	3.717***
	(0.265)
Observations	739
Note:	*p<0.1; **p<0.05; ***p<0.01

Complete GPA-Tutoring regression

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Table: College GPA and Private tutoring expenditure

	Dependent variable:					
	log(College GPA)					
	All	Top Tier	2nd Tier	3rd Tier	4th Tier	Bottom Tier
	(1)	(2)	(3)	(4)	(5)	(6)
log(Total Tutoring)	-0.003^{*}	-0.014	0.003	0.002	-0.005	-0.003
	(0.002)	(0.026)	(0.008)	(0.008)	(0.005)	(0.002)
log(CSAT Score)	0.105^{***}	1.222	0.143	-0.162	0.495	0.108^{***}
	(0.016)	(1.208)	(1.032)	(0.653)	(0.445)	(0.022)
intercept	0.762^{***}	-6.169	0.482	2.384	-1.637	0.744^{***}
	(0.095)	(7.667)	(6.455)	(4.057)	(2.740)	(0.129)
Observations	2,489	28	90	162	274	1,935
Note:				*p<0.1; **p<0.05; ***p<0.01		

Structural Estimates

	7th	8th	$9th$	10th	11th	12th
$log(PreviousTest)$ (δ_{1t})	0.2577***	0.4927***	0.5726***	0.5317***	0.9603***	0.8330***
	(0.0015)	(0.0006)	(0.0005)	(0.0007)	(0.0006)	(0.0005)
Constant (δ_{0t})	5.2058***	2.8721***	2.4381***	1.3140***	1.3293***	1.2404***
	(0.0027)	(0.0033)	(0.0027)	(0.0013)	(0.0013)	(0.0011)

back

Summary of empirical evidence

1. Tutoring has potential impacts on the lifetime income of children more
2. Household use tutoring as means to get finite seats for elite colleges more
   - The strategic interaction through the competition not formally implemented and estimated in the literature
   - Rapid cohort changes in the countries where private tutoring is popular
3. Complimentarity and substitutability of parental Investment and the child effort more
   - The child effort variable is often ignored in the literature
   - The average self-study hours soars up at the end while many students reduce or quit tutoring

Algorithm

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1. Start with initial guess $\{\bar{Q}_j^0\}_{j=1}^J$
2. Given $\{\bar{Q}_j^0\}_{j=1}^J$, I generate $\{V_{it}^0(q_{it}, \varepsilon_{it}^c; Z_{it})\}_{t=0}^T$ and $\{e_{it}^0(q_{it,}\varepsilon_{it}^c; Z_{it})\}_{t=0}^T$ using backward recursion.
3. I forwardly simulate each household's behavior, using stored $\{V_{it}^0(q_{it}, \varepsilon_{it}^c; Z_{it})\}_{t=0}^T$ and $\{e_{it}^0(q_{it,}\varepsilon_{it}^c; Z_{it})\}_{t=0}^T$
4. Then I will have a generated q_{iT} and its distribution $F^0(q_T)$
5. Conditional on the generated test score distribution, $F^0(q_T)$, find a set of generated cutoff $\{\bar{Q}_j^1\}_{j=1}^J$, given the definition of $\bar{q}_j$
6. Update the guess for the set of cutoffs, using $\{\bar{Q}_j^1\}_{j=1}^J$

Do 2 through 5 until $\|\{\bar{Q}_j^n\}_{j=1}^J - \{\bar{Q}_j^{n+1}\}_{j=1}^J\| < \varepsilon$.

Define such set of thresholds as $\{\bar{Q}_j^*\}_{j=1}^J$

Predicted Lifetime income

	Tier 1	Tier 2	Tier 3	Tier 4	Tier 5 (Baseline)
Predicted Lifetime Income ($)	3.08 mil	2.34mil	2.07mil	1.33mil	0.96mil
$\frac{\text{Lifetime Income of the Tier}}{\text{Baseline}} \times 100$	321	244	215	138	100

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OLS Results of Lifetime Income

	loginc
intage_1	0.083***
	(0.00)
intage_2	0.065***
	(0.00)
intage_3	0.065**
	(0.00)
intage_4	0.037***
	(0.00)
byear_	0.022***
	(0.00)
age_	0.072***
	(0.00)
agesq	-0.001***
	(0.00)
_cons	-36.255***
	(0.84)
N	47293

Figure: Log income Equation

Discrete

$$\ln y_{it} = \sum_{Tier=1}^{4} \sum_{D_{age}}^{4} \beta_{tier}(D^{Tier}{}_{it} \cdot D_{age}) + Z\gamma,$$

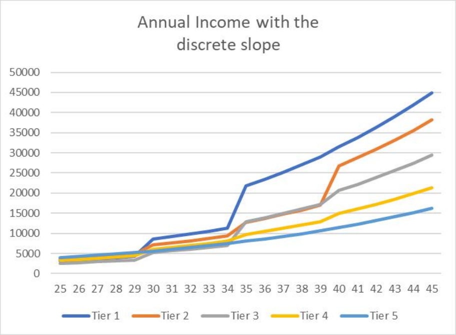

Figure: Predicted Annual income of Graduates by College Tiers

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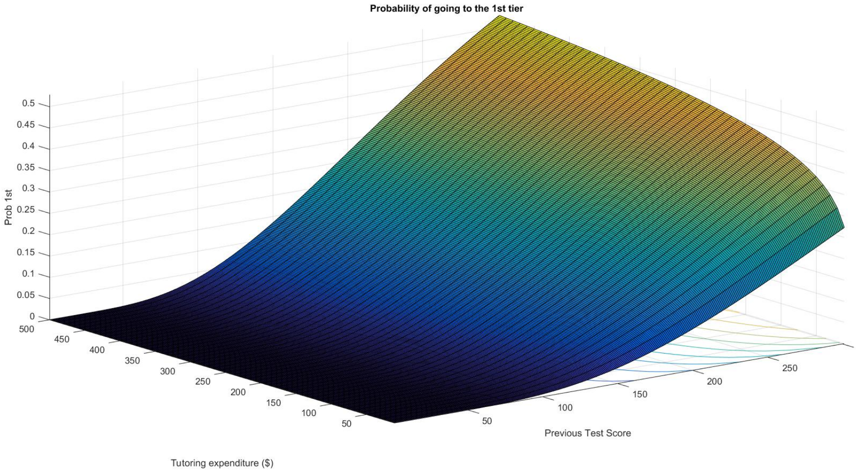
The Model Properties

- Model properties and comparative statics
  - Households with higher income spend more on tutoring expenditure
  - Tutoring expenditure increases (decreases) probability of going to the higher (lower) tiers
  - As the premium of higher college tier $(v_j - v_{j+1})$ increases, households spend more on tutoring expenditure

Probability of going to the 1st tier



OtherTiers

Bottom tier

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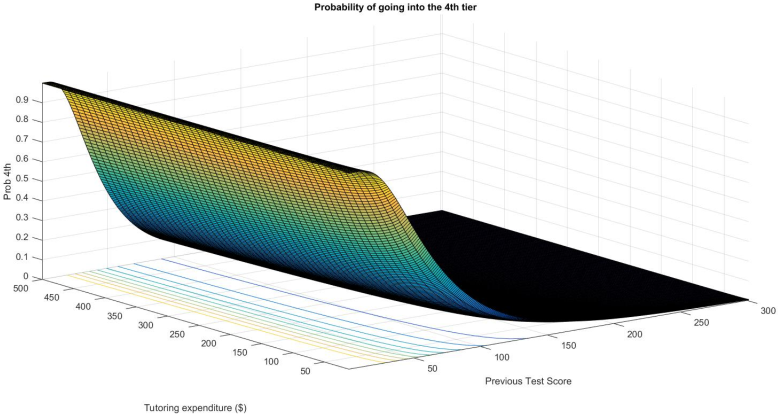
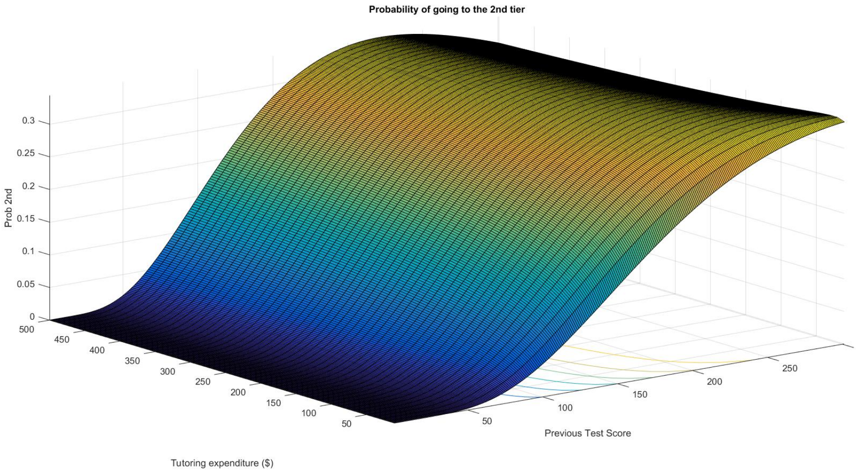
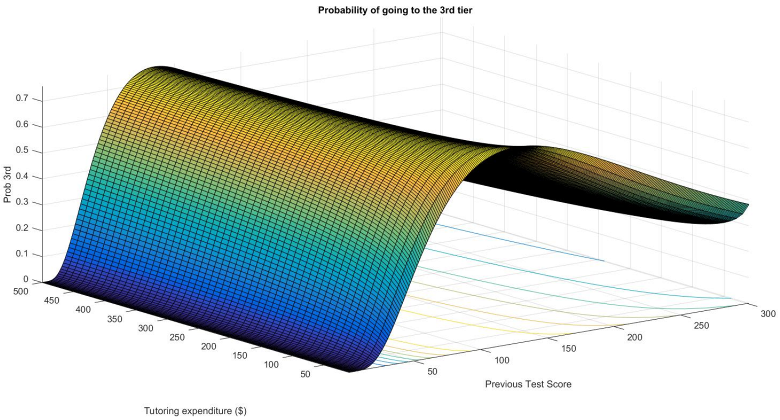


Second tier



Probability of going to the 2nd tier
Prob 2nd
0.3
0.25
0.2
0.15
0.1
0.05
0
500
450
400
350
300
250
200
150
100
50
Tutoring expenditure ($)
50
100
150
200
250
Previous Test Score

Third tier



Probability of going to the 3rd tier
Prob 3rd
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
500
450
400
350
300
250
200
150
100
50
Tutoring expenditure ($)
50
100
150
200
250
300
Previous Test Score

Additional selection process evidence

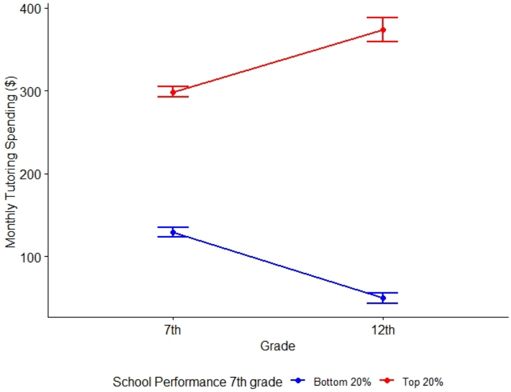


Figure: Middle school to high school

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Low association with initial wage

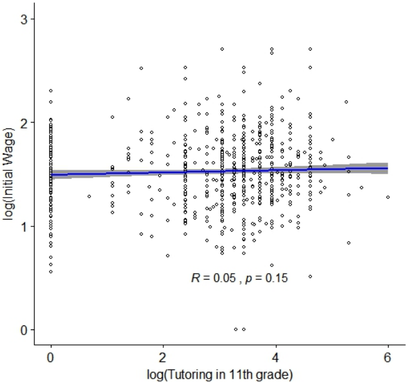

Figure: Tutoring and Labor Market Performance

Data: Korean Education and Employment Panel (2005) back