

# Learning and Dynamic Schooling Decisions

## DSE Summer School

Arnaud Maurel  
Duke University, NBER and IZA

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- Structural estimation of dynamic discrete choice models of schooling decisions started in the 90's.
- Builds on estimation methods for dynamic discrete programming models (Miller, 1984; Wolpin, 1984; Pakes, 1986; Rust, 1987...).
- Initial applications in labor focused on post-schooling decisions (e.g. labor supply, Eckstein and Wolpin, 1989).
- Keane and Wolpin (1997): dynamic life-cycle model of schooling, labor force participation and occupational decisions.

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# Introduction (Cont'd)

- Dynamic structural approach: consistent with Ben Porath's dynamic human capital accumulation model.
- Explicitly model human capital investment as resulting from an intertemporal optimization problem.
- At any given period  $t$ , forward-looking agents make the decision that maximizes their expected lifetime utility.
- Typically assume that agents perfectly know their own characteristics.
- Today: relax this assumption, allowing agents to have imperfect information and learn about their own characteristics (e.g. ability/productivity).

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- **Schooling investments under imperfect information about ability:** Altonji (1993); Arcidiacono (2004); Stange (2012); Stinebrickner and Stinebrickner (2012, 2014), Thomas (2019); Proctor (2022); Larroucau and Rios (2022); Arcidiacono et al. (2025)...
- **Occupational choice with learning:** Miller (1984); James (2012); Antonovics and Golan (2012); Papageorgiou (2014); Sanders (2014); Hincapié (2020); Pastorino (2024); de Paula et al. (2025)...
- **Dynamic learning models:** Erdem and Keane (1996); Crawford and Shum (2005); Ching et al. (2013); Aguirregabiria and Jeon (2020); Bunting et al. (2025)...

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- Substantial returns to receiving a four-year college degree (Heckman et al., 2006, Goldin and Katz, 2008, Bound and Turner, 2011, Ashworth et al., 2021).
- Low bachelor's completion rates: in the US, 40% of the students entering four-year college do not earn a bachelor's degree within six years (NCES, 2021).
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# Motivation (Cont'd)

- Learning can take place both in college and in the labor market.
- Students often take breaks before completing their degree.
  - In the NLSY97, 43% of the individuals who left college before graduation returned to college at some point (*stopouts*).
- Descriptive evidence suggests that learning about schooling ability and labor market productivity plays a role.
  - Those with negative GPA shocks more likely to leave college in the following period.
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What are the extent of imperfect information on ability, and its impact on schooling/occupational choices & school-to-work transitions?

Using the NLSY97, we estimate a dynamic model that allows:

- Individuals to enroll or re-enroll in two or four-year colleges (Science/non-Science majors) in every period.
- Work part-time, full-time, or not at all - potentially while in college.
- Two sectors: blue- and white-collar. White-collar jobs only available with probability  $\lambda$ .
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# Choice sets and expectations

- Choice set before college graduation:
  - School: 2-year; 4-year science, 4-year non-science, none.
  - Work: i) Part-time, Full-time, none; and ii) blue-collar or white-collar job (prob.  $\lambda < 1$  if haven't worked in white-collar in  $t - 1$ ).
  - Home: reference alternative.
- College graduates choose among the different work alternatives.
- Time is discrete, individuals choose the sequence of actions maximizing the present value of *expected* lifetime utility.
- Expectation wrt. the distribution of:
  - Future idiosyncratic shocks;
  - Ability signals associated with the alternative choice paths;
  - Aggregate labor market shocks;
  - Receiving an offer in white-collar sector;
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Two main dimensions of unobserved heterogeneity:

- ❶ Individuals have imperfect information about their schooling ability and labor market productivity.
  - College: learn about their ability by observing their performance (GPA) at the end of the year.
  - Gap between observed and expected GPA is an ability signal, which is used to update their belief in a Bayesian fashion.
  - Also provides some information about their ability in other types of colleges and majors, along with their productivity → *correlated learning*.
  - Same for wages.
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Throughout the analysis, maintain the assumption that agents have rational expectations.

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**Throughout the analysis, maintain the assumption that agents have rational expectations.**

- Focus on the unknown portion of ability.
- Ability is multidimensional, given by  $A = (A_{i2}, A_{i4s}, A_{i4ns}, A_{iw}, A_{ib})'$ .
- Denote  $S_{it}$  as the vector of noisy signals the individual has received in period  $t$ .
  - Signals from grades, wages, or both.
- The prior ability mean is  $E_{it}(A_i)$  where at  $t = 1$  expected ability is zero.
- Denote the prior variance  $\Sigma_{it}(A_i)$  where at  $t = 1$  the prior variances is the population variance.
- Denote  $\Omega_{it}$  as a  $5 \times 5$  matrix with 1 divided by the transitory variances on the diagonal for signals received and zeros everywhere else.

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# Learning - updating

Assuming ability and signals are normally distributed,  $E_{it}(A_i)$  and  $\Sigma_{it}(A_i)$  are updated according to (DeGroot, 1970):

$$\begin{aligned}E_{it}(A_i) &= (\Sigma_{it-1}^{-1}(A_i) + \Omega_{it})^{-1} (\Sigma_{it-1}^{-1}(A_i)E_{t-1}(A_i) + \Omega_{it}S_{it}) \\ \Sigma_{it}(A_i) &= (\Sigma_{it-1}^{-1}(A_i) + \Omega_{it})^{-1}\end{aligned}$$

With additional signals, prior variance moves towards zero, giving more weight to the prior and less to the signal.

Unidimensional case: reduces down to the usual formula

$$E_{it}(A_i) = \frac{\sigma_A^2}{\sigma_A^2 + \sigma_\varepsilon^2} S_t + \frac{\sigma_\varepsilon^2}{\sigma_A^2 + \sigma_\varepsilon^2} E_{t-1}(A).$$



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- Grades in two-year colleges and in the first two years of four-year colleges are given by, denoting by  $\tau$  the period of college enrollment and  $j$  the type of college/major :

$$G_{ij\tau} = \gamma_{0j} + X_{ij\tau}\gamma_{1j} + A_{ij} + \varepsilon_{ij\tau}$$

where  $X_{ij\tau}$  is known to the individual  $i$  (demographics, ability, work while in college),  $A_{ij}$  is an unknown ability factor, and  $\varepsilon_{ij\tau}$  is a noise distributed  $\mathcal{N}(0, \sigma_{j\tau}^2)$ .

- Noisy signal on ability  $A_{ij}$  given by:

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- Let  $AI_{ij\tau} = \gamma_{0j} + X_{ij\tau}\gamma_{1j} + A_{ij}$  (academic index). For four-year colleges and periods  $\tau > 2$ , grades are given by:

$$G_{ij\tau} = \lambda_{0j} + \lambda_{1j}AI_{ij\tau} + \varepsilon_{ij\tau}$$

- Parsimonious location-scale specification that allows returns to ability to vary across periods of college enrollment and majors.
- Graduation probability: depends on demographics, observed ability, current ability beliefs, accumulated years of college and major.

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- Wages in the white-collar sector:

$$\ln(W_{iwt}) = \delta_t + X_{iwt}\gamma_w + A_{iw} + \varepsilon_{iwt}$$

- Wages in the blue-collar sector:

$$\ln(W_{ibt}) = \delta_t + X_{ibt}\gamma_b + A_{ib} + \varepsilon_{ibt}$$

- Productivity shocks ( $\varepsilon_{iwt}, \varepsilon_{ibt}$ ): normally distributed (with sector-specific variances), independent over time, across sectors, and of the other state variables.
- Aggregate shocks: individuals form expectations over the  $(\delta_{t'})_{t' \geq t+1}$  assuming an AR(1) process.

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# Wages (Cont'd)

- For in-school work, log-wages in sector  $l$  given by:

$$\ln(W_{ilt}) = \delta_{lt} + \lambda_{0l} + \lambda_{1l}PI_{ilt} + \varepsilon_{ilt}^s$$

where  $PI_{ilt} = \gamma_{0l} + X_{ilt}\gamma_{1l} + A_{il}$  (sector- $l$  productivity index).

- Allow for noisier signals from in-school vs. out-of-school work.
- Controls: demographics, completed years of college (and major for white-collar wages), HS GPA, experiences in blue- and white-collar sectors, and work part-time.

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# Flow utilities and consumption

Flow utility for a particular schooling ( $j$ ) /work (intensity  $k$ , sector  $l$ ) combination is:

$$U_{jkl}(Z_{it}, \varepsilon_{ijklt}) = \alpha_{jkl} + \alpha_C E(U(C_{ijklt})) + Z_{1it}\alpha_j + Z_{2it}(\alpha_k + \alpha_l) + \varepsilon_{ijklt}$$

where the  $(\varepsilon_{ijklt})$ 's are distributed i.i.d. Type 1 extreme value.

- CRRA utility of consumption ( $\theta$  set using grid search):

$$U(C_{ijklt}) = \frac{C_{ijklt}^{1-\theta}}{1-\theta}.$$

- Consumption depends on labor income, parental transfers, tuition fees and educational grants/loans.
- Decisions based on *expected* utility of consumption, as individuals don't see their actual wages until after the choice is made.

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$$C_t = \max(C_t^*, \underline{C})$$

with

$$C_t^* = \begin{cases} W_t & \text{if working \& not in school \& } t < T^* \\ W_t + PT_t + G_t + L_t - TF_t & \text{if working while in school \& } t < T^* \\ PT_t + G_t + L_t - TF_t & \text{if in school \& not working \& } t < T^* \\ W_t - SLR_t & \text{if working \& not in school \& } t \geq T^* \\ 0 & \text{if not in school \& not working} \end{cases}$$

where  $W_t$  denotes labor income,  $PT_t$  parental transfers,  $G_t$  educational grants,  $L_t$  educational loans,  $TF$  tuition and fees and  $SLR_t$  loan repayment.

Consumption floor  $\underline{C} = \$2,800$  (Hai and Heckman, 2017); assume loan repayment begins after  $T^*$ .

- State variables that transition over time are:
  - ➊ **Prior ability means and variances.**
  - ➋ Age, experiences, accumulated schooling and four-year college degree.
  - ➌ Lagged decisions (switching costs).
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- The conditional value function is given by:

$$v_{jkl}(Z_{it}) = u_{jkl}(Z_{it}) + \beta E_t[V_{t+1}(Z_{it+1}) | Z_{it}, d_{it} = (j, k, l)],$$

- Given that the  $\varepsilon$ 's are i.i.d. Type 1 extreme value and white collar offers are uncertain

$$\begin{aligned} v_{jkl}(Z_{it}) = & u_{jkl}(Z_{it}) + \beta \lambda_{i,t+1}^{(jkl)} E_t \left[ \ln \left( \sum_j \sum_k \sum_l \exp(v_{jkl}(Z_{it+1})) \right) \middle| Z_{it}, d_{it} = (j, k, l), \text{Offer}_{it+1} = 1 \right] \\ & + \beta (1 - \lambda_{i,t+1}^{(jkl)}) E_t \left[ \ln \left( \sum_j \sum_k \exp(v_{jkl}(Z_{it+1})) \right) \middle| Z_{it}, d_{it} = (j, k, l), \text{Offer}_{it+1} = 0 \right] + \beta \gamma. \end{aligned}$$

- Information set of the individual at the beginning of period  $t$  includes the ability signals received from periods 1 to  $t - 1$ .

# Finite dependence

- We re-express the future payoffs to avoid solving the full backward recursion problem.
- **This is key to the computational feasibility of estimation for this type of correlated learning model.**
- Conditional on the one-period-ahead state variables besides  $\varepsilon$ , the following equalities hold:

$$\ln \left( \sum_{j,k,l} \exp(v_{jkl}(\mathbf{Z}_{it+1})) \right) = v_{j'k'l'}(\mathbf{Z}_{it+1}) - \ln(p_{j'k'l'}(\mathbf{Z}_{it+1}))$$

for any choice  $\{j', k', l'\}$ .

- Allows to reformulate the estimation problem such that the differenced future utility term depends only on CCPs a few periods ahead and flow utilities.
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# Finite dependence (Cont'd)

- For alternatives (say,  $a$ ) that do not involve white-collar work, this is straightforward.
- Consider the paths  $\{a, \text{home}, \text{home}\}$  and  $\{\text{home}, a, \text{home}\}$ .
- One can check that both choice paths result in the same distribution of states, and hence the same expected future utility at  $t + 3$ .
- $v_a - v_{\text{home}}$  obtained as a function of the flow utilities and CCPs two periods ahead.
- For choices involving white-collar work, this requires more work since prob. of receiving a white-collar offer  $\lambda < 1$ .
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- Conditional on known heterogeneity, selection on observables only.
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- Outcome equation parameters (grades and wages) identified via a control function argument.
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- Bunting, Diegert and Maurel (2025) study identification of a general class of learning models.
- Relative to Arcidiacono et al. (2025): (much) more flexible on the decision process, and does not rely on measurements for the latent factors.
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# Estimation steps (pure learning case)

Consider first the case without (known) unobserved heterogeneity.

Step 1: Use the EM algorithm to estimate parameters of the wage and grade equations, along with the ability covariance matrix.

Step 2 (Flow utility parameters):

- Estimate reduced-form conditional choice probabilities (CCP) using flexible logits.
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# Step 1: Estimation of outcome and learning parameters

Use the EM algorithm (Dempster et al., 1977) applied to a case where unobserved heterogeneity is *continuous*.

- Iterate, until convergence, between E(xpectation)- and M(aximization)-steps.
- **M-step:** taking as given the posterior ability distribution, maximize the expected complete log-likelihood of the outcomes (separable across sectors).
- For grades (lower-classmen), boils down to OLS on obs. characteristics and expected ability.
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# Adding heterogeneity types

- Breaks down the separability between choice and outcome components of the likelihood.
- Use an adaptation of the EM algorithm to reinstate the separability between the two stages at the maximization step.
- Two-stage estimation (Arcidiacono and Miller, 2011):
  - ① EM estimation of the measurement system, unobserved heterogeneity distribution and CCPs.
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## Takeaways:

- Returns to college higher in the white-collar sector than in the blue-collar sector.
- Same is true for majoring in STEM.
- Expected academic abilities significantly affect the utilities of the college options → cost of effort.
- Working in college lowers expected grades, and working full time makes college unattractive.
- High switching costs associated with changing work or schooling options.
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# Abilities and learning

	White-collar	Blue-collar	4 yr Sci.	4 yr Non-Sci.	2 yr
<i>Correlation matrix</i>					
White-collar	1.00 (—)	0.62 (0.04)	0.28 (0.09)	0.19 (0.06)	0.15 (0.08)
Blue-collar	0.62 (0.04)	1.00 (—)	0.24 (0.10)	0.05 (0.06)	0.16 (0.08)
4 yr Sci.	0.28 (0.09)	0.24 (0.10)	1.00 (—)	0.83 (0.05)	0.47 (0.11)
4 yr Non-Sci.	0.19 (0.06)	0.05 (0.06)	0.83 (0.05)	1.00 (—)	0.67 (0.08)
2 yr	0.15 (0.08)	0.16 (0.08)	0.47 (0.11)	0.67 (0.08)	1.00 (—)
<i>(Population) Variances</i>					
<i>Variances of Raw Outcomes</i>	0.13	0.07	0.21	0.27	0.35
	0.36	0.27	0.84	0.83	1.03

- Students have a substantial amount of uncertainty about their own abilities by the end of high school.
- 1 std. increase in ability accounts for about half of a grade point.
- In the white-collar (blue-collar) sector: 36% (27%) increase in wages.
- Speed of learning heterogeneous across choice paths.
- Wages are less informative when working while in college: signal-to-noise ratio 0.20 vs. 0.49.

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# Counterfactual simulations

- We consider two counterfactual scenarios:
  - ❶ Individuals have full information about their abilities in all sectors.
  - ❷ (1) + always possible to work in the white-collar sector.
- Requires solving the model, done backwards from retirement age ( $T = 65$ ).
- In both scenarios, agents are fully informed about their abilities  $\rightarrow$  no need to integrate over the prior ability distribution to solve the DP problem.
- Fairly high dimensional state space, kept tractable using simplifying assumptions.
- In particular: no schooling decisions after 28, (data-driven) caps in school and work experience variables, discretized AR(1) aggregate labor market shock process...(see Appendix J for more details).

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# Information and educational choices

Status	Baseline model	Counterfactuals	
		Full info. alone	Full info. & no search frictions
Continuous completion (CC), Science	6.39	10.30	11.09
Continuous completion (CC), Non-Science	14.86	13.74	14.31
Stop out (SO) but graduated Science	0.97	1.74	1.94
Stop out (SO) but graduated Non-Science	3.45	4.33	4.72
Stop out (SO) then drop out	9.02	6.71	6.50
Truncated	5.76	4.73	5.07
Drop out (DO)	32.44	26.10	25.17
Never went to college	27.11	32.35	31.20
Graduate from 4-year college	25.67	30.11	32.07
Ever Switch Major	25.37	25.13	26.31
Time to degree	5.16	4.99	5.02

# Information and labor market outcomes

Sector and Education Level	Average full-time log wage, relative to blue-collar non-graduates in baseline			Choice shares (%)		
	Baseline	Counterfactual	No Frictions Cfl	Baseline	Counterfactual	No Frictions Cfl
White collar, Science graduate	0.46	0.90	0.87	3.44	5.54	6.87
White collar, Non-Science graduate	0.32	0.63	0.56	8.15	5.28	7.25
White collar, Non-graduate	0.11	0.35	0.15	5.46	0.96	4.72
Blue collar, Science graduate	0.20	0.30	0.30	2.45	5.38	4.87
Blue collar, Non-Science graduate	0.11	0.08	0.08	6.62	9.62	8.46
Blue collar, Non-graduate	0.000	0.01	0.07	41.4	49.6	43.8
Remainder	—	—	—	32.5	23.7	24.0



# Concluding remarks

- Number of exciting research avenues ahead.
- Recent advances on the econometric front and on the data/measurement side allow to make progress on important questions.
- Consumption value of schooling and preferences are key determinants of educational and occupational choices (Carneiro et al, 2003; Wiswall and Zafar, 2015; Arcidiacono et al, 2020).
- What is the role played by learning about preferences in schooling decisions?
- Much of the literature assumes Rational Expectations and Bayesian updating.
- More research needed to understand, in particular:
  - How agents form and update their beliefs.
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# Grade shocks and college attrition

Difference between actual and expected period- $t$  grades (by  $t + 1$  period college decision):

	Residual	Std Dev	Mean diff T (p-val)
Dropout from 4-year college & science	-0.203	0.629	1.87
Stay in school (any type)	0.014	0.593	(0.06)
Dropout from 4-year college & non-science	-0.104	0.686	2.00
Stay in school (any type)	0.014	0.530	(0.05)
Dropout from 2-year college	-0.163	0.901	3.78
Stay in school (any type)	0.076	0.654	(0.00)

# Wage shocks and college attrition

Log-wage residuals at time  $t$  conditional on  $t + 1$  decision and stopping-out at some point during the sample period:

	Residual	Std Dev	Mean diff T (p-val)
Stay in the labor force	0.100	0.533	2.24
Return to school	-0.054	0.346	(0.03)

# Missing majors and GPAs

- GPA and college majors are missing at a non-trivial rate.
- We deal with this issue by treating the (first) instance of unobserved GPA or major as another latent variable. Simple extension of the previous procedure.
- First stage: now also estimate the distribution of unobserved majors and GPAs (discretized into quartiles), conditional on each heterogeneity type.
- Second stage: weighted multinomial logit, where the weights are given by  $Pr(\text{Type}, \text{Major}, \text{GPA} | \text{data})$  (instead of  $Pr(\text{Type} | \text{data})$ ).

▶ 19.33



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# Transitory variances

<i>Period</i>	Skilled	Unskilled	4 yr Sci.	4 yr Non-Sci.	2 yr
1	0.148 (0.004)	0.161 (0.002)	0.646 (0.057)	0.670 (0.039)	0.897 (0.050)
2			0.160 (0.026)	0.212 (0.017)	0.352 (0.029)
3			0.140 (0.044)	0.135 (0.024)	0.372 (0.028)
4			0.120 (0.041)	0.111 (0.022)	
5+			0.321 (0.085)	0.199 (0.033)	

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## **Schooling ability:**

- ASVAB Arithmetic Reasoning
- ASVAB Coding Speed
- ASVAB Mathematical Knowledge
- ASVAB Numerical Operations
- ASVAB Paragraph Comprehension
- ASVAB Word Knowledge
- SAT I Math
- SAT I Verbal

## Schooling preferences:

- Number of times the individual reported being late for school without excuse
- How strongly the individual agrees with the following statement: “When I was in school, I broke the rules regularly”
- How many hours per week the individual spent taking extra classes (such as music lessons, etc.)
- If the individual ever took classes during a school break (this could either be for remedial or accelerative reasons)
- If the individual took classes during break, the reason for doing so (e.g. “To accelerate, for fun, for enrichment” or “To make up classes”)

## Work motivation:

- How strongly the individual agrees with the following statement: “I have high standards at work”
- How strongly the individual agrees with the following statement: “I make every effort to do what is expected of me”
- The individual's subjective likelihood of working part- or full-time at age 30 (reported as a percent chance on a scale from 0-100)
- The parent's subjective likelihood of the individual working part- or full-time at age 30 (reported on the same scale as above)

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