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Predicting students' academic performance: a challenging issue in statistical modelling

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Outline

- Introduction
- Literature review
- Case study: performance of freshmen at the University of Florence
- Modelling strategies:
  - Regression chain graph
  - Hurdle model
  - Binomial mixture models with concomitant variables
- Discussion

We are still working on them

Grilli L., Rampichini C., Varriale R. (2013) Binomial mixture modelling of university credits.
to appear in *Communications in Statistics - Theory and Methods*
pre-print at `http://local.disia.unifi.it/grilli/papers.htm`

Predicting academic performance (so important, so difficult…)

- Predicting students' academic performance is a key step in order to improve the efficiency of university systems
- Universities rely on **info about the high school career**, e.g. type of school and various measures of proficiency
- However, the results at high school are **not fully appropriate** to predict the academic performance:
  - mismatch between competencies evaluated at high school and competencies required for a given degree program
  - heterogeneity in the criteria for awarding marks (variability across types of schools and across geographical regions)
- A partial remedy: **pre-enrolment assessment test** tailored on the needs of each degree program (lack of commonly accepted guidelines and shortage of empirical evidence about the predictive ability)

A look at the literature

- The empirical research about predicting students' academic performance is scattered in various journals, ranging from *Psychology* to *Economics*; some noteworthy papers are
  - **Murray-Harvey (1993)** Identifying characteristics of successful tertiary students using path analysis. *Australian Educational Researcher*
  - **Wedman (1994)** The Swedish Scholastic Aptitude Test: Development, Use, and Research. *Educational Measurement: Issues and Practice*
  - **Hoefer and Gould (2000)** Assessment of Admission Criteria for Predicting Students' Academic Performance in Graduate Business Programs. *Journal of Education for Business*
  - **Murphy et al. (2001)** Entrance score and performance: A three year study of success. *Journal of Institutional Research*
  - **Maree et al. (2003)** Predicting success among first-year engineering students at the rand afrikaans university. *Psychological Reports*
  - **Dancer and Fiebig (2004)** Modelling Students at Risk. *Australian Economic Papers*

A look at the literature (cont.)

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- **Win and Miller (2005)** The Effects of Individual and School Factors on University Students' Academic Performance. *Australian Economic Review*
- **Smith and Naylor (2005)** Schooling Effects on Subsequent University Performance: Evidence for the UK University Population'. *Economics of Education Review*
- **Birch and Miller (2006)** Student Outcomes At University In Australia: A Quantile Regression Approach. *Australian Economic Papers*
- **Mills et al. (2009)** Factors associated with the academic success of first year Health Science students. *Advances in Health Science Education*
- **Mallik and Lodewijks (2010)** Student Performance in a Large First Year Economics Subject: Which Variables are Significant? *Economic Papers*
- **Bianconcini and Cagnone (2012)** A General Multivariate Latent Growth Model With Applications to Student Achievement. *Journal of Educational and Behavioral Statistics*
- **Adelfio et al. (2013)** Quantile regression on a new indicator for higher education performance. *Working Paper*, CNR Solar

Freshmen at the University of Florence: Pre-enrolment test

- In a.y. 2008/2009, the School of Economics of the University of Florence introduced a ***compulsory pre-enrolment test*** to evaluate the background of the students
- 40 multiple-choice items covering 3 areas: ***Logic*** (12 items), ***Reading*** (10 items) and ***Mathematics*** (18 items)
  - for each item, 1 out of 5 alternatives is correct
  - scoring system: 1 if correct, 0 if blank, -0.25 if wrong

- The test has a main edition in September and several supplementary editions later
- Candidates with a total score lower than 9 are advised against enrolment: they could still enrol, but they could take examinations only after 'passing' the test during one of the later editions

`www.economia.unifi.it/vp-586-test-di-accesso.html`

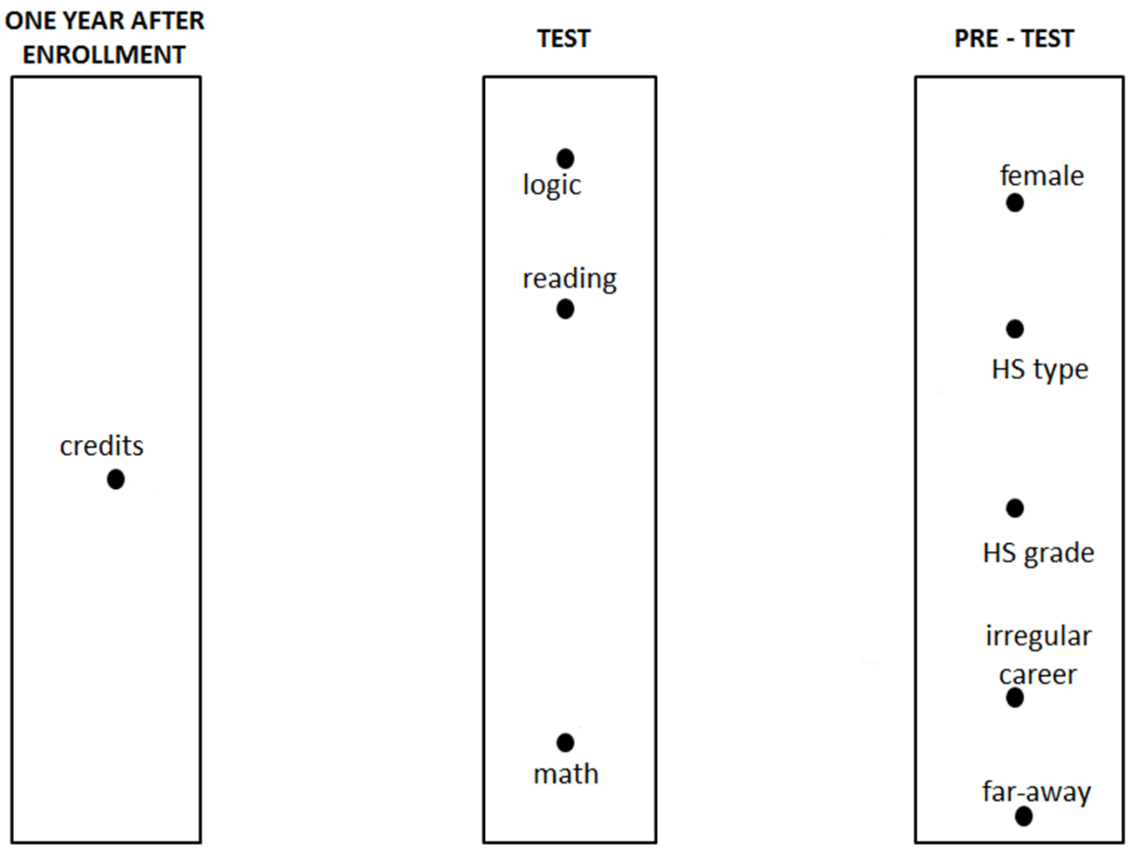
Freshmen at the University of Florence: Administrative data

- We analyse data on ***690 freshmen*** of the School of Economics in Florence in a.y. 2008/2009, considering the students who took the pre-enrolment test in September 2008
- The data set is obtained by merging *data collected at the test* and *administrative data*
  - Pre-test:
    - **Gender**
    - **High school type** (Scientific, Humanities, Technical, Other)
    - **High school grade** (from 60 to 100, centered at 80)
    - **High school irregular career** (indicator for age at diploma > 19)
    - **Far-away resident**
  - Test: **Partial test scores** (Logic, Reading, Mathematics)
  - Post-test: **Credits gained during the first year** (from 0 to 60)

Regression chain graph

- Formal representation of prior knowledge and working hypotheses
- Effective tool to represent model and results
- Disentangling **direct** and **indirect** effects

Wermuth N., Sadeghi K. (2012) Sequences of regressions and their independences. *Test*, 1-38

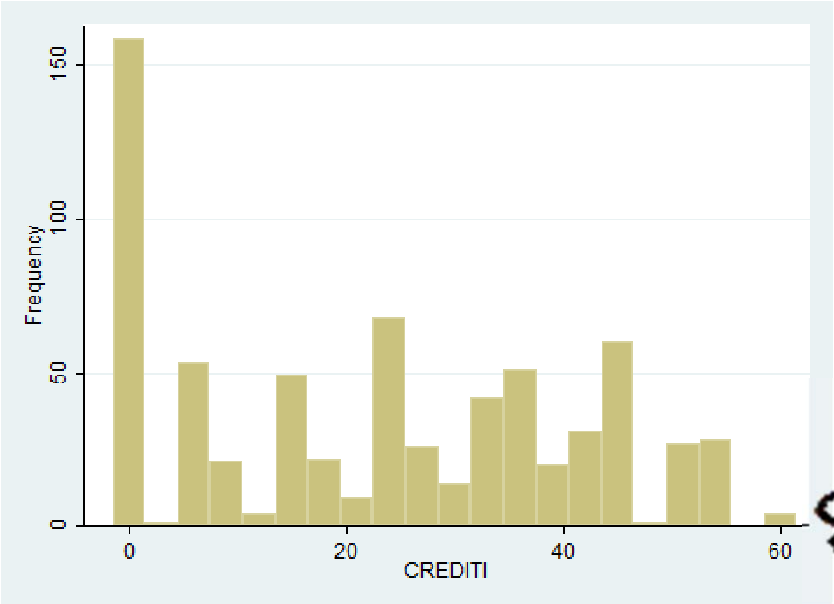


<u>Step 0</u>: collect variables into ordered blocks

<u>Step 1</u>: Regress the three (standardized) test scores on pre-test covariates

<u>Step 2</u>: Regress gained credits on test scores *and* pre-test covariates

Modelling gained credits

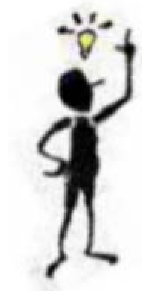


Gained credits after one year are in the interval [0,60]

Exams have different credits (multiples of 3), usually 6, 9 or 12 → the distribution of gained credits is quite irregular!

- peak at the minimum (23% of freshmen did not gain any credit)
- the distribution of positive credits is quite irregular, showing **peaks** at 6, 15, 24, 36 and 45 credits

- Standard parametric models are not suitable → solutions
  1. Hurdle (or two-part) model
  2. Binomial mixture model
  3. Quantile regression



Modelling gained credits solution #1: hurdle model

- Our 'hurdle' or 'two-part' model has two components:
  1. A ***logit model*** for the probability of gaining at least one credit

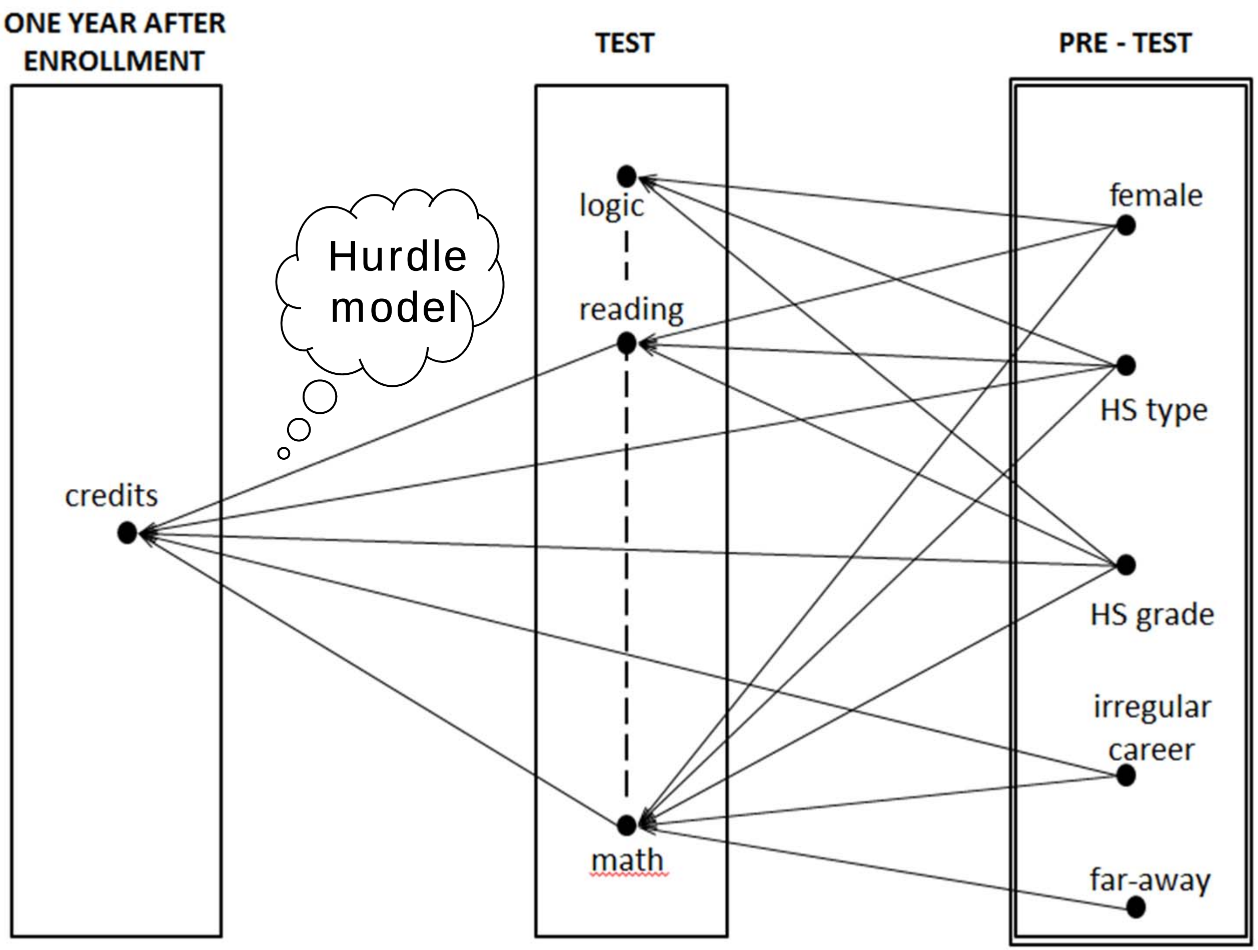
$$P(y_i > 0 \mid \boldsymbol{z}_i)$$

  2. A ***linear model*** for the expected number of gained credits (fitted on the subset of students who gained at least one credit)

$$E(y_i \mid y_i > 0, \boldsymbol{x}_i)$$

- The covariates of the two sub-models are distinct in principle, but they can even be the same
- No parametric distribution is suitable for the distribution of credits: to avoid distributional assumptions, we estimate the parameters of the linear model via OLS and use robust standard errors

Fitted regression chain graph



An arrow is traced when the regression coefficient is statistically significant

- NODES represent VARIABLES
- BLOCKS represent SET OF VARIABLES in a partial ordering based on subject-matter considerations (such as timing)
- EDGES represent ASSOCIATIONS

Main findings

- Even controlling for pre-test covariates, the standardized partial test scores have a significant effect on credits:
  - higher **score on Reading** → a higher probability of gaining credits P(Y>0)
  - higher **score on Math** → higher expected number of gained credits E(Y)
- The **score on Logic** does not help predict the gaining of credits when the scores on Reading and Math are known
- The effects of pre-test covariates are mediated by the test scores, with the notable exceptions of
  - **high school grade** (positive effect)
  - **irregular career** (negative effect)

Proxies of abilities and attitudes of the students that are not fully captured by the pre-enrolment test

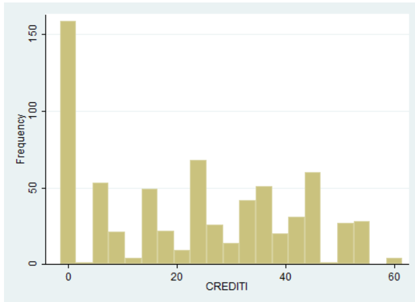
Modelling gained credits
solution #2: binomial mixture model

- Response (count): $y_i = credits_i \,/\, 3$
- Distribution: $y_i \sim Bin(t\!=\!20,\, \theta_k)$

credits range from 0 to 60 in blocks of 3

- Mixture components represented by the categorical random variable u_i, taking values $k = 1,\ldots,K$ with ***prior probabilities*** π_k

$$P(y_i) = \sum_{k=1}^{K} \pi_k P(y_i \mid u_i = k)$$



where all the conditional distributions $P(y_i \mid u_i)$ are ***binomial with common number of trials*** t and component-specific probabilities of success θ_k

$$P(y_i \mid u_i = k) = \binom{t}{y_i} \theta_k^{y_i} (1-\theta_k)^{t-\theta_k^{y_i}}$$

McLachlan G., Peel D. (2000). Finite Mixture Models. New York: Wiley.

Binomial mixture model: fit without covariates

- Given K the model can be ***fitted with ML using the EM algorithm*** – we used Latent Gold (Vermunt & Magidson, 2008)
  - we later replicated the analysis with the R package `flexmix`: code and data available at `http://local.disia.unifi.it/grilli`
- Selection of the number of components K with BIC, bootstrap LRT and EM test Li and Chen (2010) → they all select K=5

Component	π_k	θ_k	$E(credits\|u=k)$	$P(credits=0\|u=k)$	$P(credits \geq 54\|u=k)$
1	0.22	0.00	0	1.000	0.000
2	0.15	0.14	9	0.045	0.000
3	0.25	0.39	23	0.000	0.000
4	0.28	0.65	39	0.000	0.012
5	0.10	0.85	51	0.000	0.381

- The first component (size 0.22) is almost degenerate in 0, accounting for the excess zeroes in the sample distribution:

$$P(credits = 0) \approx 0.22 \times 1.000 + 0.15 \times 0.045 = 0.230$$

(equal to the sample proportion)

- In general, the fit is satisfactory in all the support

Binomial mixture model: fit with covariates (concomitant var.)

- In a **concomitant variable** specification the covariates affect the component probabilities π_k (Dayton and Macready, 1988)

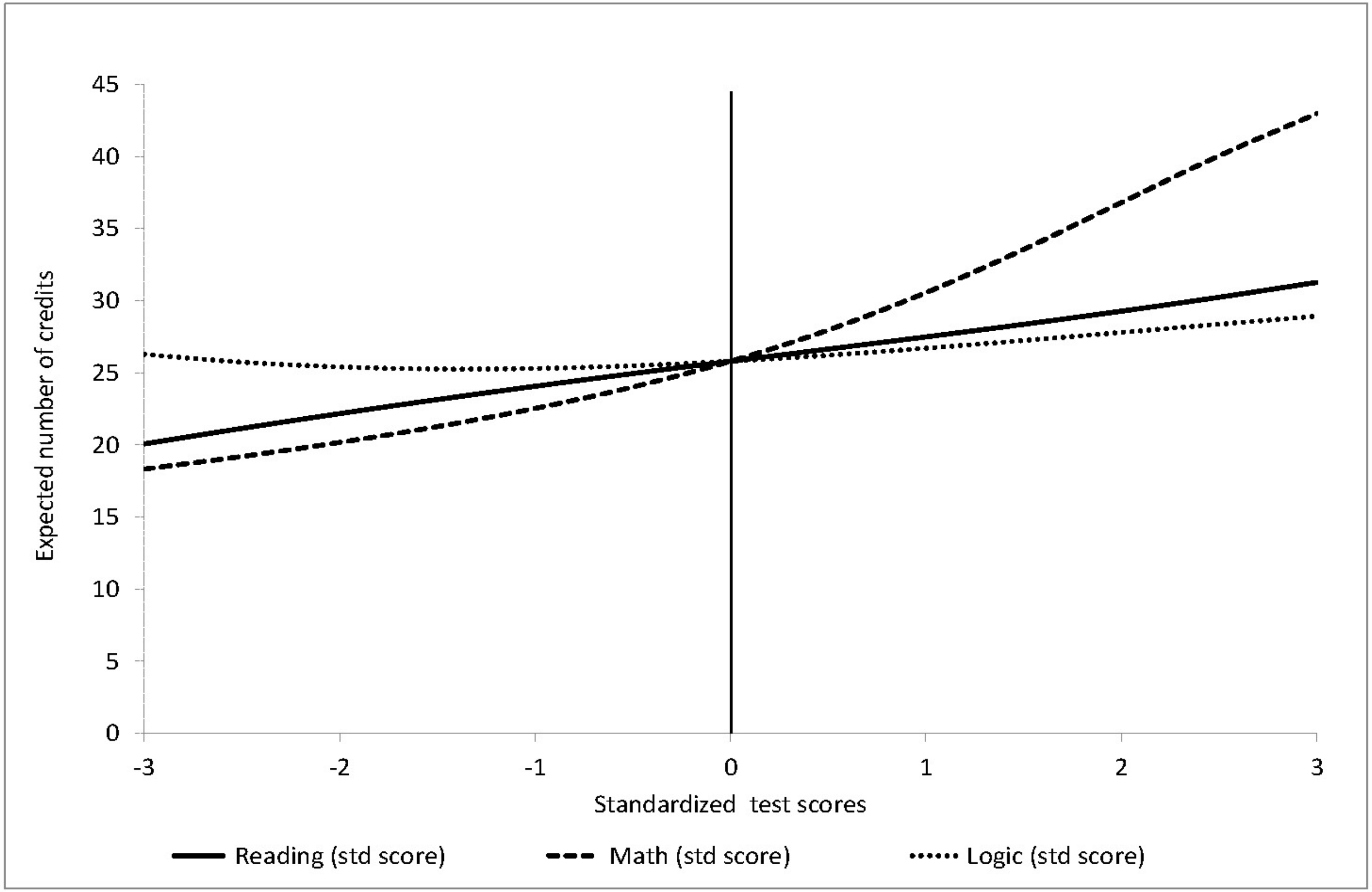
$$P(y_i \mid \mathbf{z}_i) = \sum_{k=1}^{K} \pi_{k|\mathbf{z}_i} P(y_i \mid u_i = k)$$

$$\pi_{k|\mathbf{z}_i} = P(u_i = k \mid \mathbf{z}_i) = \frac{\exp(\mathbf{z}_i^T \boldsymbol{\beta}_k)}{\sum_{l=1}^{K} \exp(\mathbf{z}_i^T \boldsymbol{\beta}_l)}$$

	Latent class					p-value
	1	2	3	4	5	
Binomial probability θ_k	0.00	0.15	0.38	0.64	0.85	-
Multinomial logit model[a] for π_k						
Constant	-	-0.03	0.22	*0.96*	-0.57	0.000
HS Technical/other	-	-0.63	0.18	-0.40	*-1.43*	0.013
HS irregular career	-	-0.39	*-0.79*	*-3.08*	*-0.57*	0.012
HS grade	-	-0.01	0.01	*0.06*	*0.12*	0.000
Logic (std score)	-	-0.11	0.21	0.26	-0.34	0.052
Reading (std score)	-	*0.51*	*0.33*	*0.29*	*0.79*	0.001
Math (std score)	-	-0.09	0.00	0.25	*1.10*	0.000

Effect of test scores on *E*(*credits*)

Expected number of gained credits by test scores
(the value in zero refers to the ***baseline*** student: HS Scientific/Humanities, HS grade at midpoint, regular career)



Effect of test scores on *P(first class)*

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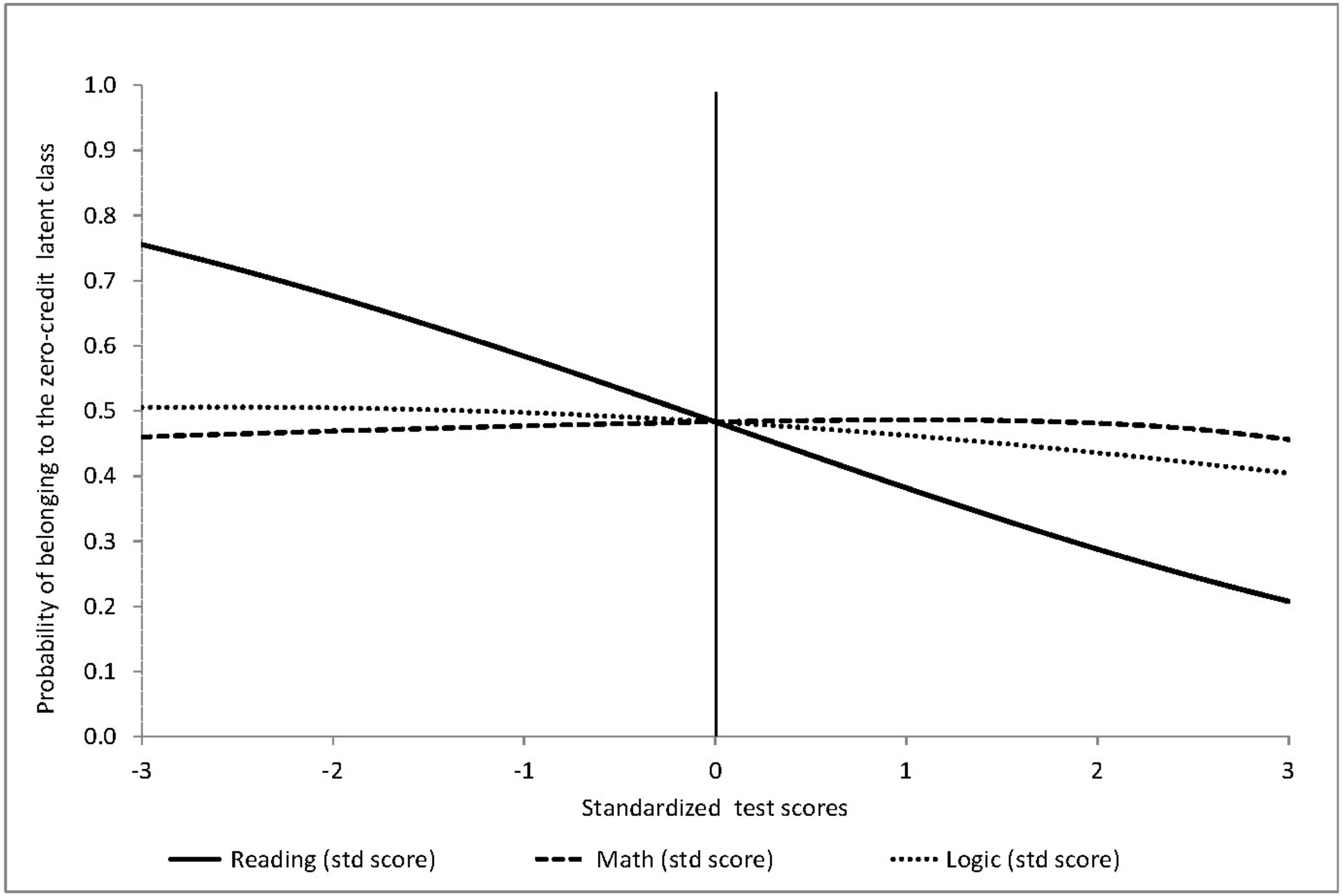
Probability of belonging to the zero-credit latent class by test scores (the value in zero refers to the ***weak*** student: HS Technical/other, HS grade at minimum, irregular career)



Hurdle vs binomial mixture

- The hurdle model (logit+linear) is **simple** and it may be used for studying associations
- In our application it yields the same findings as the binomial mixture model about the pre-enrolment test, namely
  - a ***low Reading score*** is related to a ***difficult start-up*** of the university career
  - a ***low Math score*** is related to a ***slow progression***, likely for problems encountered in Math and Statistics (which are often the hardest exams)
- However, the hurdle model should not be used for making predictions: unbounded response → **non-admissible predictions**, e.g. negative number of gained credits

Can we really predict gained credits?

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- The linear part of the hurdle model has R-squared = 0.24
- Binomial mixture model → Mean Absolute Error of prediction (10-fold cross-validation):
  - Null model: MAE = 15.7
  - Model with only background characteristics: MAE = 13.3 (-15%)
  - Model with background char. + test scores : MAE = 12.7 (-4%)
- In terms of prediction ability, the background characteristics give a relevant contribution
- The pre-enrolment test yields a ***further slight improvement***, even if the predictive ability remains modest (students' careers are difficult to predict!)

Tests vs unstructured interviews

- The results about the predictive ability of pre-enrolment tests are not exciting… what about **unstructured interviews**?
- Apart from the high expense, unstructured interviews are **ineffective** in predicting the students performance:
  - DeVaul R., Jervey F., Chappell J., Caver P., Short B., & O'Keefe S. (1987). Medical school performance of initially rejected students. *Journal of the American Medical Association*, 257, 47-51.
  - Dana J., Dawes R.M., Peterson N.R. (2012) Belief in the Unstructured Interview: The Persistence of an Illusion. Draft

http://www.sas.upenn.edu/~danajd/interview.pdf

In addition to the vast evidence suggesting that unstructured interviews do not provide incremental validity, we provide direct evidence that **they can harm accuracy**. […] interviewers are likely to feel they are getting useful information from unstructured interviews, even when they are useless. ***Our simple recommendation for those who make screening decisions is not to use them***.

Thanks for your attention!

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