Shooting stars? Firms and Education as Mediators of the Returns to Skills

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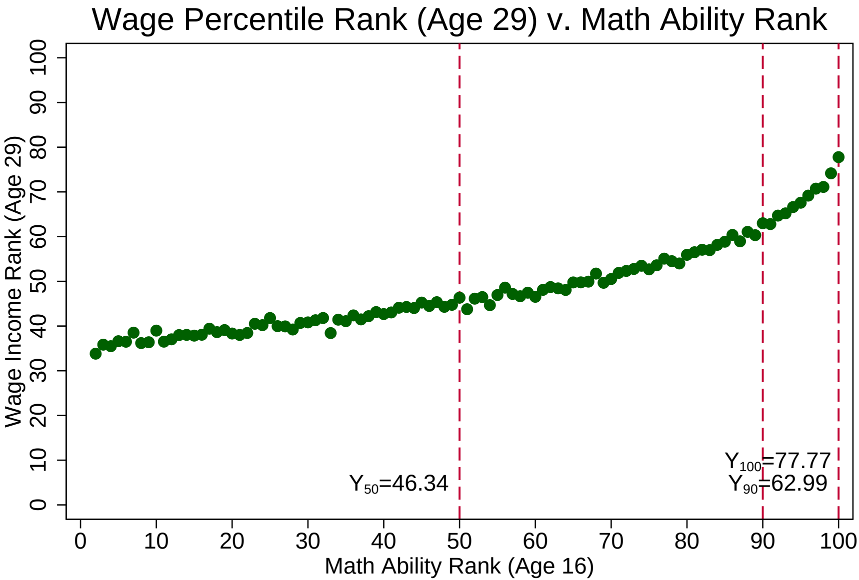

Note: Includes Language Rank as a Control Variable

Research Questions

1. What are the returns to (early) math and language skills in the labor market?
   - Are the relationships non-linear?
   - Additional return for skill 'superstars'? (Rosen 1981).
   - Which skills offer larger returns — math vs. language skills?
2. Through which channels does education mediate the returns to these skills?
   - Are there differential effects once college quality, types of degrees attained, and fields of degree are considered?
3. What is the role of firms in mediating the returns to skills?
   - If assortative matching takes place: does it happen immediately at labor market entry? Do workers climb up the firm ladder as they age?
   - Are the matching effects non-linear across the skill distribution?
4. + Two bonus tracks

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This paper in the context of the literature

- Returns to skills in the labor market.
  - Importance of skills and skill-biased technical change (Acemoglu and Autor 2011, Lindqvist and Vestman 2011, Prada and Urzua 2017, Deming 2017).
  - Math vs. language skills?
- Education and skills.
  - Pre-labor market abilities/skills and educational attainment (Heckman et al. 2006).
  - Heterogeneous returns to education and skills (Rodriguez et al. 2015).
- Worker, firm and match effects (Abowd et al. 1999, Card et al. 2013, 2018).
  - Worker quality is identified from individual FEs — related to pre-LM skills?
  - Do high-skilled workers match with high-quality firms?
  - If so, how do firms mediate the returns to skill?

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Our data

- Data challenges are large:
  1. Early skills measures (pre-college).
  2. Human capital: years of education, type and field of HE degree, HEI quality.
  3. Matched employee-employed data on labor market outcomes.

- Take advantage of administrative data for two cohorts of Chileans.
  1. Test scores on a nationally-administered standardized math and language exam given to 10^{th} graders in 2001 and in 2003 — 1985 and 1987 birth cohorts.
     - Sample sizes in excess of 270,000 students. SIMCE
     - Individual-level scores are not reported to students.
  2. Degrees received from any HEI between 2006 and 2016. SIES
     - Degrees received, granting institution and field of degree for 90,000+ higher education graduates by age 29.
  3. Matched employee-employer data for 2002-2016: monthly frequency of employment spells for workers in formal sectors (240,000+ workers matched).
     - Follow workers from labor market entry through age 29-31. Data

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Exploratory results

Estimate returns to pre-labor market skills $\boldsymbol{\theta_i}$ from:

$$\ln \text{Wage}_{it} = \beta_0 + \beta_1 \boldsymbol{\theta_i} + \beta_2 age_{it} + \lambda_t + \varepsilon_{it} \qquad (1)$$

Estimate the effect across each percentile of the distribution $\boldsymbol{\theta_{ji}}$:

$$\ln \text{Wage}_{it} = \beta_0 + \sum_{j=1}^{100} \beta_j \boldsymbol{\theta_{ji}} + \beta_2 age_{it} + \lambda_t + \varepsilon_{it}$$

(Castex and Dechter 2014, Deming 2017, Hellerstein et. al. 2019)

Exploratory results: Point Estimates

Table: Returns to Ability in Chile (Log Monthly Wages)

	(1)	(2)	(3)
Math	0.224***		0.203***
Language		0.163***	0.034***
Age	0.054***	0.052***	0.055***
Year FE	X	X	X
R^2	0.124	0.090	0.125
Observations		10,170,432	
Individual Observations		243,267	

Note: SE clustered at the individual level. * p<0.05, ** p<0.01, *** p<0.001. SIMCE scores from 2003. SIES Higher Education Degrees — 2007-2016.

Unemployment Insurance: 2002-2016. Ability measures are standardized. Wages are measured monthly in 2010 Real CLP in the highest paid job.

Non-Linear Returns

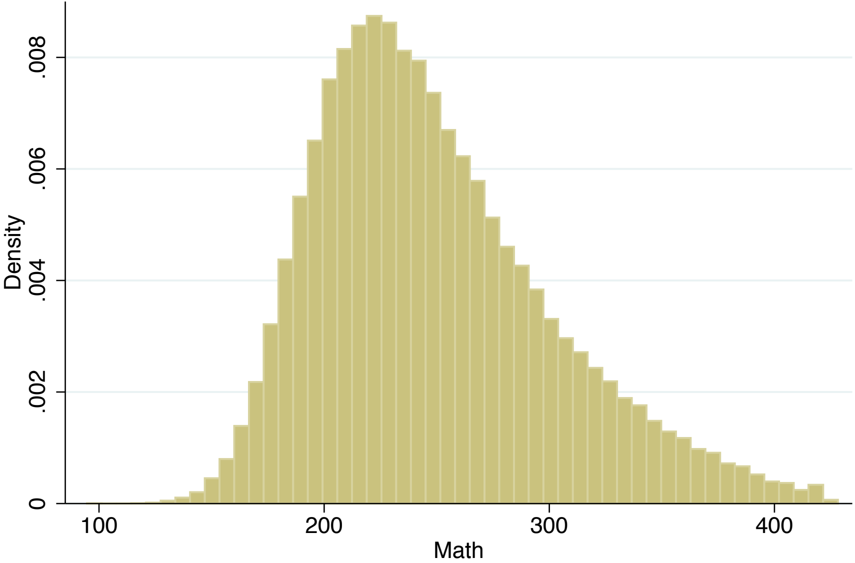
Exploratory results: Point Estimates with Interactions

Table: Returns to Ability in Chile (Monthly Wages) ▸ Age Splines

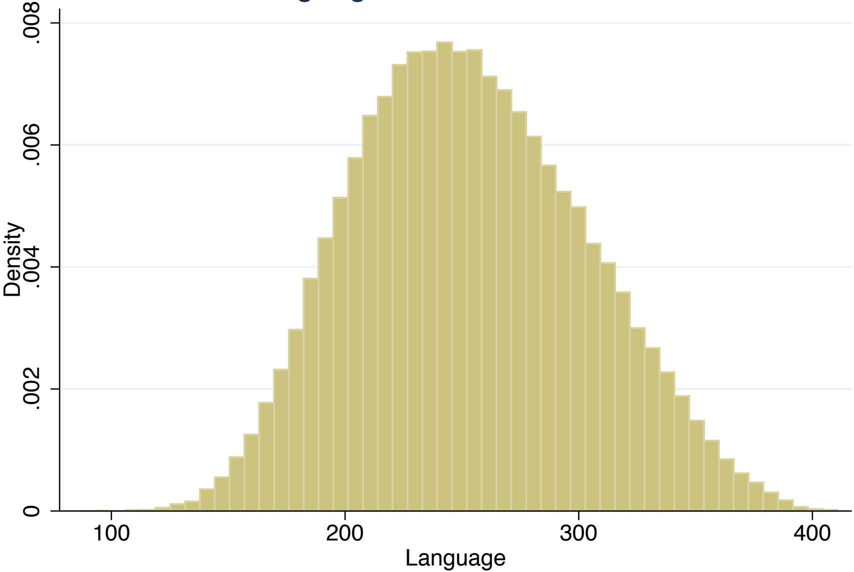
	(1)	(2)
Math	0.147***	0.141***
Math × Age	0.024***	0.019***
Language		0.009***
Language × Age		0.008***
Year FE	X	X
R^2	0.123	0.124
Observations	10,170,432	
Individual Observations	243,267	

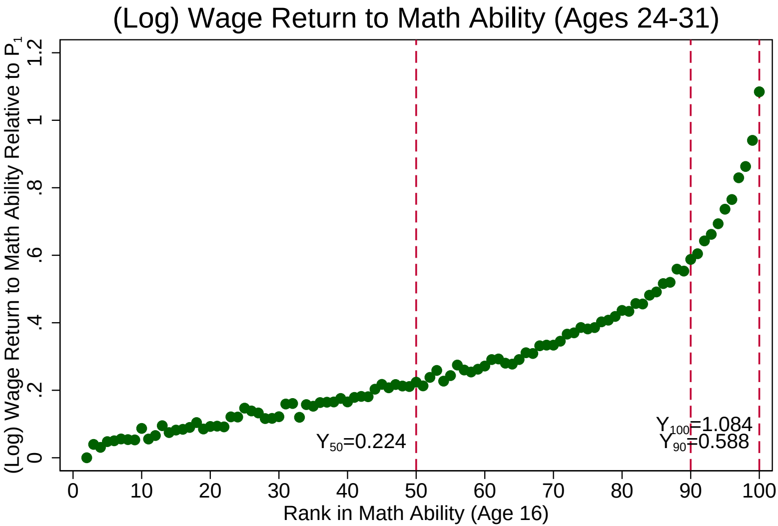
Note: SE clustered at the individual level. * p<0.05, ** p<0.01, *** p<0.001. SIMCE scores from 2003. SIES Higher Education Degrees — 2007-2016. Unemployment Insurance: 2002-2016. Ability measures are standardized. Wages are measured monthly in 2010 Real CLP in the highest paid job.

Distribution of Math Test Scores – 10 Graders in 2001



Distribution of Language Test Scores – 10 Graders in 2001





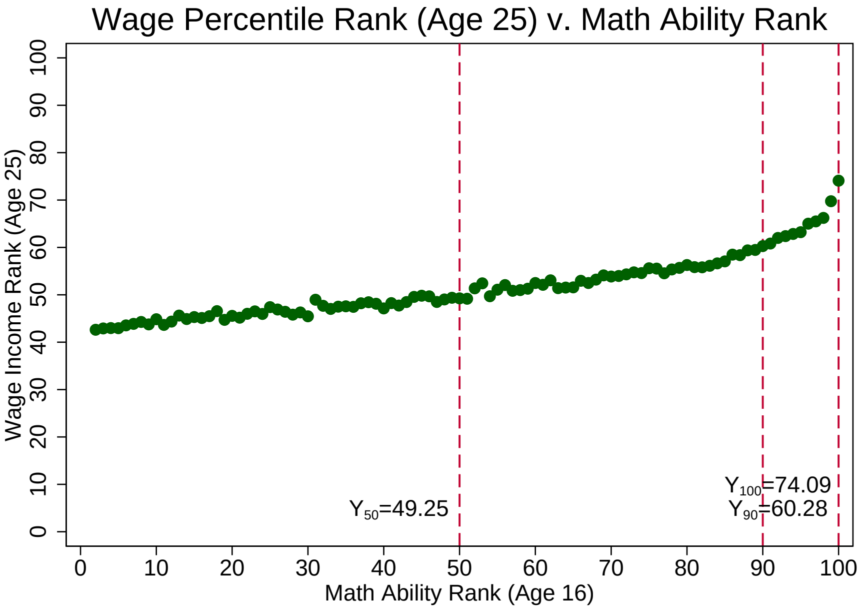
Note: Includes Language Rank as a Control Variable

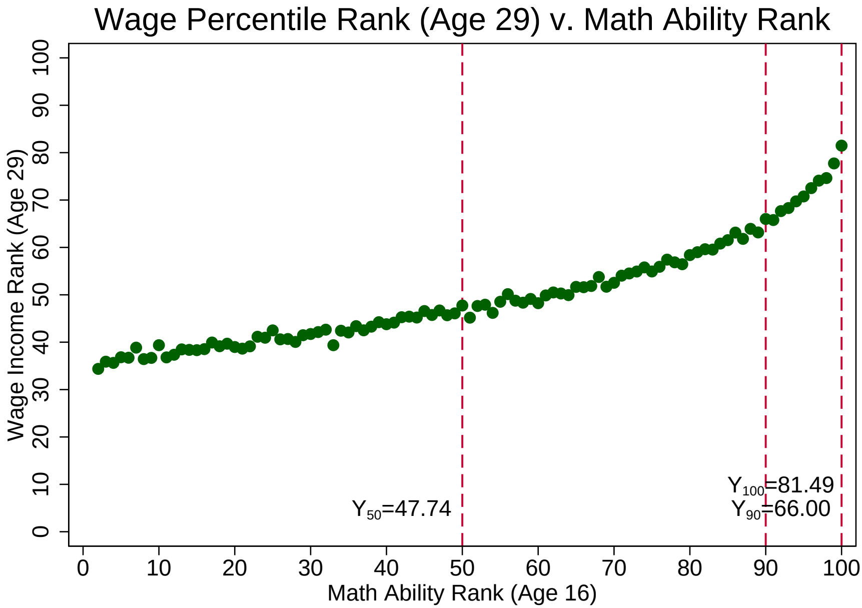
No Controls

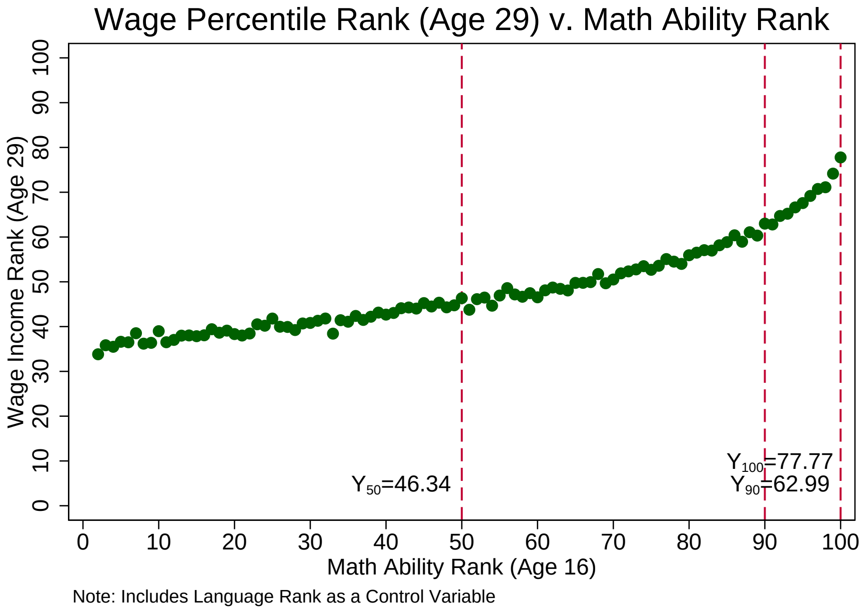
- We seek to capture mobility between early skills ranks and wage rankings.
  - We rank individuals by their position in their cohort's annual earnings distribution by year.
- In practice, we estimate semi-parametric specifications of the form:

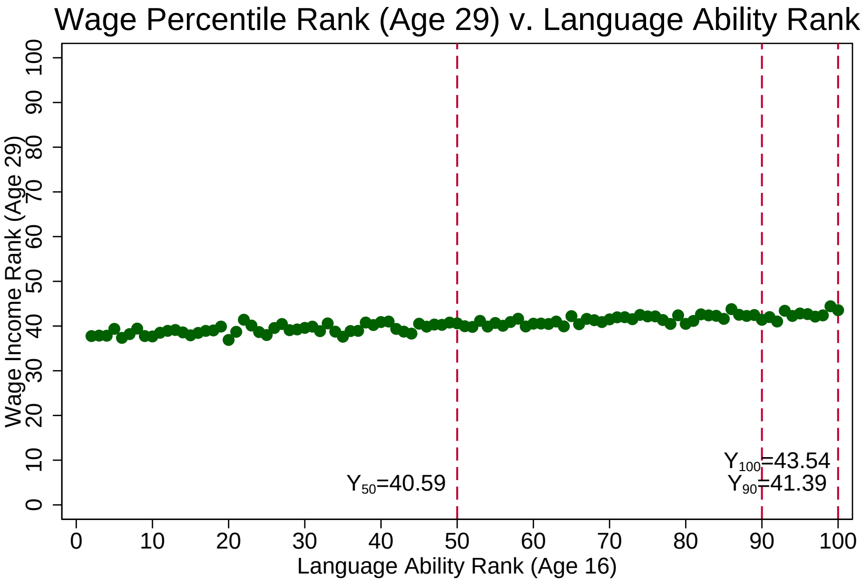
$$rank_{it}^{w} = \beta_0 + \beta_1 rank_i^{\theta} + \epsilon_{it}$$

- Horse race: Math vs. language.
- Rank-Rank Regressions are extensively used intergenerational mobility literature (Chetty et al. 2014, 2017, Carr and Wiemers 2016).


Wage Percentile Rank (Age 25) v. Math Ability Rank
Wage Income Rank (Age 25)
0
10
20
30
40
50
60
70
80
90
100
Math Ability Rank (Age 16)
0
10
20
30
40
50
60
70
80
90
100
Y50=49.25
Y100=74.09
Y90=60.28


Wage Percentile Rank (Age 29) v. Math Ability Rank
Wage Income Rank (Age 29)
Math Ability Rank (Age 16)
0
10
20
30
40
50
60
70
80
90
100
Y50=47.74
Y100=81.49
Y90=66.00

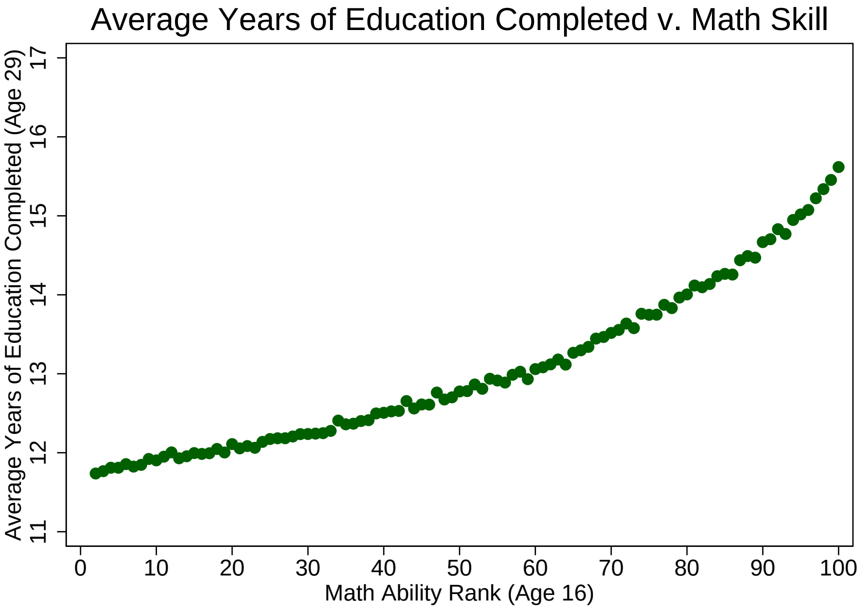

Wage Percentile Rank (Age 29) v. Math Ability Rank
Wage Income Rank (Age 29)
0
10
20
30
40
50
60
70
80
90
100
Math Ability Rank (Age 16)
Y_{50}=46.34
Y_{100}=77.77
Y_{90}=62.99
Note: Includes Language Rank as a Control Variable

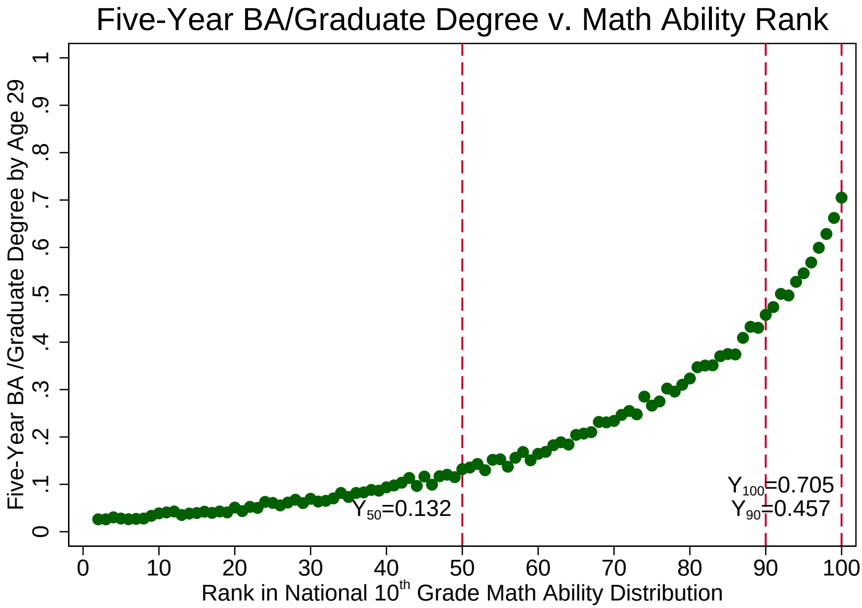


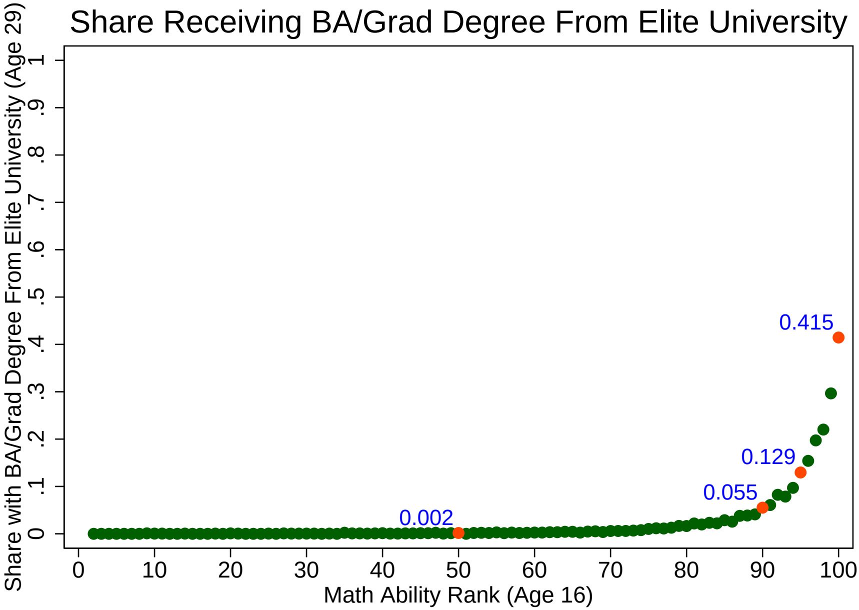
Note: Includes Mathematics Rank as a Control Variable

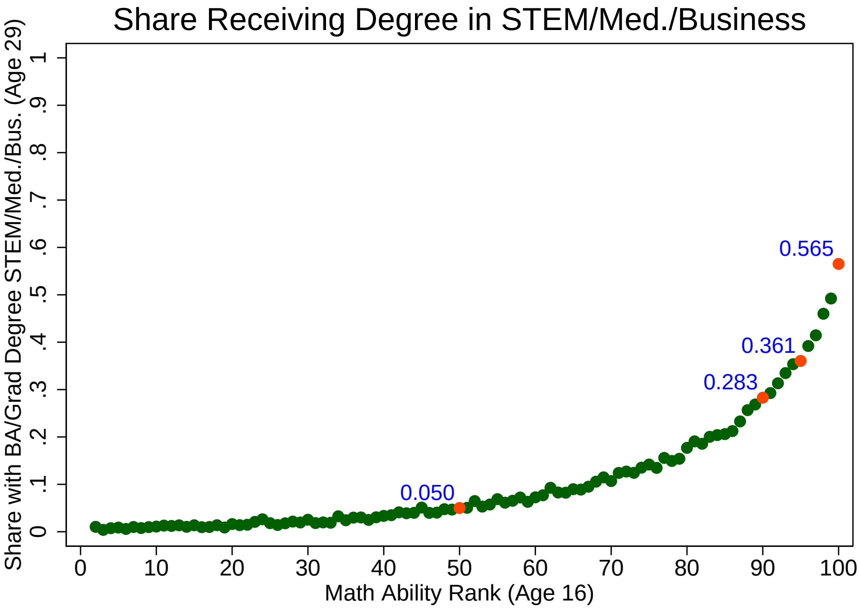
Mechanisms I: Educational Attainment

- Returns to ability are mediated through educational attainment (Heckman et al. 2006, Lindqvist and Vestman 2011, Deming 2017).
- Existing literature defines educational attainment by years of education or degree earned.
- Educational sorting across the skill distribution may also take place through:
  1. University quality.
  2. Field of degree. ▸ Field of Degree
- We first document attainment patterns across skill distribution: $E[S_i|rank_i^\theta]$.


Average Years of Education Completed v. Math Skill
Average Years of Education Completed (Age 29)
11
12
13
14
15
16
17
0
10
20
30
40
50
60
70
80
90
100
Math Ability Rank (Age 16)


Five-Year BA/Graduate Degree v. Math Ability Rank
Five-Year BA /Graduate Degree by Age 29
0
.1
.2
.3
.4
.5
.6
.7
.8
.9
1
Y50=0.132
Y100=0.705
Y90=0.457
0
10
20
30
40
50
60
70
80
90
100
Rank in National 10th Grade Math Ability Distribution


Share Receiving BA/Grad Degree From Elite University
Share with BA/Grad Degree From Elite University (Age 29)
0
.1
.2
.3
.4
.5
.6
.7
.8
.9
1
0
10
20
30
40
50
60
70
80
90
100
Math Ability Rank (Age 16)
0.002
0.055
0.129
0.415


Share Receiving Degree in STEM/Med./Business
Share with BA/Grad Degree STEM/Med./Bus. (Age 29)
0
.1
.2
.3
.4
.5
.6
.7
.8
.9
1
0
10
20
30
40
50
60
70
80
90
100
Math Ability Rank (Age 16)
0.050
0.283
0.361
0.565

Regression Analysis: Human Capital and skills

- We re-estimate equation (1):

$$\ln Y_{it} = \beta_0 + \beta_1 \boldsymbol{\theta_i} + \beta_2 age_{it} + \beta_3 \boldsymbol{S_{it}} + \lambda_t + \varepsilon_{it}$$

  where $\boldsymbol{S_{it}}$ includes different definitions of educational attainment.

- UI data allows us to directly measure formal labor market experience for all individuals as well as firm-tenure (Rucci et al. 2019, Altonji and Shakokto 1987, Topel 1991):

$$\ln Y_{it} = \beta_0 + \beta_1 \boldsymbol{\theta_i} + \beta_2 age_{it} + \beta_3 \boldsymbol{S_{it}} + \gamma_1 exper_{it} + \eta_1 tenure_{it} + \lambda_t + \varepsilon_{it}$$

OLS Results: Controlling for education

Table: Earnings Regressions

	(1)	(2)	(3)	(4)	(5)
Math	0.217***	0.162***	0.159***	0.152***	0.141***
Language	0.048***	0.014***	0.014***	0.013***	0.021***
Experience	0.073***	0.110***	0.112***	0.112***	0.111***
Experience^2	-0.004	-0.005	-0.005	-0.005	-0.005
Tenure	0.053***	0.047***	0.047***	0.047***	0.047***
Year FE	X	X	X	X	X
Years of Ed.		X			
Degrees Received			X		
University Quality				X	
Field of Degree					X
R^2	0.161	0.206	0.209	0.213	0.223
Observations			10,170,432		
Individual Observations			243,267		

Non-Linear Returns

Mechanisms II: Firms

- We examine how workers' pre-labor market ability relates with firm quality and how this pattern evolves through the early career.
    - How do firms mediate the returns to skills?
- Firms explain an important share of the variance of wages (Abowd, Kramarz and Margolis, 1999).
- AKM-models can be used to examine patterns of assortative matching between high-quality workers and high-quality firms.
    - Early literature found negative matching — opposite result in recent work.
    - However, worker quality is directly identified through labor market outcomes — unclear how it relates to pre-labor market characteristics of workers.
- Parallel literature has examined which types of workers move up job ladder.
    - Haltiwanger et al. (2018a): less-educated workers move up the ladder.

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Mechanisms II: Firms

- We create an annual ranking of firm quality (φ_{ft}) based on employment-weighted measures of: (1) average wages, (2) median wages, (3) p_{25} wages (Haltiwanger et al. 2018b).
- We also estimate firm quality using the estimated firm fixed-effect from an AKM regression for all workers in the UI data.
  - Validity of this measure depends depends on exogenous mobility.

Thus, how workers match with firms across the ability distribution:

$$\varphi_{ift} = \beta_0 + \beta_1 \boldsymbol{\theta_i} + \beta_2 age_{it} + \lambda_t + \varepsilon_{ift}$$

And then :

$$\ln Y_{ift} = \beta_0 + \beta_1 \boldsymbol{\theta_i} + \beta_2 age_{it} + \beta_3 \boldsymbol{S_{it}} + \beta_4 \boldsymbol{\varphi_{ift}} + \gamma_1 exp_{it} + \eta_1 ten_{it} + \lambda_t + \varepsilon_{ift}$$

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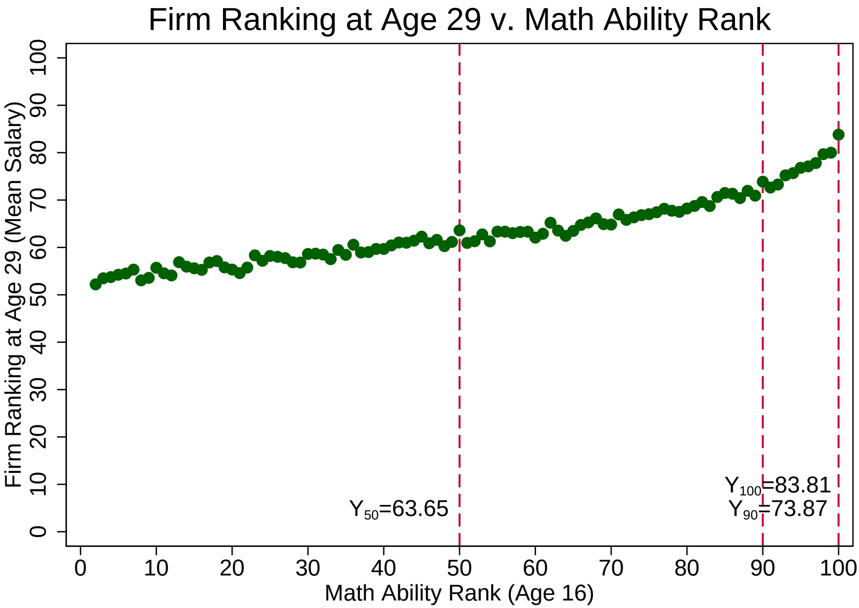
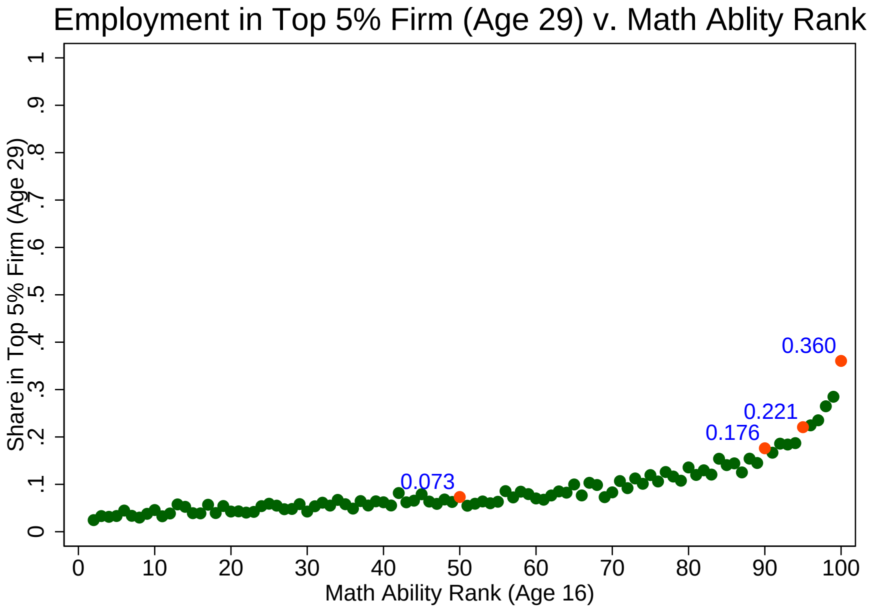

Firm Ranking at Age 29 v. Math Ability Rank
Firm Ranking at Age 29 (Mean Salary)
0
10
20
30
40
50
60
70
80
90
100
Math Ability Rank (Age 16)
Y50=63.65
Y100=83.81
Y90=73.87

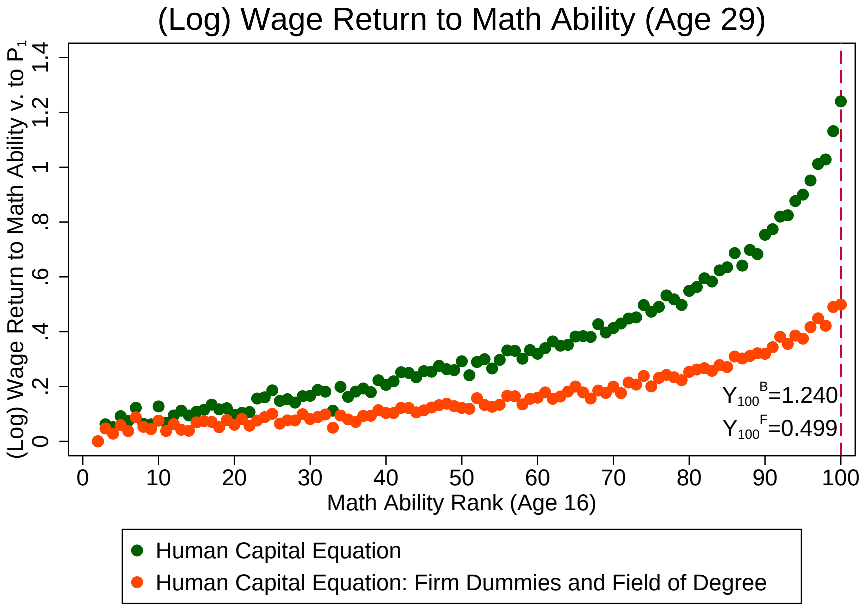

Employment in Top 5% Firm (Age 29) v. Math Ablity Rank
Share in Top 5% Firm (Age 29)
0
.1
.2
.3
.4
.5
.6
.7
.8
.9
1
0.073
0.176
0.221
0.360
0
10
20
30
40
50
60
70
80
90
100
Math Ability Rank (Age 16)

Regression Analysis: Returns to pre-labor market skills.

Table: Returns to Skills: Importance of Firms and Education

	(1)	(2)	(3)	(4)
Math	0.217***	0.141***	0.122***	0.081***
Language	0.048***	0.021***	0.016***	0.002
Experience	0.073***	0.111***	0.041***	0.067***
$Experience^2$	-0.004	-0.005	-0.003	-0.004
Tenure	0.053***	0.047***	0.036***	0.033***
Year FE	X	X	X	X
Field of Degree		X		X
Firm Quality			X	X
R^2	0.161	0.244	0.437	0.468
Observations	10,170,432			
Individual Observations	243,267			

Firm Quality Definition
Non-Linear Returns


(Log) Wage Return to Math Ability (Age 29)
(Log) Wage Return to Math Ability v. to P1
0
.2
.4
.6
.8
1
1.2
1.4
0
10
20
30
40
50
60
70
80
90
100
Math Ability Rank (Age 16)
Y100B=1.240
Y100F=0.499
Human Capital Equation
Human Capital Equation: Firm Dummies and Field of Degree

Quantifying the contributions

- To explore how education and firm quality mediate the returns to skill:

$$\ln Y_{ift} = \beta_0^B + \beta_1^B \boldsymbol{\theta_i} + \beta_2^B age_{it} + \gamma_1^B exp_{it} + \eta_1^B ten_{it} + \varepsilon_{ift}$$

$$\ln Y_{ift} = \beta_0^F + \beta_1^F \boldsymbol{\theta_i} + \beta_2^F age_{it} + \gamma_1^F exp_{it} + \eta_1^F ten_{it} + \beta_3^F \boldsymbol{S_{it}} + \beta_4^F \boldsymbol{\varphi_{ift}} + \varepsilon_{ift}$$

- Disentangling separate contribution of schooling and firms is not clear-cut.
- Intermediate equations with one component suffer from sequence dependence.
- Gelbach (2016) provides a solution for this problem using the omitted variables bias formula. Gelbach Decomposition

Gelbach Decomposition

Gelbach (2016) proposes the following steps:

1. Estimate the full model and recover (β_1^F, β_2^F, γ_1^F, η_1^F, β_3^F, *and* β_4^F).
2. Run a regression of $\boldsymbol{S_{it}}$ on $\boldsymbol{\theta_i}$, yielding a coefficient τ_S.
3. Do the same for $\boldsymbol{\varphi_{ft}}$ on $\boldsymbol{\theta_i}$, yielding τ_φ. These are the differences in educational attainment and firm quality by math ability.
4. The difference in the changes in the estimated returns to ability is given by:

$$\beta_1^F - \beta_1^B = \beta_3^F \tau_S + \beta_4 \tau_\varphi \tag{2}$$

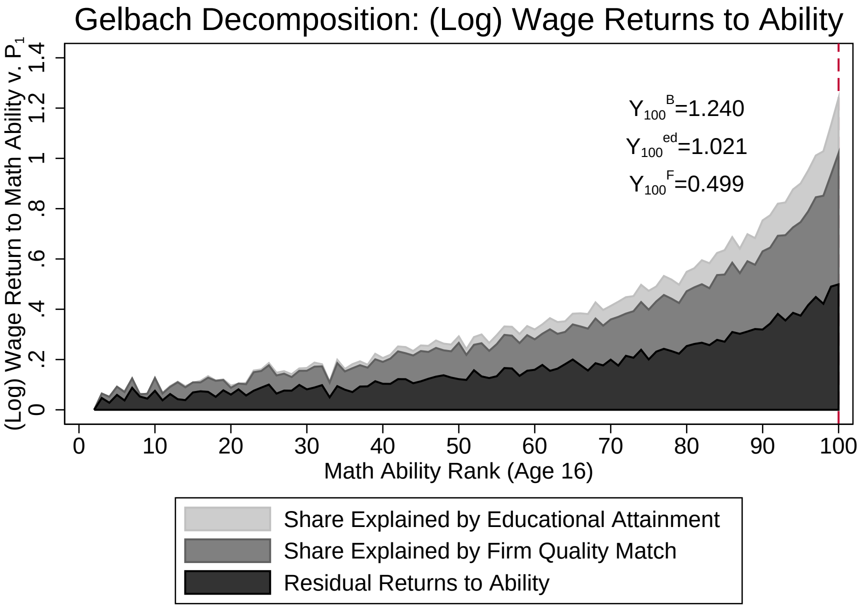
- The share of change in β_1 explained by educational attainment is given by $\beta_3^F \tau_S$.

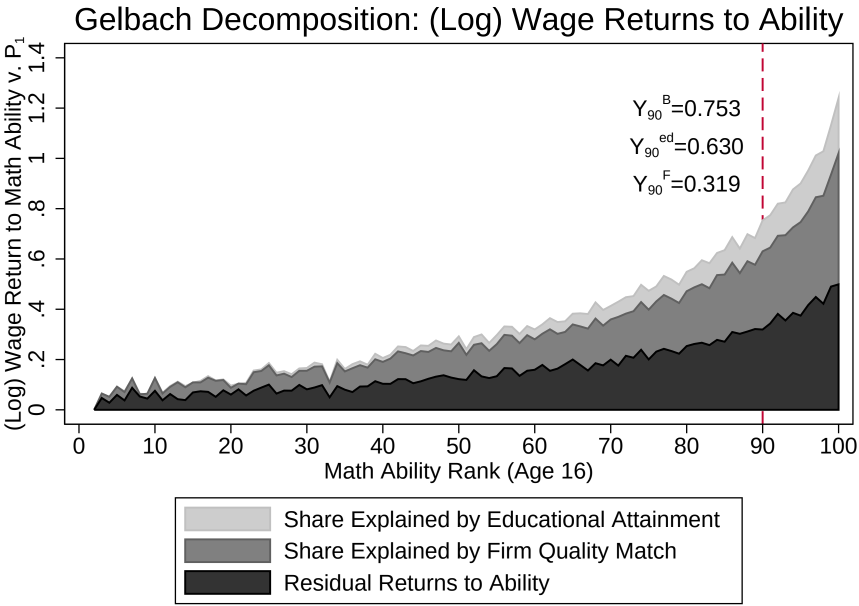
Results

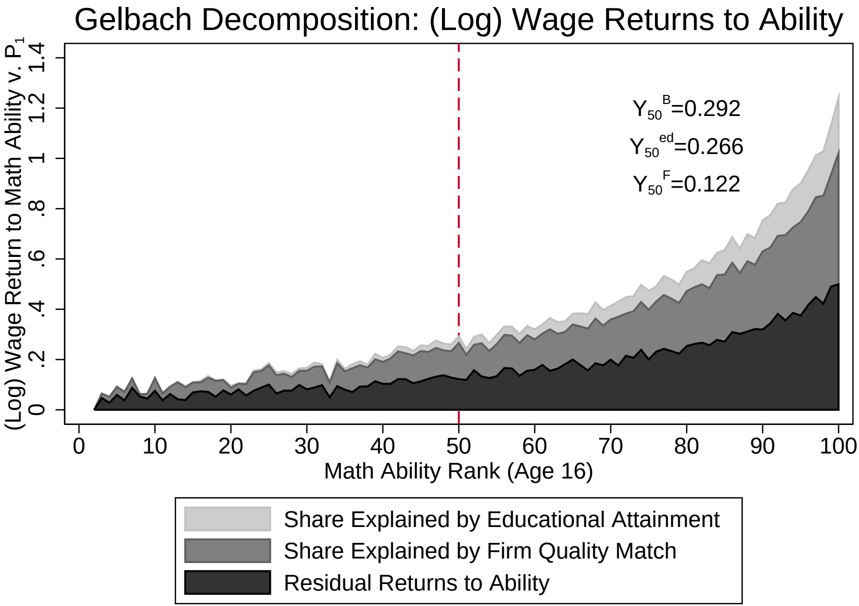
Table: Returns to Ability: Gelbach Decomposition (Linear specification)

	(1) Baseline	(2) Full	(3) Education	(4) Firm Quality
Math	0.217***	0.076***	0.045***	0.096****
	(0.0003)	(0.0003)	(0.0001)	(0.0002)
			[0.319]	[0.681]
Language	0.048***	0.002***	0.017***	0.029***
	(0.0003)	(0.0003)	(0.0001)	(0.0002)
Contributions			0.369	0.631
Year FE	X	X		
Field of Degree		X		
Firm Rank Dummies		X		
R^2	0.161	0.468		
Observations	10,170,432			
Individual Observations	243,267			

▸ Non-Linear Decomposition


Gelbach Decomposition: (Log) Wage Returns to Ability
(Log) Wage Return to Math Ability v. P1
0
.2
.4
.6
.8
1
1.2
1.4
0
10
20
30
40
50
60
70
80
90
100
Math Ability Rank (Age 16)
Y100B=1.240
Y100ed=1.021
Y100F=0.499
Share Explained by Educational Attainment
Share Explained by Firm Quality Match
Residual Returns to Ability


Gelbach Decomposition: (Log) Wage Returns to Ability
(Log) Wage Return to Math Ability v. P1
0
.2
.4
.6
.8
1
1.2
1.4
0
10
20
30
40
50
60
70
80
90
100
Math Ability Rank (Age 16)
Y90 B=0.753
Y90 ed=0.630
Y90 F=0.319
Share Explained by Educational Attainment
Share Explained by Firm Quality Match
Residual Returns to Ability

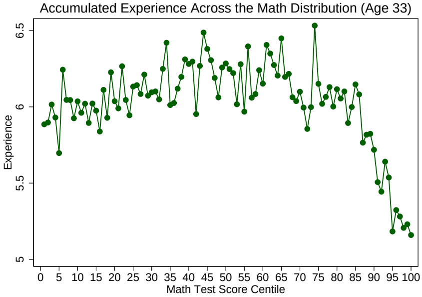


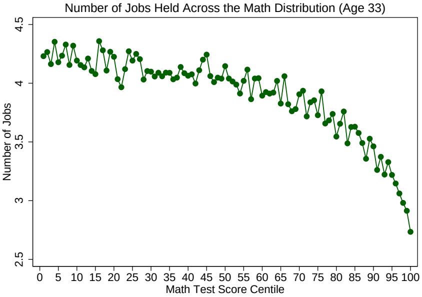
Gelbach Decomposition: (Log) Wage Returns to Ability
(Log) Wage Return to Math Ability v. P1
0
.2
.4
.6
.8
1
1.2
1.4
0
10
20
30
40
50
60
70
80
90
100
Math Ability Rank (Age 16)
Y50^B=0.292
Y50^ed=0.266
Y50^F=0.122
Share Explained by Educational Attainment
Share Explained by Firm Quality Match
Residual Returns to Ability

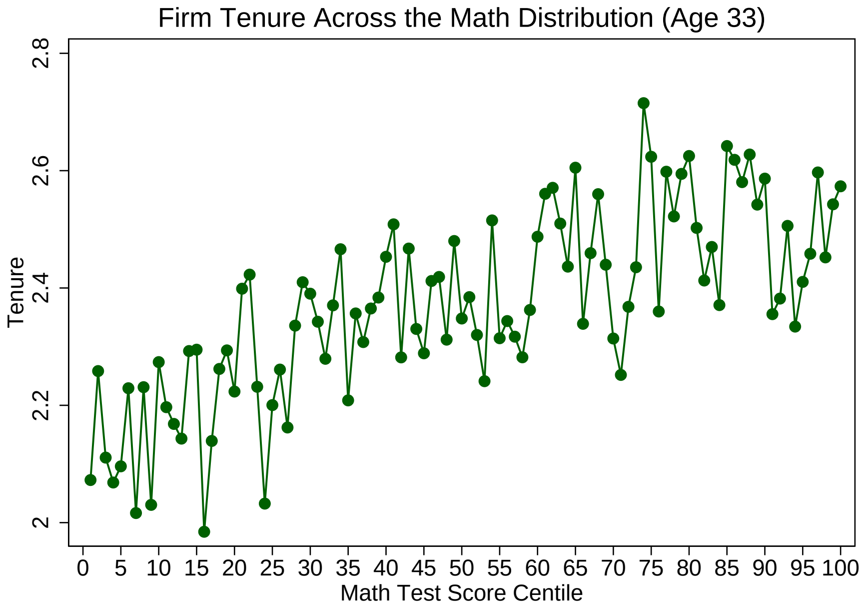
Discussion

- Increasing returns to math ability (rank analysis). Why?
- *On-the-job learning* (A1) : Individuals working at the same firm "take advantage" of their talents and improve firm's ranking.
- *Job Ladder* (A2): Individuals "take advantage" of their latents and access better firms.

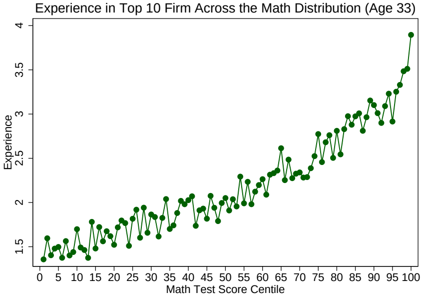
Labor Market Experience and Number of jobs across the Simce distribution

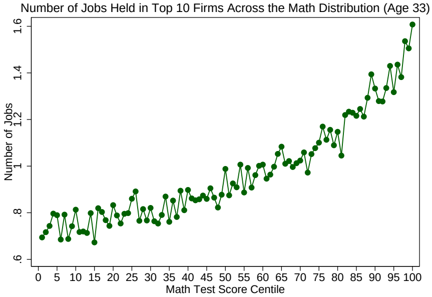


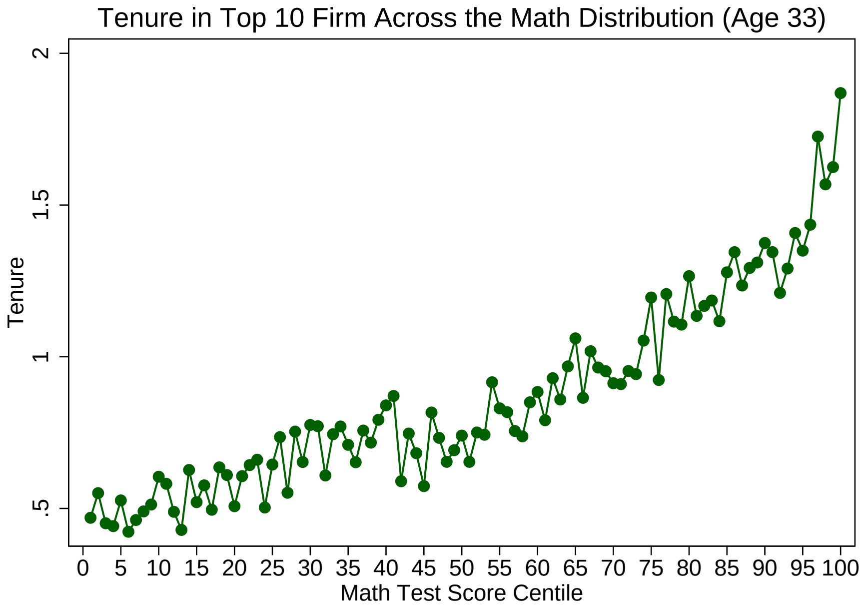



Firm Tenure Across the Math Distribution (Age 33)
Tenure
2
2.2
2.4
2.6
2.8
0 5 10 15 20 25 30 35 40 45 50 55 60 65 70 75 80 85 90 95 100
Math Test Score Centile

Labor Market Experience and Number of jobs across the Simce distribution: Top 10 Firms






Tenure in Top 10 Firm Across the Math Distribution (Age 33)
Tenure
2
1.5
1
.5
0 5 10 15 20 25 30 35 40 45 50 55 60 65 70 75 80 85 90 95 100
Math Test Score Centile

Conclusion

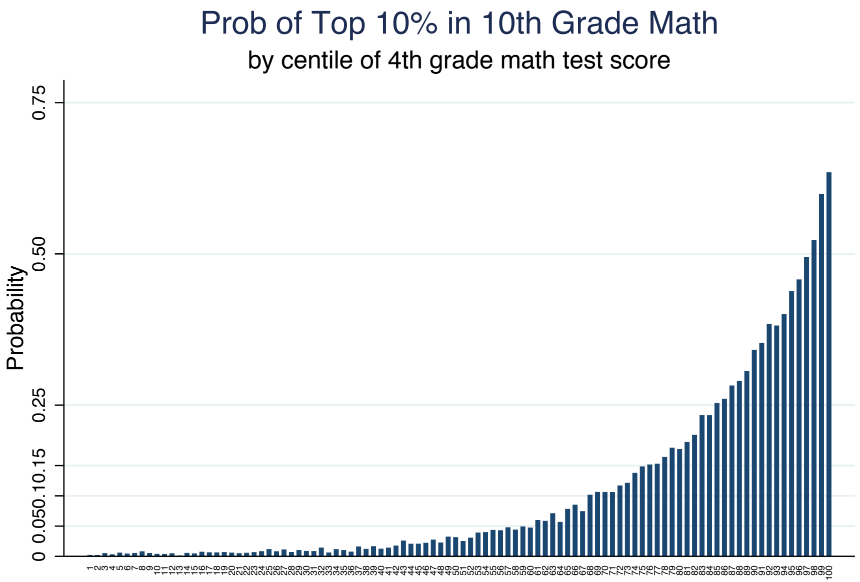
- We have shown that the returns to mathematical ability are highly non-linear.
- Similar patterns emerge for the relationship between ability and educational attainment.
- High-ability workers match to high-quality firms immediately upon labor market entry — there is limited movement up the job ladder as workers age.
- Non-linear returns to ability are largely mediated through educational attainment and firm matches – with the latter explaining about two-thirds of the estimated returns.
- On-the-job learning seems to trigger the increasing returns to ability.

Next I:

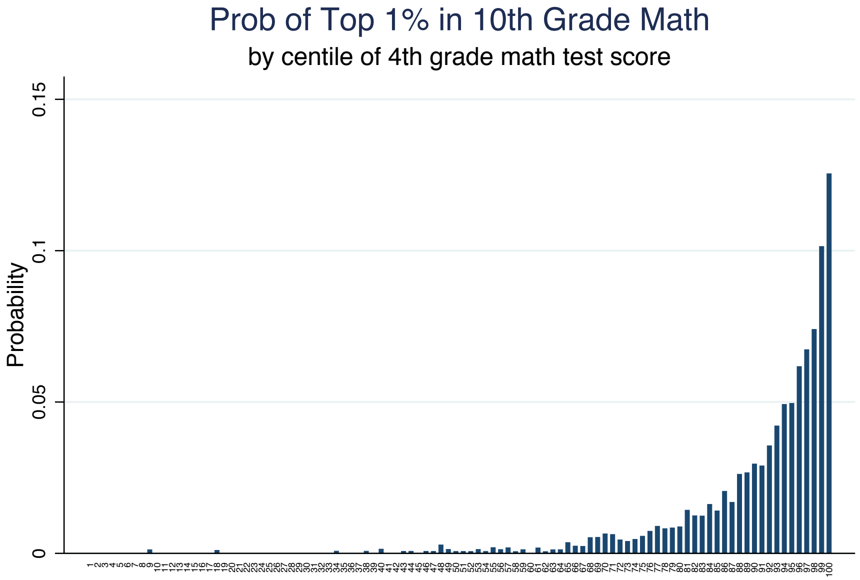
How early can we identify "stars"?

Where are they coming from?

How do they define inequality?



Source: Own calculations based on administrative data.

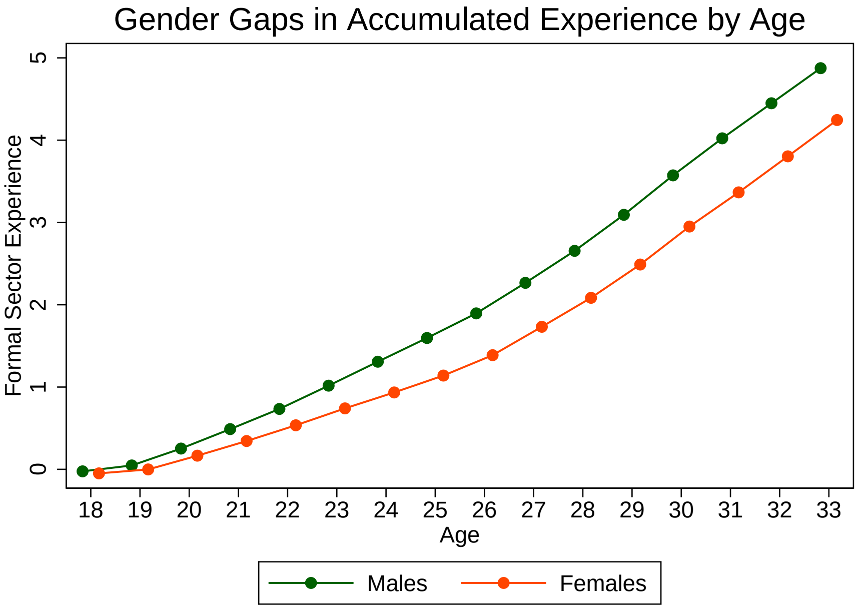


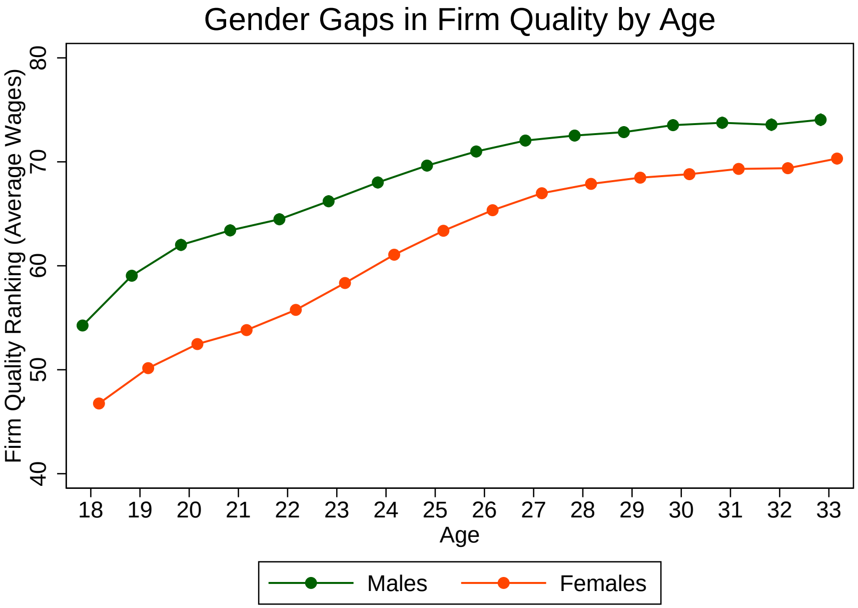
Source: Own calculations based on administrative data.

Bonus Track II:

What factors explain the (growing) gender wage gap?
Does the extent of the wage gap vary significantly across the math skill distribution?
How do they define inequality?


Gender Wage Gap by Age
Average Gender Wage Gap
.15
.2
.25
.3
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
Age


Gender Gaps in Accumulated Experience by Age
Formal Sector Experience
0
1
2
3
4
5
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
Age
Males
Females


Gender Gaps in Firm Quality by Age
Firm Quality Ranking (Average Wages)
40
50
60
70
80
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
Age
Males
Females

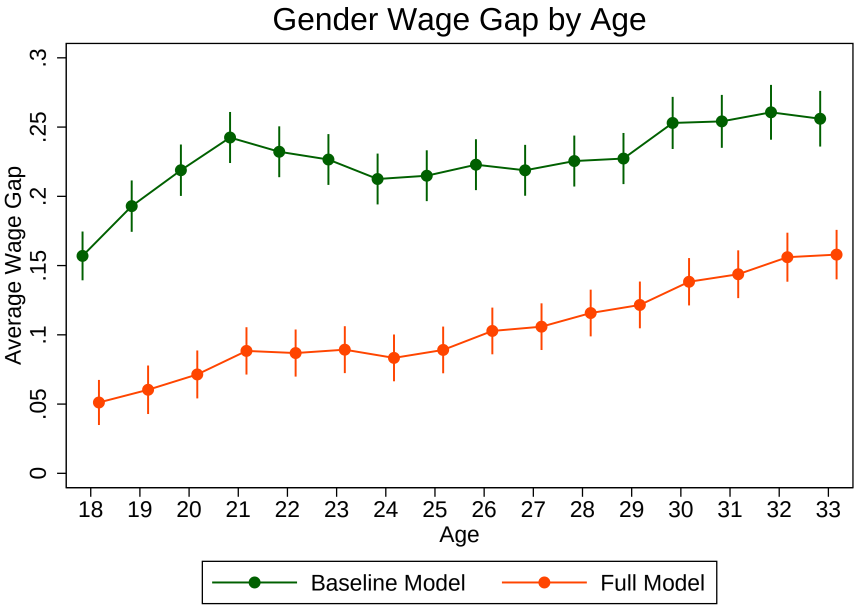
Firm Quality

- We examine how workers' firm quality and evolves through the early career by gender (Card et al. 2016)

- Quantify the importance of firm quality, experience and tenure to wage gaps in:

$$\begin{aligned} \ln \text{wage}_{ift} &= \gamma_0 + \sum_{j=18}^{33} \gamma_j male_i \times age_j \\ &\quad + \gamma_f \boldsymbol{\varphi_{ift}} + \eta_1 exper_{it} + \eta_2 tenure_{it} + \lambda_t + \varepsilon_{ift} \end{aligned}$$

Do not consider importance of schooling: no gender gaps in educational attainment.


Gender Wage Gap by Age
Average Wage Gap
0
.05
.1
.15
.2
.25
.3
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
Age
Baseline Model
Full Model

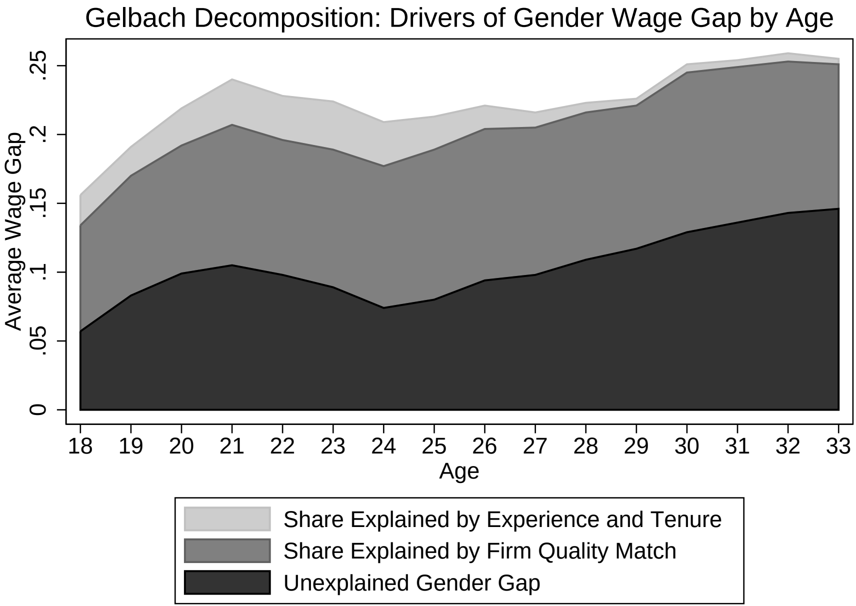
Quantifying the Contributions

- Examine how experience, tenure and firms contribute to the wage gap in:

$$\ln \text{wage}_{ift} = \gamma_0 + \sum_{j=18}^{33} \gamma_j \text{Male}_i \text{Age}_j + \lambda_t + \varepsilon_{ift}$$

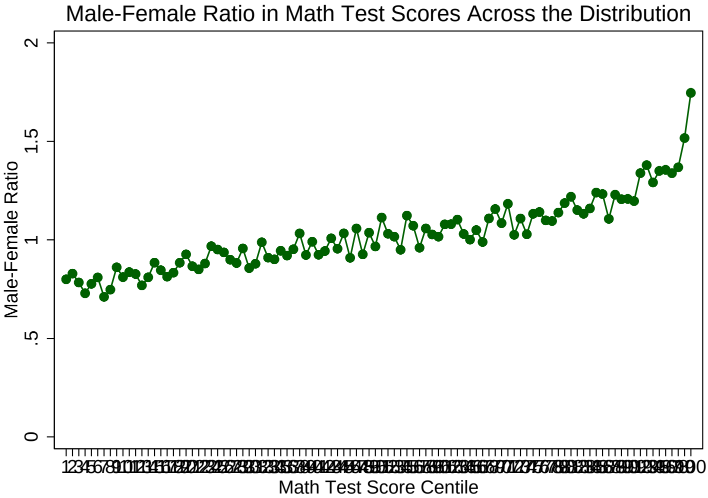
$$\ln \text{wage}_{ift} = \gamma_0 + \sum_{j=18}^{33} \gamma_j \text{Male}_i \text{Age}_j + \gamma_f \boldsymbol{\varphi_{ift}} + \eta_1 \text{Exper}_{it} + \eta_2 \text{Tenure}_{it} + \lambda_t + \varepsilon_{ift}$$

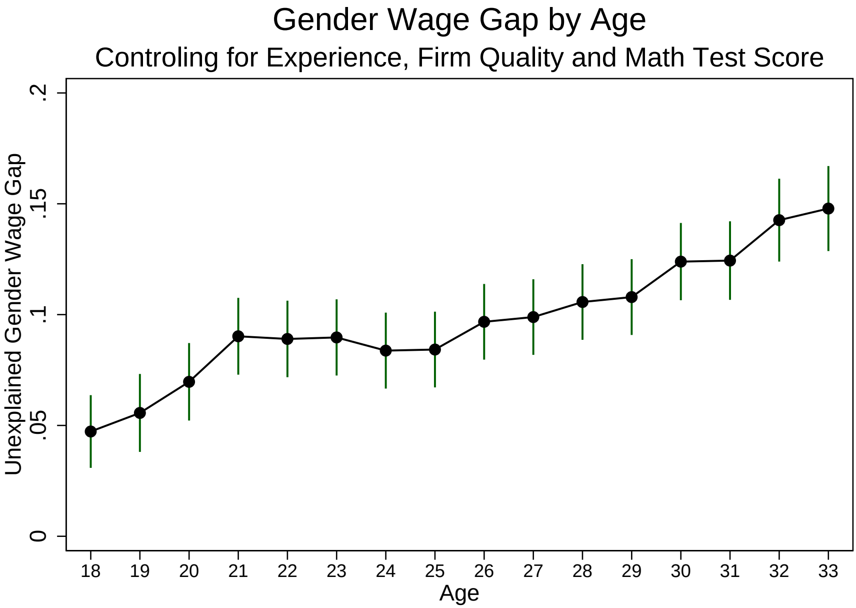
- Disentangling separate contribution of experience and firms is not clear-cut.
- Intermediate equations with one variable suffer from sequence dependence.
- Gelbach (2016) provides a solution for this problem using the omitted variables bias formula.


Gelbach Decomposition: Drivers of Gender Wage Gap by Age
Average Wage Gap
0
.05
.1
.15
.2
.25
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
Age
Share Explained by Experience and Tenure
Share Explained by Firm Quality Match
Unexplained Gender Gap

Math Test Scores

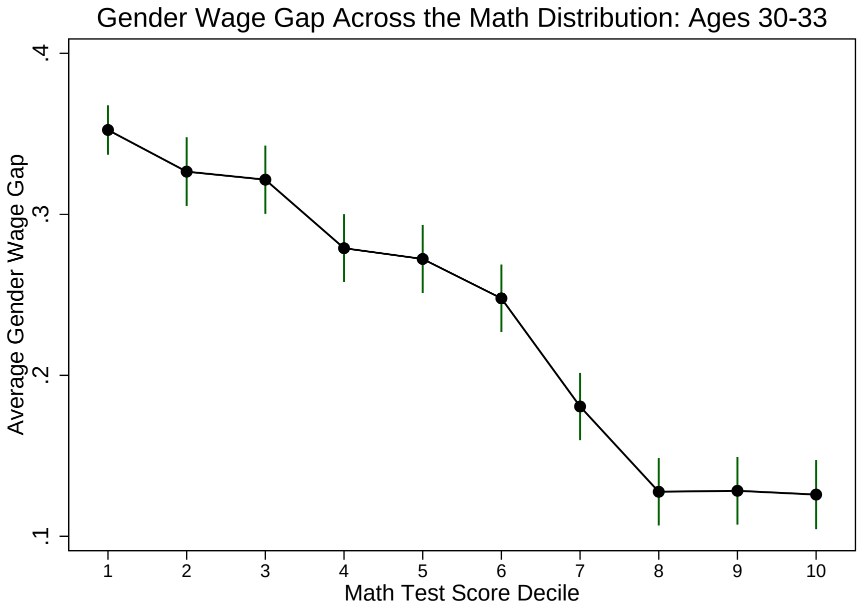
Gender gaps in test scores — could they explain part of the wage gap?

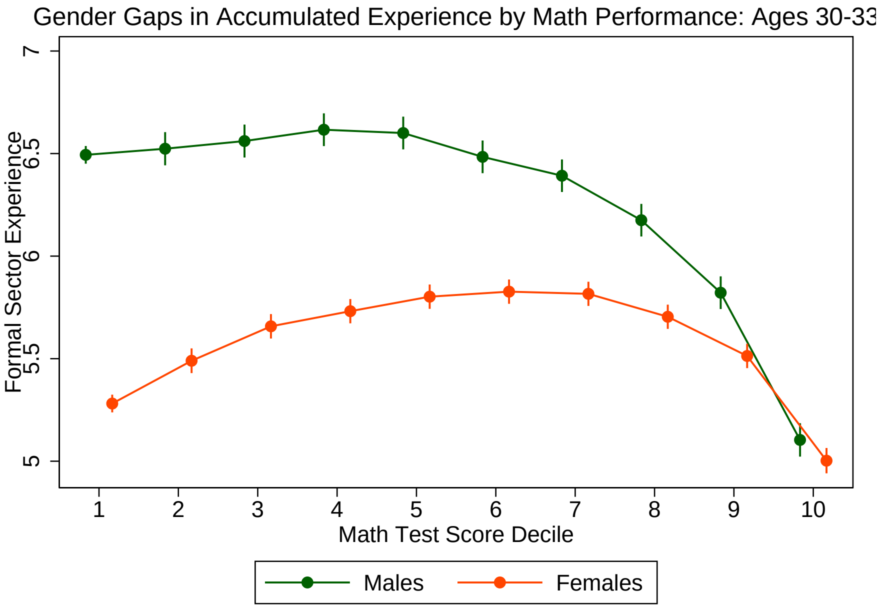


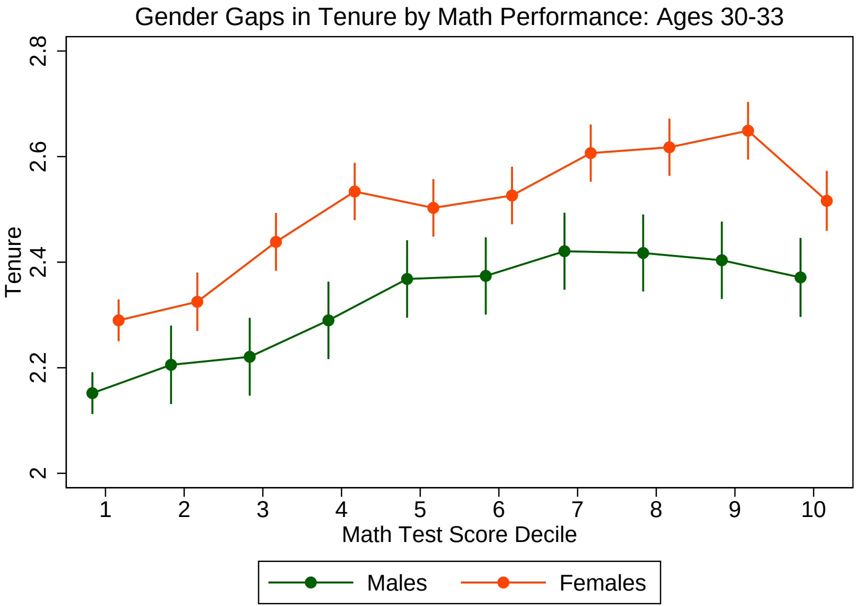

Gender Wage Gap by Age
Controling for Experience, Firm Quality and Math Test Score
Unexplained Gender Wage Gap
0
.05
.1
.15
.2
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
Age

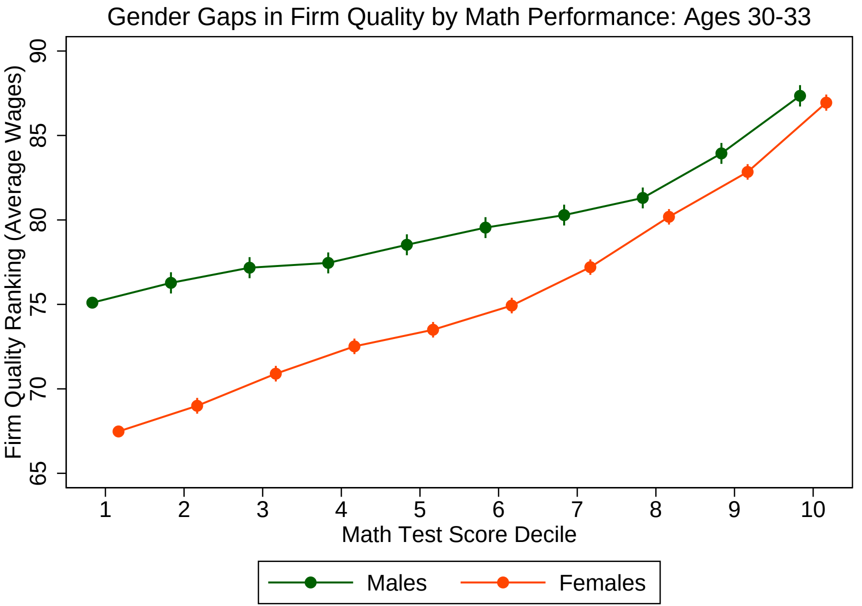
Importance of Math Test Scores

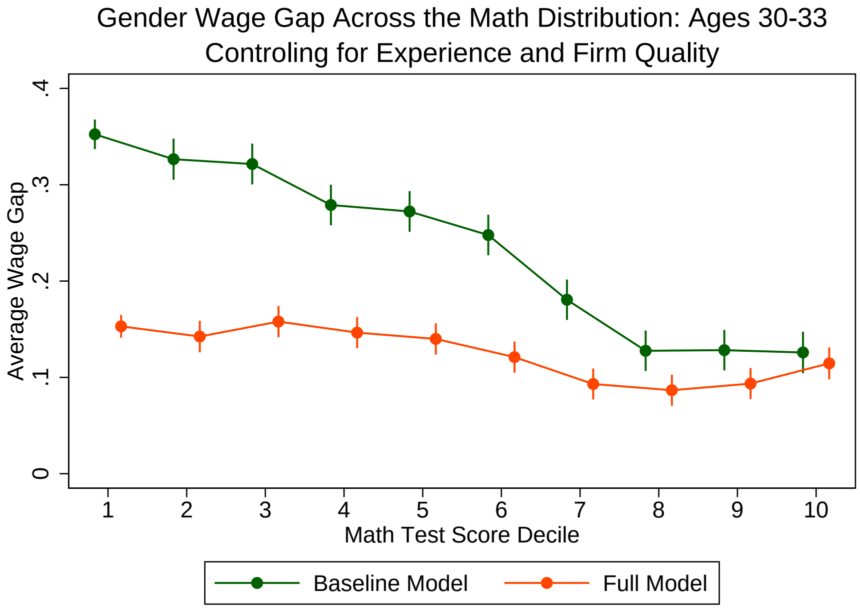
- Despite differences in high school performance, math test scores do not contribute to gender wage gap.
- Nonetheless, analyzing whether the wage gap differs across the skill distribution can help in developing potential policy solutions to reduce the gap.
  - Presence of large unexplained wage gaps at the top of the skill distribution could explain emergence of glass ceilings (Bertrand 2017).
  - Large wage gaps at the bottom of the distribution could be explained by differential labor market participation.
- We examine the gender wage gap across math test score deciles in the early career.


Gender Wage Gap Across the Math Distribution: Ages 30-33
Average Gender Wage Gap
.1
.2
.3
.4
1
2
3
4
5
6
7
8
9
10
Math Test Score Decile


Gender Gaps in Accumulated Experience by Math Performance: Ages 30-33
Formal Sector Experience
7
6.5
6
5.5
5
1
2
3
4
5
6
7
8
9
10
Math Test Score Decile
Males
Females


Gender Gaps in Tenure by Math Performance: Ages 30-33
Tenure
2
2.2
2.4
2.6
2.8
1
2
3
4
5
6
7
8
9
10
Math Test Score Decile
Males
Females


Gender Gaps in Firm Quality by Math Performance: Ages 30-33
Firm Quality Ranking (Average Wages)
65
70
75
80
85
90
1
2
3
4
5
6
7
8
9
10
Math Test Score Decile
Males
Females


Gender Wage Gap Across the Math Distribution: Ages 30-33
Controling for Experience and Firm Quality
Average Wage Gap
0
.1
.2
.3
.4
1
2
3
4
5
6
7
8
9
10
Math Test Score Decile
Baseline Model
Full Model

Thanks

Appendix

Gelbach Decomposition

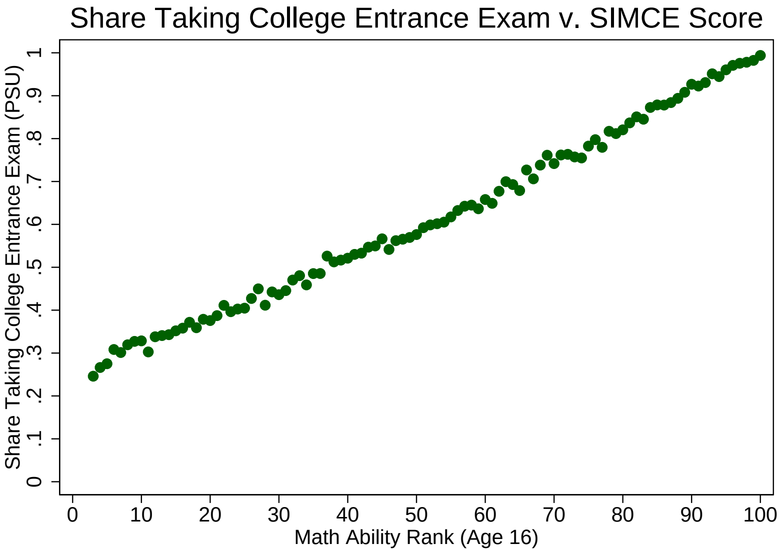
Gelbach (2016) proposes the following steps:

1. Estimate the full model and recover all parameters of interest.
2. Run a regression of $\boldsymbol{S_{it}}$ on $\boldsymbol{\theta_i}$, yielding a coefficient τ_S.
3. Do the same for $\boldsymbol{\varphi_{ft}}$ on $\boldsymbol{\theta_i}$, yielding τ_φ. These are the differences in educational attainment and firm quality by math ability.
4. The difference in the changes in the estimated returns to ability is given by:

$$\beta_1^F - \beta_1^B = \beta_3^F \tau_S + \beta_4 \tau_\varphi \qquad (3)$$

- The share of change in β_1 explained by educational attainment is given by $\beta_3^F \tau_S$.

Go Back


Share Taking College Entrance Exam v. SIMCE Score
Share Taking College Entrance Exam (PSU)
0
.1
.2
.3
.4
.5
.6
.7
.8
.9
1
0
10
20
30
40
50
60
70
80
90
100
Math Ability Rank (Age 16)

Go Back

Results

Table: Returns to Ability in Chile (Monthly Wages) ▸ Go Back

	(1)	(2)
Math	0.149***	0.143***
	(0.0007)	(0.0008)
Math × Age 25	0.0532***	0.048***
	(0.0009)	(0.0009)
Math × Age 26	0.0974***	0.087***
	(0.0009)	(0.0009)
Math × Age 27	0.124***	0.108***
	(0.0009)	(0.0009)
Math × Age 28	0.141***	0.120***
	(0.0009)	(0.0009)
Math × Age 29	0.152***	0.127***
	(0.0009)	(0.0009)
Math × Age 30	0.162***	0.133***
	(0.0009)	(0.0009)
Math × Age 31	0.160***	0.126***
	(0.0009)	(0.0009)
Language		X
Year FE	X	X
R^2	0.123	0.124
Observations	10,170,432	
Individual Observations	243,267	

▸ Go Back

Results

Table: Non-Linear Returns to Mathematical Ability (Monthly Wages)

	(1)	(2)
$P_{51} - P_{80}$	0.210***	0.182***
	(0.0007)	(0.0008)
$P_{81} - P_{90}$	0.415***	0.362***
	(0.0009)	(0.0009)
$P_{91} - P_{95}$	0.583***	0.519***
	(0.0009)	(0.0009)
$P_{96} - P_{99}$	0.770***	0.697***
	(0.0009)	(0.0009)
P_{100}	1.011***	0.930***
	(0.0009)	(0.0009)
Language		X
Year FE	X	X
R^2	0.125	0.126
Observations	10,170,432	
Individual Observations	243,267	

Go Back

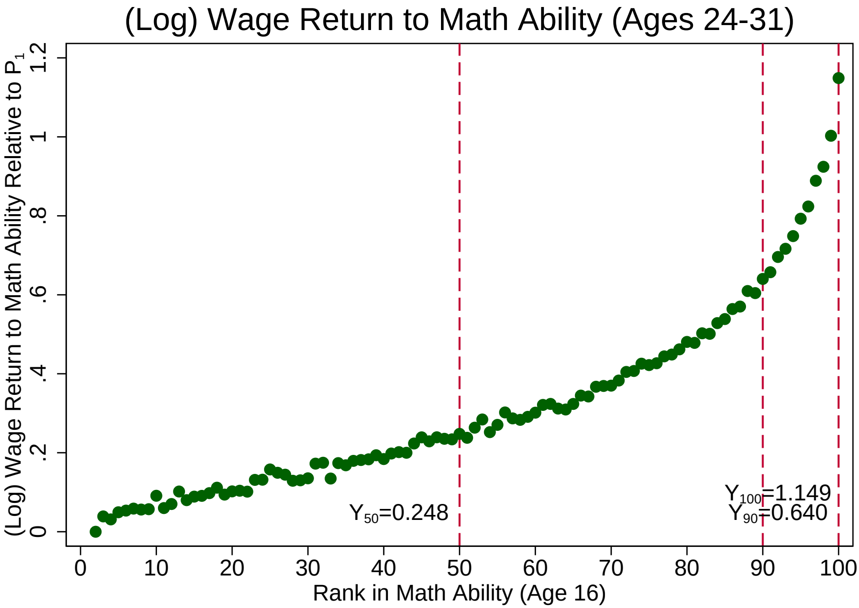

(Log) Wage Return to Math Ability (Ages 24-31)
(Log) Wage Return to Math Ability Relative to P1
0
.2
.4
.6
.8
1
1.2
Y50=0.248
Y100=1.149
Y90=0.640
0
10
20
30
40
50
60
70
80
90
100
Rank in Math Ability (Age 16)

Table: Non-Linear Returns to Mathematical Ability (Monthly Wages)

	(1)	(2)	(3)	(4)	(5)
$P_{51} - P_{80}$	0.185***	0.129***	0.129***	0.130***	0.125***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
$P_{81} - P_{90}$	0.389***	0.281***	0.277***	0.277***	0.253***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
$P_{91} - P_{95}$	0.569***	0.421***	0.414***	0.405***	0.367***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
$P_{96} - P_{99}$	0.765***	0.584***	0.575***	0.540***	0.495***
	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
P_{100}	1.010***	0.787***	0.777***	0.695***	0.644***
	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0025)
Year FE	X	X	X	X	X
Years of Ed.		X			
Degrees Received			X		
University Quality				X	
Field of Degree					X
R^2	0.165	0.233	0.234	0.236	0.244
Observations			10,170,432		
Individual Observations			243,267		

Go Back

Results

Table: Returns to Ability: Firm Quality Definition

	(1)	(2)	(3)	(4)	(5)
Math	0.141***	0.081***	0.076***	0.099***	0.098***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Language	0.021***	0.002	0.002	0.010***	0.016***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Experience	0.111***	0.067***	0.066***	0.064***	0.075***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
$Experience^2$	-0.005	-0.004	-0.003	-0.003	-0.003
	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Tenure	0.047***	0.033***	0.033***	0.032***	0.032***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Year FE	X	X	X	X	X
Field of Degree	X	X	X	X	X
Firm Rank (Mean Wage)		X			
Firm Rank Dummies			X		
Firm Rank (p_{50})				X	
Firm Rank (p_{25})					X
R^2	0.244	0.468	0.482	0.425	0.402
Observations			10,170,432		
Individual Observations			243,267		

Go Back

Table: Non-Linear Returns to Mathematical Ability (Monthly Wages)

	(1)	(2)	(3)	(4)
$P_{51} - P_{80}$	0.185***	0.125***	0.069***	0.068***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
$P_{81} - P_{90}$	0.389***	0.253***	0.142***	0.137***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
$P_{91} - P_{95}$	0.569***	0.367***	0.214***	0.200***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)
$P_{96} - P_{99}$	0.765***	0.495***	0.297***	0.269***
	(0.0013)	(0.0013)	(0.0013)	(0.0013)
P_{100}	1.010***	0.644***	0.385***	0.331***
	(0.0025)	(0.0025)	(0.0025)	(0.0025)
Year FE	X	X	X	X
Field of Degree		X	X	X
Firm Rank (Mean Wage)			X	
Firm Rank Dummies				X
R^2	0.165	0.244	0.468	0.482
Observations	10,170,432			
Individual Observations	243,267			

Go Back

Results

Table: Non-Linear Returns to Ability: Gelbach Decomposition

	(1) Baseline	(2) Full	(3) Education	(4) Firm Quality
$P_{51} - P_{80}$	0.185***	0.068***	0.056***	0.127****
	(0.0003)	(0.0003)	[0.318]	[0.672]
$P_{81} - P_{90}$	0.389***	0.137***	0.098***	0.212***
	(0.0003)	(0.0003)	[0.315]	[0.685]
$P_{91} - P_{95}$	0.569***	0.200***	0.139***	0.288****
	(0.0003)	(0.0003)	[0.326]	[0.674]
$P_{96} - P_{99}$	0.765***	0.269***	0.186***	0.378***
	(0.0003)	(0.0003)	[0.328]	[0.672]
P_{100}	1.010***	0.331***	0.220***	0.461****
	(0.0003)	(0.0003)	[0.323]	[0.677]
R^2	0.165	0.482		
Observations	10,170,432			
Individual Observations	243,267			

Go Back

Test Score Data

- Data on test scores comes from the 2001 and 2003 Measurement System of Education Quality Exam (SIMCE).
    - SIMCE is a standardized exam which measures individual performance on minimum curricula requirements in math and language skills.
- The exam is carried out nationally for all enrolled 10^{th} graders.
    - Rank students by their score percentile in the national distribution.
- Students do not learn their score on the test.
- Sample size includes 130,000+ of-age-test-takers in 2001; 140,000 in 2003.
- Previous work has used college entrance test as a measure of ability in Chile (Zimmerman 2017, Reyes et al. 2016, Hastings et al. 2013).
    - SIMCE scores allow us to observe students across ability distribution. PSU

Go Back

Educational Attainment Data

- Data on educational progress through high school from administrative records of student enrollment from 2002 through 2016.
  - Can identify high school dropouts and high school graduates.
- Information on post-secondary degrees from administrative registers of the Chilean Ministry of Education from 2007 through 2016.
  - Information on 150+ degree-granting institutions.
  - Information on type of degree received: classify by: associate's, certificates, four-year bachelors, five-year bachelors, and graduate degree.
  - Six-digit codes on fields of degree — narrow down to four broad categories: STEM, medicine, business and other.
- 92,000+ students received a degree by age 29 — 47% earned a five-year bachelors and 30% earned an associate's degree.

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Data on Labor Market Outcomes

- Data on labor market outcomes comes from the Ministry of Labor's Unemployment Insurance (UI) — a matched employee-employer database.
- Records monthly earnings for all workers with formal contracts in the country from 2002 through 2016.
    - Allows us to exactly identify exact month of labor market entry for workers, track their transitions across employers with precise detail.
    - For multiple job holders, we focus on the highest-paid job per month.
    - Allows us to track workers in my sample through their early thirties.
- 243,000 students are observed in the UI database at least once.
- **Limitations:** Does not include informal sector employment records.
    - Covers 20% of employment in Chile — smallest in Latin America.

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