Skills, Inequality and Labor Markets

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The elevator pitch:

- Since 2000 income inequality has declined among Latin America Countries.
- This was not the result of structural reforms.
- Challenges remain with the additional pressure of sustaining/extending current trends:
  - Innovation in Public Policies

The Good

– Decline in income inequality

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The Bad:

- Delays (inaction) have been extremely costly.
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- Delays (inaction) have been extremely costly.
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The Ugly:

- Schooling systems disconnected from labor markets.
- Little understanding of labor market dynamics.

Where are LACs?

2000-12:

Source: www.data.worldbank.org

2000-12:

The phenomenon followed high and stable levels of income inequality

Source: www.data.worldbank.org

Why?

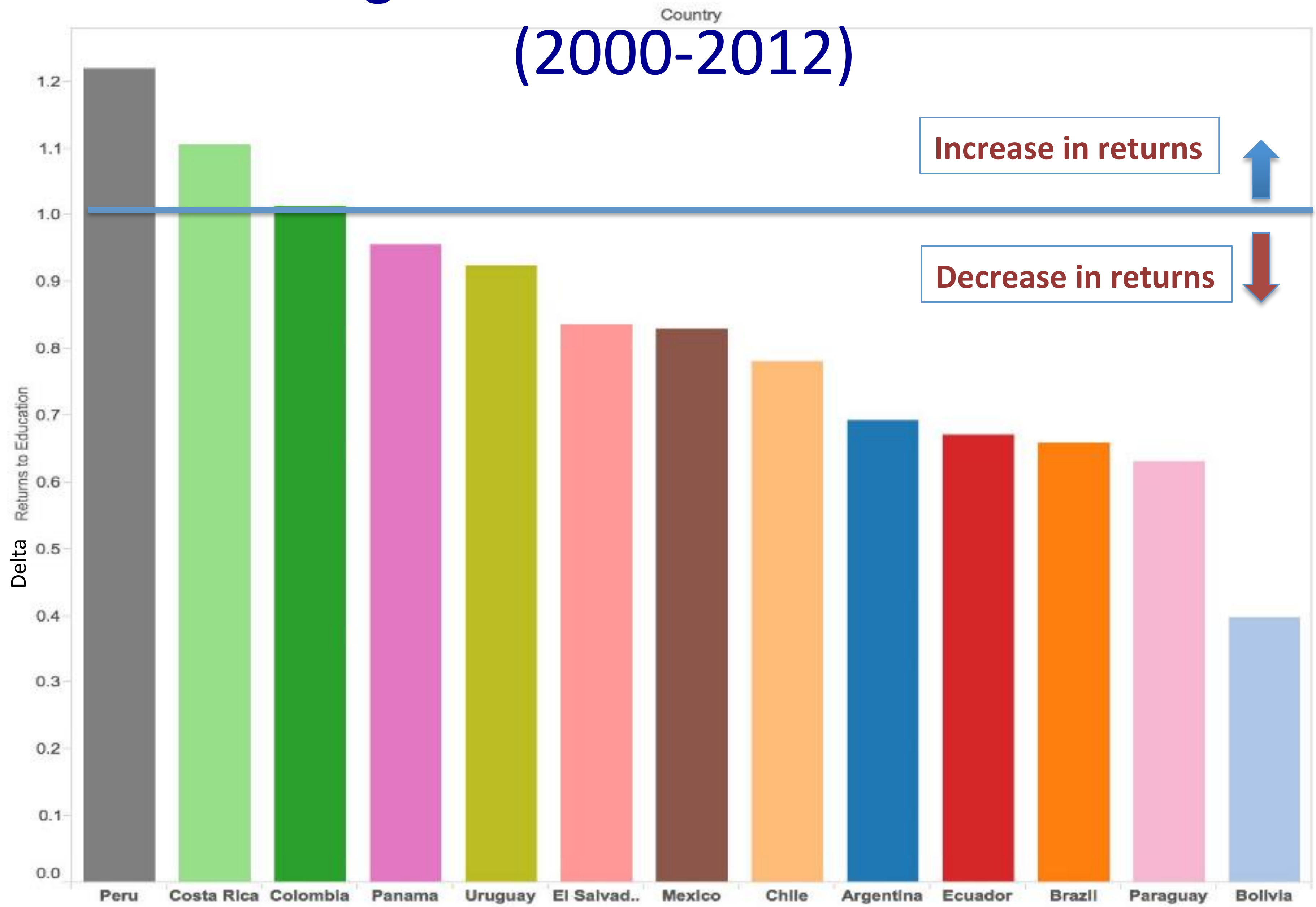
Higher education in the grip of the typhoon

(missing the target?)

And these efforts correlate with the decline in inequality

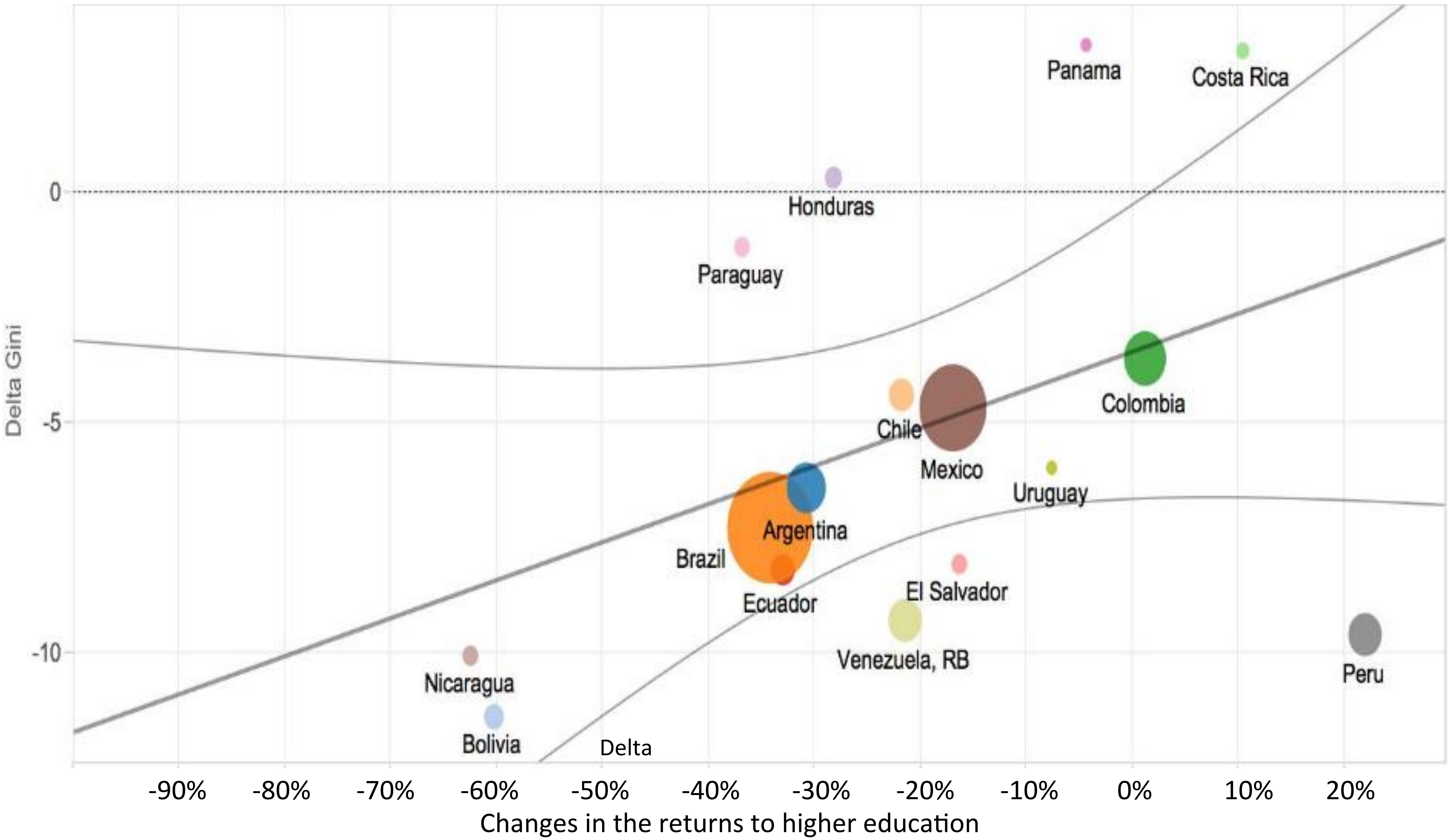
Potential mechanism?
Reduction in returns to higher education

Changes in Returns to Education (2000-2012)



Returns to education: Labor income high level of education/low level of education (SEDLAC and WB)

Decline in Inequality and Changes in Returns to Education (2000-2012)



See also Ferreyra et. al. (2016)

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Was really education?

- Commodity booms (00s)
- Social programs
- CCT
- Unconditional transfers
- Employment
- Labor income
- FDI
- “Generous” economic policies: Minimum Wage

Term of trade as proxy

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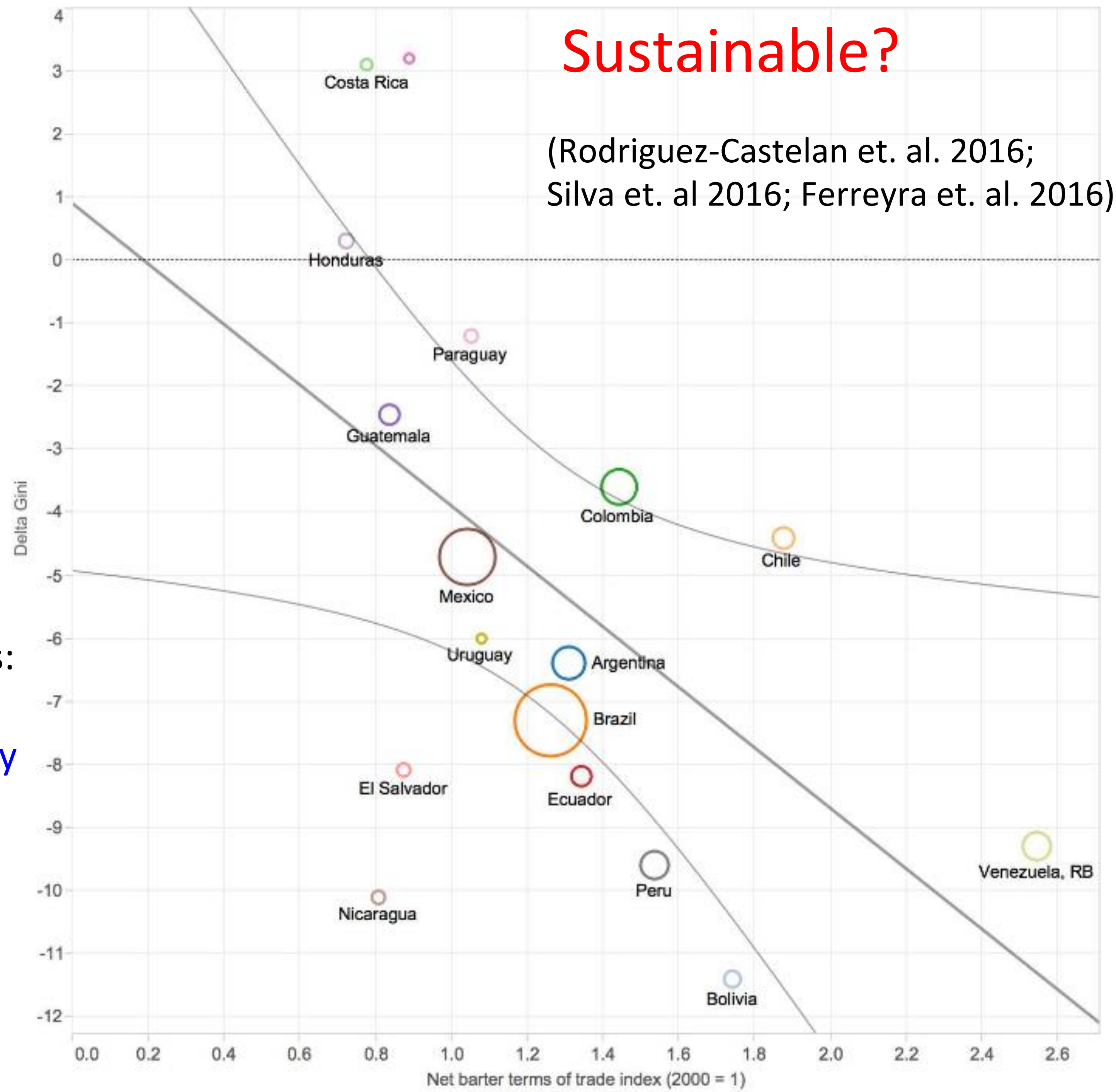


The Transmission of Commodity Price Super-Cycles

Felipe Benguria [†] Felipe Saffie [‡] Sergio Urzua[§]

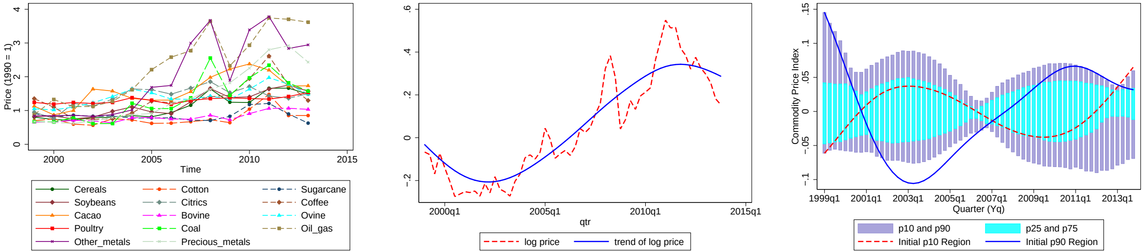
August 9, 2018

Abstract

We examine the channels through which commodity price super-cycles affect the economy. Higher commodity prices increase domestic demand (*wealth* channel), disproportionately benefiting non-exporters, and induce wage increases (*cost* channel) especially among unskilled workers, hurting unskilled-intensive industries. By exploiting regional variation in exposure to commodity price shocks and administrative firm-level data from Brazil we empirically disentangle these transmission channels. We introduce a dynamic model with heterogeneous firms and workers to further quantify the mechanisms and evaluate welfare. The *cost* channel explains two-thirds of intersectoral labor reallocation, and the *wealth* channel explains two-thirds of the labor reallocation between exporters and non-exporters.

Keywords: Commodity shocks, local labor markets, skill premium, heterogeneous firms.

JEL classification: E32, F16, F41



a) Individual Commodity Prices b) Commodity Price Index c) Regional Commodity Prices

Figure 1: Commodity Prices

Note: The graph on the left shows the path of the prices in real U.S. dollars of the 14 commodities included in our commodity price index. These prices are normalized to one in 1990. The graph on the middle shows the path of the commodity price index for Brazil (dashed line) and its trend (solid line). The graph on the right shows the percentiles of the distribution of the residual regional commodity price index after extraction region and period fixed effects. The outer bars mark the 10th and 90th percentiles and the inner bars mark the 25th and 75th percentiles. The dashed (solid) line marks the path of the residual price for the region at the 10th (90th) percentile in the initial period.

Table 1: Commodity Prices and Skill Premium

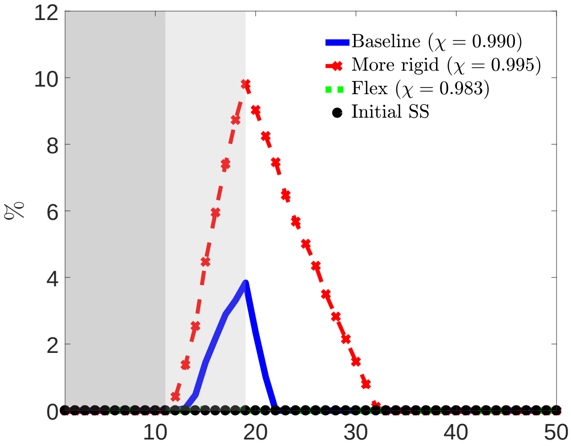
	(1) Annual	(2) Monthly
(log) Price_{rt}	-0.140**	-0.128***
	(0.057)	(0.058)
Observations	8363	7912
R^2	0.694	0.687

NOTE: This table reports the results of the estimation of equation (4). Column 1 and, 2 correspond to annual and monthly (December) earnings respectively. Each regression includes region as well as time (year) fixed effects that are allowed to vary by macroregion. Standard errors are clustered by region. ***, **, and * denote statistical significance at a 1, 5 and 10 percent confidence level.

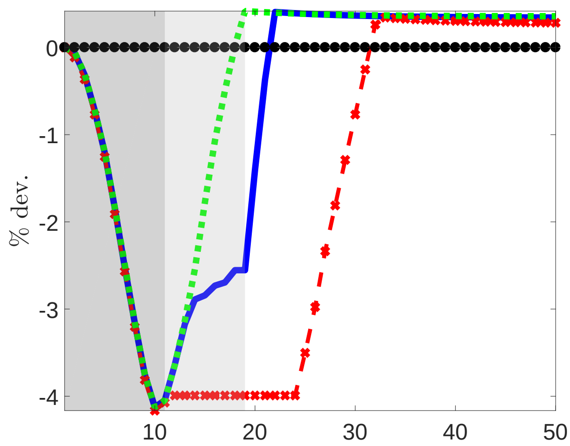
Table 2: Commodity Prices and Firm-Level Employment: The *Cost* Channel

	Commodity	Tradable		Nontradable	Commodity	Tradable		Nontradable
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(log) Price_{rt}	0.131***	-0.136***	-0.140***	0.010	0.100**	-0.136***	-0.138***	0.014*
	(0.041)	(0.016)	(0.018)	(0.008)	(0.039)	(0.016)	(0.018)	(0.008)
Skill Intensity_i x (log) Price_{rt}					3.467***	0.795***	0.943***	0.845***
					(0.312)	(0.074)	(0.077)	(0.021)
Observations	1,007,633	8,086,964	6,960,963	30,453,468	1,007,570	8,007,422	6,881,423	30,453,457
R^2	0.907	0.873	0.867	0.849	0.908	0.873	0.866	0.849

NOTE: This table reports the results of the estimation of equation (2) by sector. The first four columns exclude the interaction between commodity price and industry's skill intensity. Column 1 corresponds to the commodity sector. Column 2 and 3 corresponds to the tradable sector. Column 3 excludes commodity-intensive industries. Column 4 corresponds to the nontradable sector. Columns 5 to 8 include the interaction term, which allows the identification of the *cost* channel. Column 5 displays the results for the commodity sector. Columns 6 and 7 (excluding commodity-intensive industries) display the results for the tradable sector. Column 8 presents point estimates for the nontradable sector. Each regression includes firm and time (quarter) fixed effects that are allowed to vary by state. Note we estimate equation (2) demeaning the commodity price index and skill intensity variables. Standard errors are clustered by firm. ***, **, and * denote statistical significance at a 1, 5 and 10 percent confidence level.



a) Unemployment Rate



b) Skill Premium

Figure 6: Response of the Unemployment Rate and the Skill Premium to a Commodity Price Super-Cycle

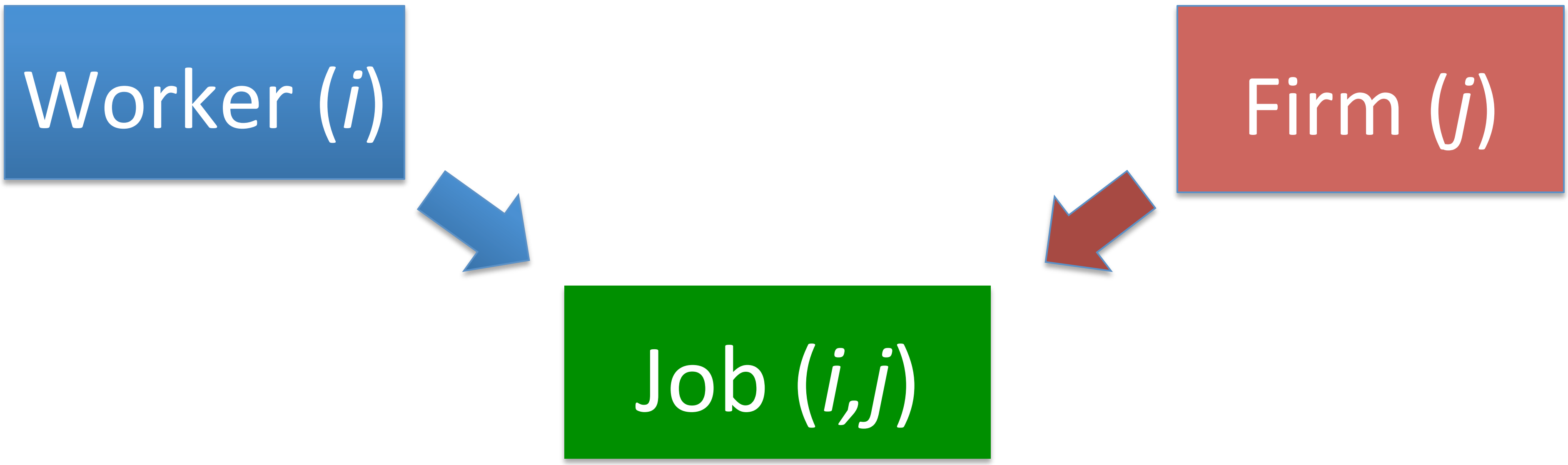
NOTE: This figure shows the response of the unemployment rate (left) and the skill premium (right) to the to the commodity price super-cycle shown in figure 3. The different lines correspond to the i) economy with flexible wages (green dashed line) ii) baseline (moderately rigid) economy (solid blue line) iii) highly rigid economy (red crossed line) and iv) steady state level (black circled line).

All in all, recent success cannot be interpreted as permanent

New evidence confirms inequality has deep roots

Conceptual Framework

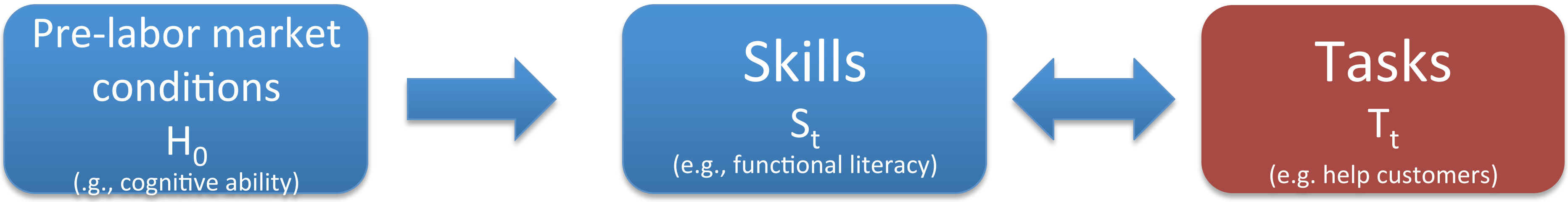
We need to understand "jobs" to understand inequality



$$W(i,j) = W\big(X(i), Z(j)\big)$$

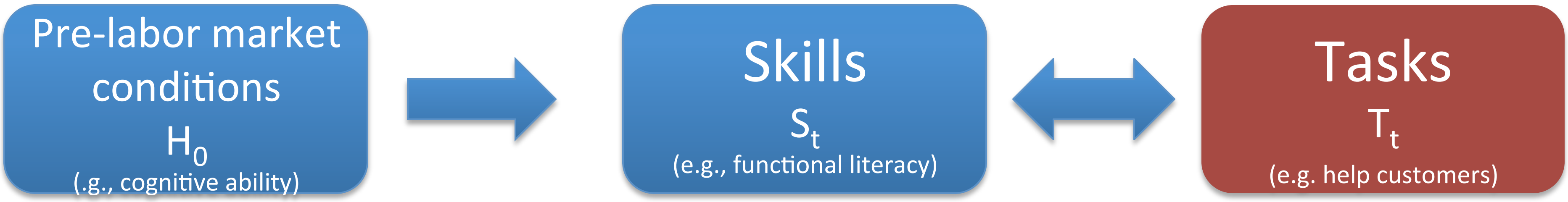
Hedonic models (e..g., Mincer 1957, Griliches, 1977; Card 2001)
Decompositions (e.g, Juhn, Murphy, Pierce; 1983)
Heterogeneity across firms vs. individuals (e.g., Abowd et al. 1999)

We need to understand "jobs" to understand inequality



Formal discussion: Acemoglu & Autor (2010), Autor et al (2003).

We need to understand "jobs" to understand inequality



$$W_t(i,j) = W\Big(\underbrace{H_0(i), S_t(i)}_{\substack{\text{Individual} \\ \text{(circumstances vs. efforts)}}}, \overbrace{Z_t(j)}^{\text{Firms}}, \underbrace{T_t(i,j)}_{\text{Match}}\Big)$$

$$GINI_t = G\left[\left\{\{W_t(i,j)\}_{i=1}^{N(j)}\right\}_{j=1}^{J}\right]$$

Formal discussion: Acemoglu & Autor (2010), Autor et al (2003).

Missing the target I:

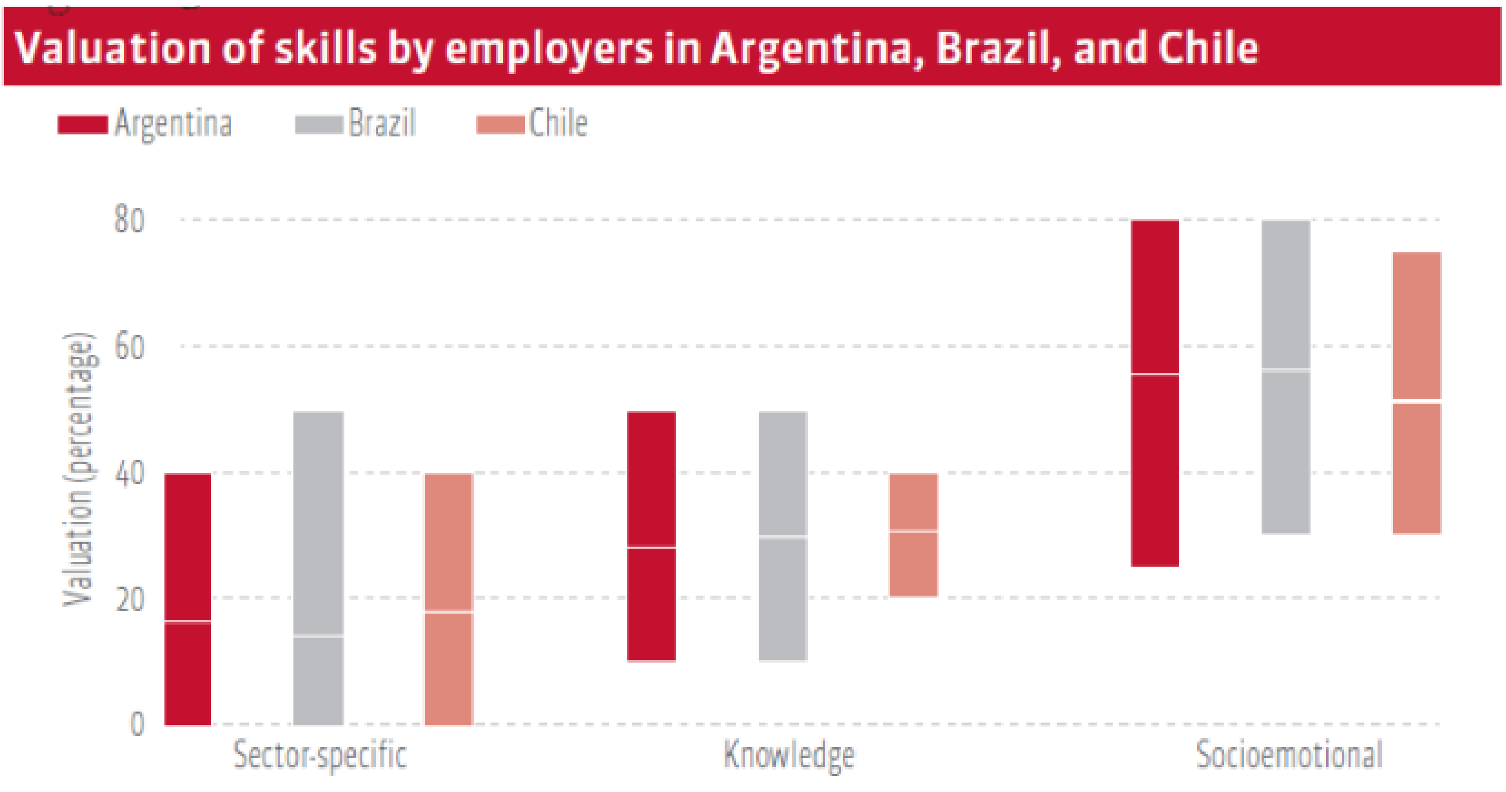
Skills

Beyond positive trends in
enrollment rates…

…what about quality/relevance?
Skills?

Windows of opportunities?

What type of skills are demanded by firms in LACs?



Source: Disconnected (2012)
Survey of Skilll Demand(Argentina, Brasil, Chile)

Missing the target II:

Pre-labor market endowments

(Intergenerational Transmission of Inequality)

Disparities emerge early on with major impact on future income inequality

Is private education worth it? Evidence from Chilean high schoolers*

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Universidad de Chile

Jorge Rodríguez
Universidad de Los Andes

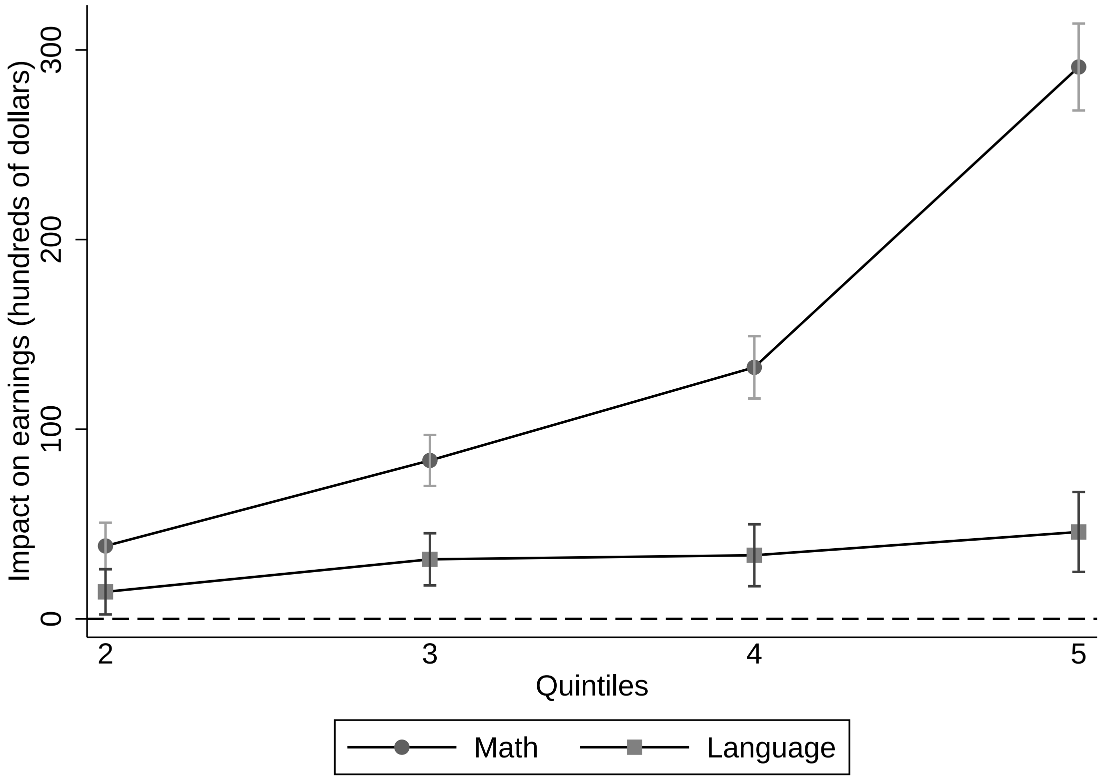
Sergio Urzúa
University of Maryland
and NBER

This version: August 13, 2018

Abstract

This paper investigates the labor market returns of attending different high school types. Our empirical strategy exploits a newly linked administrative data describing the school-to-work transition of the universe of Chilean students attending tenth grade in 2001. The resulting panel contains detailed employee-employer data (adult earnings and firm characteristics) integrated with individuals' socioeconomic background variables, school characteristics, and pre-labor market test scores. We discuss the role of self-selection into school types and present bounds for the treatment effects of interest. We find that attending private high schools has large and positive effects on adult earnings. In addition, the estimated returns to school-level value-added measures and monetary investments in education are higher for private- than public-school students. Our findings provide new insights into the association of school choice and income inequality.

Figure 3: Labor market returns of academic achievement



Notes: We show OLS estimates of a regression of 2013 monthly average earnings on a set of dummy variables indicating test scores quintiles. The baseline category is the first quintile of each test. Each point in the graph represents the effect of scoring in each quintile relative to the baseline. We control for exogenous characteristics, family background, and test scores (see Section 4 for details). Whiskers indicate a 95% confidence interval based on clustered robust standard errors.

Table 6: Earnings regressions: effects of number of years spent in school on earnings

Variables	Lower bound	Upper bound
Private-voucher	0.019	0.044***
	(0.013)	(0.013)
Private-fee-paying	0.181***	0.244***
	(0.019)	(0.019)
Exogenous characteristics	Yes	Yes
Family background	Yes	Yes
Test scores	Yes	No
Observations	110,228	110,228

Notes: We estimate the lower and upper bound of the effect of one year at a private-fee-paying and private-voucher school relative to spending one year in a public school. We obtain these estimates running:

$$w_i = \sum_s NS'_{is}\rho_s + \boldsymbol{X}'_i\alpha + v_i,$$

where NS_{is} corresponds to the number of years that student i has spent in school s up until 10th grade. This table shows upper and lower bound on $\rho_z - \rho_{\text{public}}$, where $z \in \{\text{private-fee-paying}, \text{private-voucher}\}$. To obtain the bounds, we compare regressions with and without math and language test scores. In parenthesis, we show bootstrapped standard errors that are clustered at the school level (*** $p < 0.01$, **$p < 0.05$, *$p < 0.1$).

Table 7: Earnings regressions with firm and location fixed-effects

Variables	No F.E.		Firm F.E.		Comuna F.E.	
	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
Private-voucher	0.263**	0.484***	0.223*	0.376**	0.259**	0.467***
	(0.122)	(0.173)	(0.118)	(0.149)	(0.114)	(0.164)
Private-fee-paying	1.987***	2.845***	1.440***	2.045***	1.822***	2.627***
	(0.241)	(0.300)	(0.234)	(0.273)	(0.224)	(0.283)
Exogenous characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Family Background	Yes	Yes	Yes	Yes	Yes	Yes
Test scores	Yes	No	Yes	No	Yes	No
Observations	55,858	55,858	55,858	55,858	55,622	55,622

Notes: We show our estimated lower and upper bounds (equations 3 and 4) of the effects of schooling choices on earnings from October, 2013 (not including zeros). We obtain the lower bound from a regression that includes math and language test scores. We estimate the upper bound from a regression that does not control for test scores. Both types of equations control for observed family and exogenous, individual characteristics (see Section 4 for details). We present upper and lower bounds for three types of models: without fixed-effects, firm fixed-effects, and location fixed-effects. The baseline category is public school (coefficients on high school dummies represent impacts relative to the baseline). Standard errors (in parenthesis) are clustered at the school level (*** $p < 0.01$, **$p < 0.05$, *$p < 0.1$).

Missing the target III:

Tasks

Tasks versus Skills

- Decomposing the sources of inequality using administrative data
  - Between- and within-firm inequality
    - USA: Davis et al. (1991), Abowd et al. (1999) Barth et al. (2014), Song et al. (2015)
    - Germany: Card, Henning and Kline (2013)
    - Brazil: Latin America: Rucci et. al. (2016), Benguria et. al. (2016a,b), Alvarez et al. (2016), Saltiel & Urzua (2016)
- How do skills and tasks contribute to wage inequality?
  - Autor, Katz and Kearney (2008), Acemoglu and Autor (2010)
  - Limited evidence in developing countries

Tasks versus Skills

- Task (T): a unit of work activity that produces output
  - Non-Routine Analytic Tasks
    - Ex. Developing plans, establishing rules, evaluating results.
  - Non-Routine Personal Tasks
    - Ex: interacting with customers, managing employees.
  - Routine Manual Tasks
    - Ex: Operating machines, printing materials.
- Skill (S): a worker's endowment of capabilities for performing various tasks.

Learning About Tasks

- We can take advantage of matched employee-employer data from Brazil.
  - Information on
    - Worker observables, industry of employment, wages and occupations.
- We take advantage of O*NET data (Occupational Information Network) to examine task prevalence across occupations.
    - Classify different occupations by task prevalence.
    - First focus: Rio de Janeiro and Sao Paulo in 2003:
      - 14 million workers
    - We successfully match O*NET for 1,307 of the 1,366 reported occupations in Brazil.

From theory to practice: Capturing Tasks

Figure. Different occupations by task importance (O*Net)
O*Net: Occupational Information Network

Occupation	Non-Routine Cognitive Analytic	Non-Routine Cognitive Personal	Routine Cognitive	Routine Manual
Architects	5	5	3	1
Economists	5	3	2	1
Knitting Machine Operators	3	2	3	3
Taxi Drivers	1	1	5	3

Source: Saltiel & Urzua (2016)

Evidence from Brazil

Variables	Sao Paulo			Rio de Janeiro		
	(A)	(B)	(C)	(A)	(B)	(C)
Years of Education	0.112	0.07	0.047	0.115	0.071	0.048
Non-Routine Cognitive Analytic			0.061			0.089
Non-Routine Cognitive Personal			0.081			0.066
Routine Cognitive			0.000			-0.025
Routine Manual			-0.03			-0.003
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	Yes	Yes	No	Yes	Yes
R2	0.29	0.66		0.31	0.69	
N		11,270,604			3,474,056	

Source: Saltiel and Urzua (2016). Controls includes: Gender, Race, Potential Experience.
Coefficients are significant at 1%.

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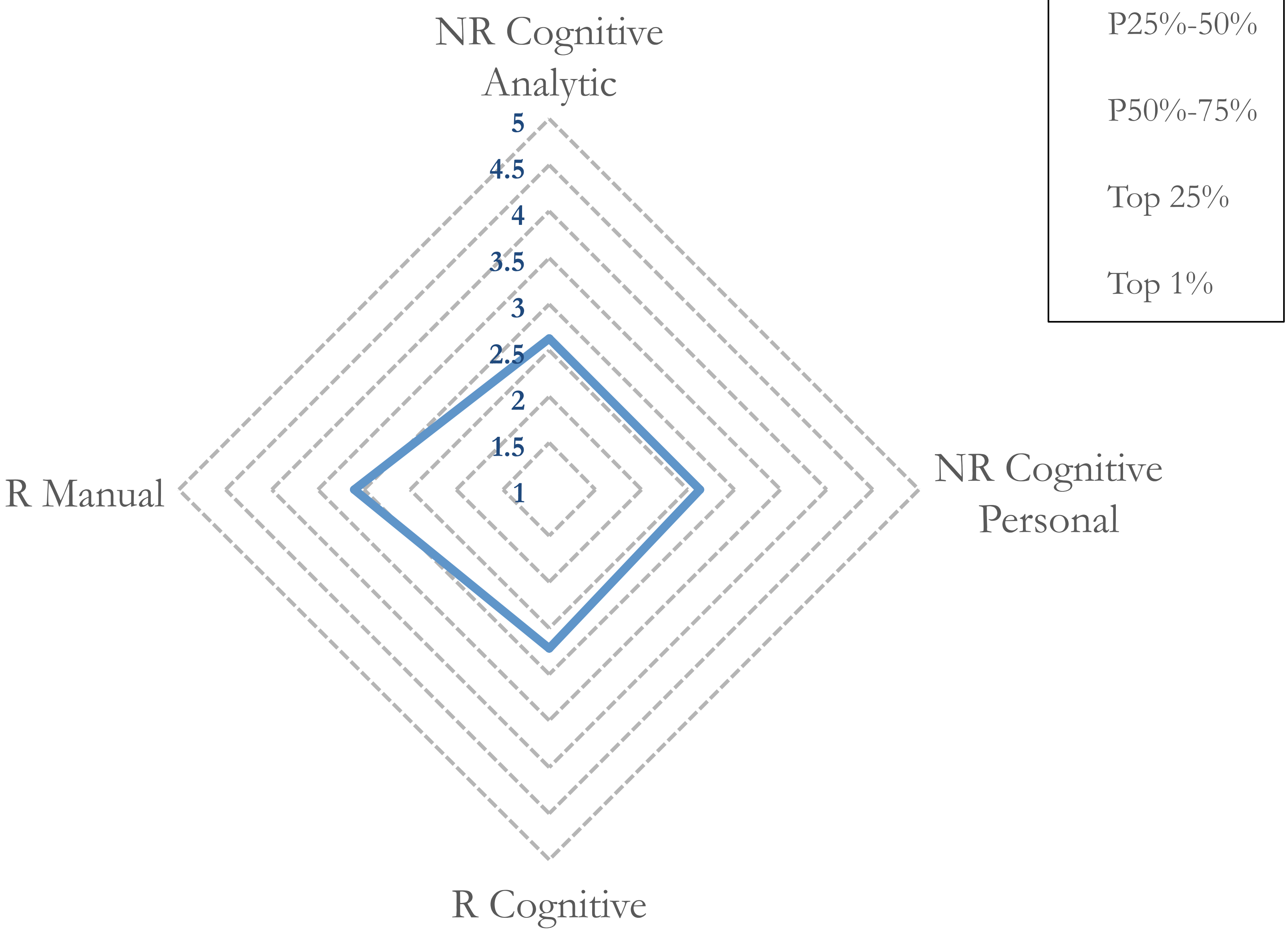

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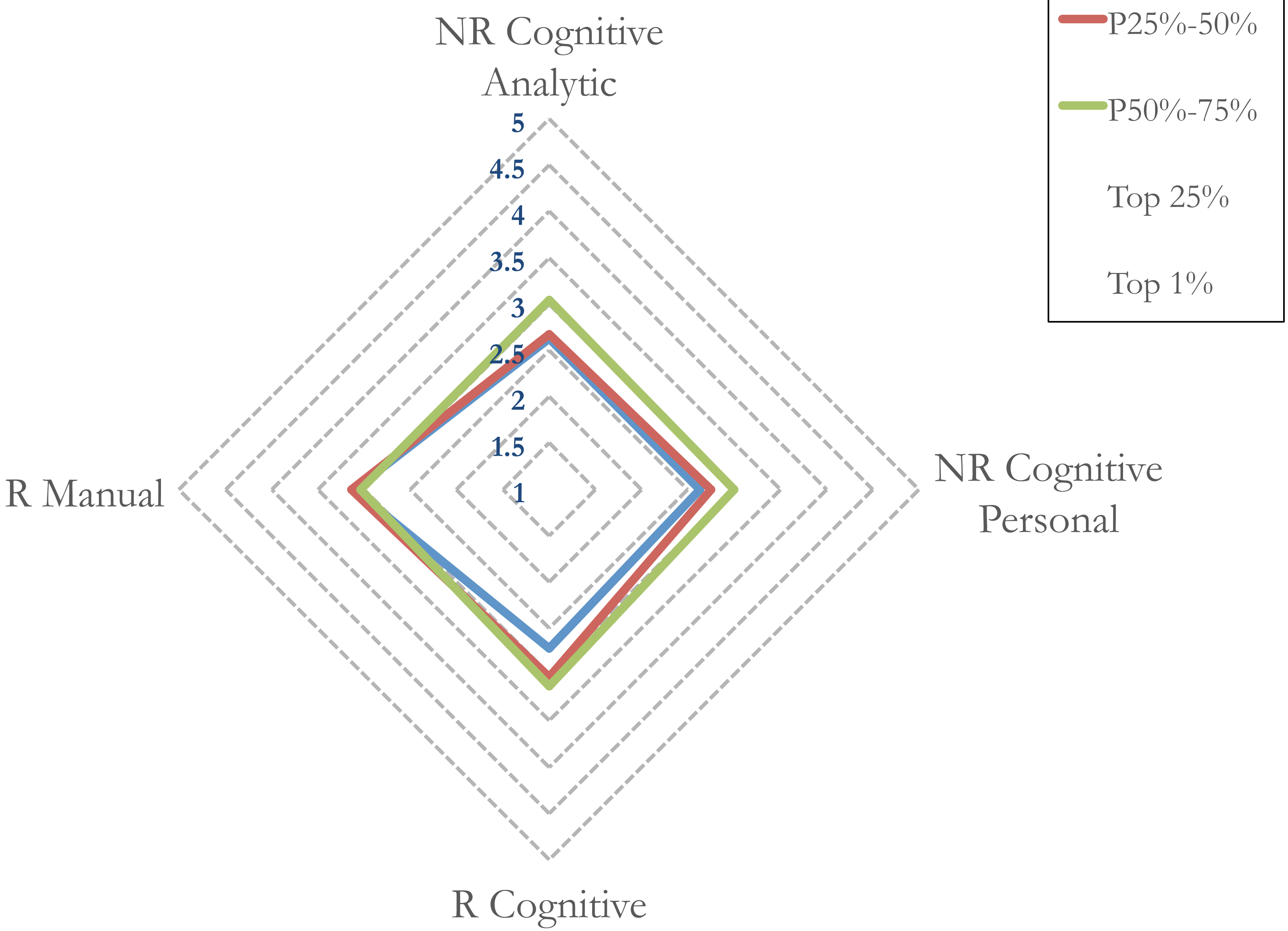

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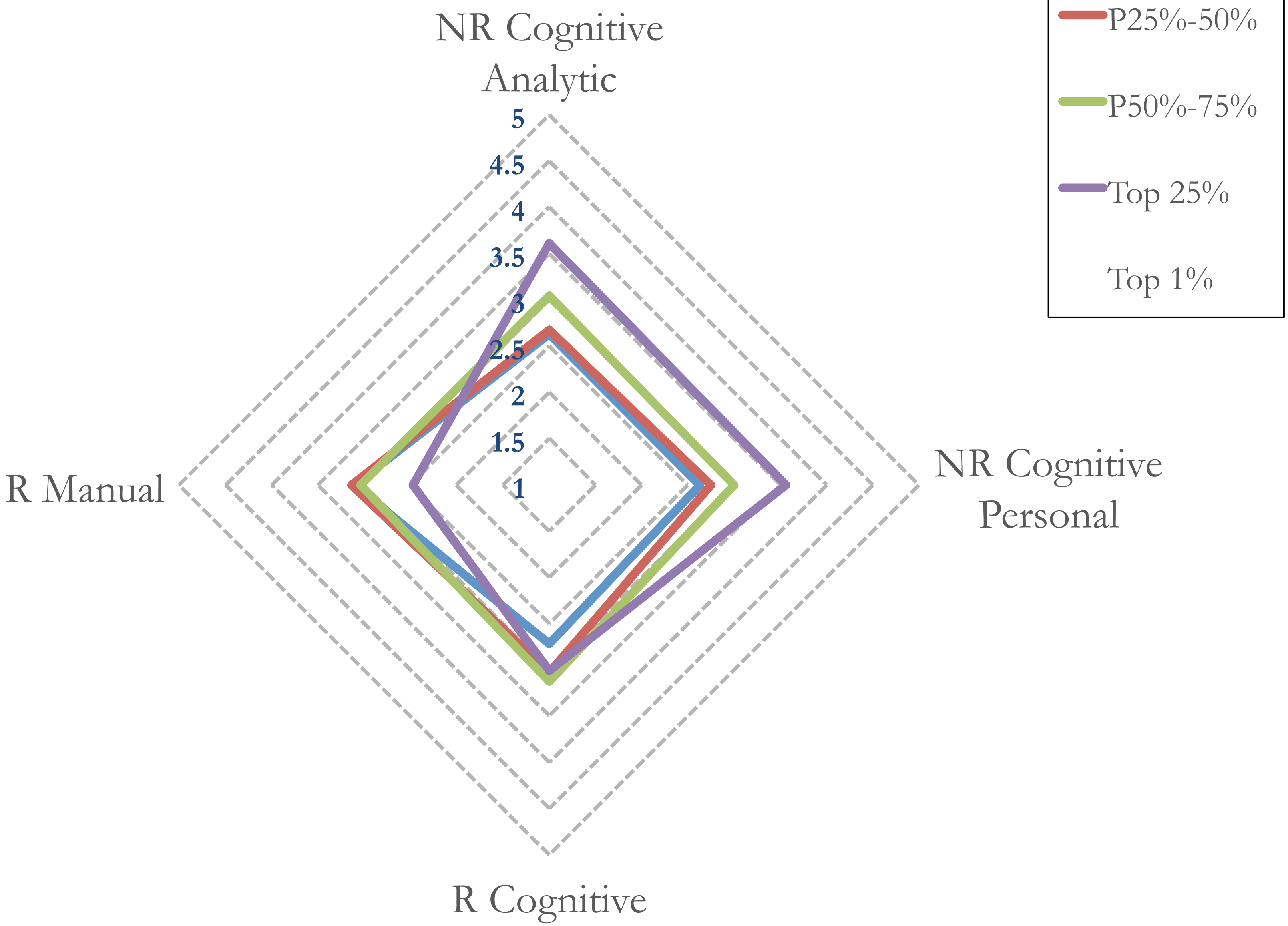

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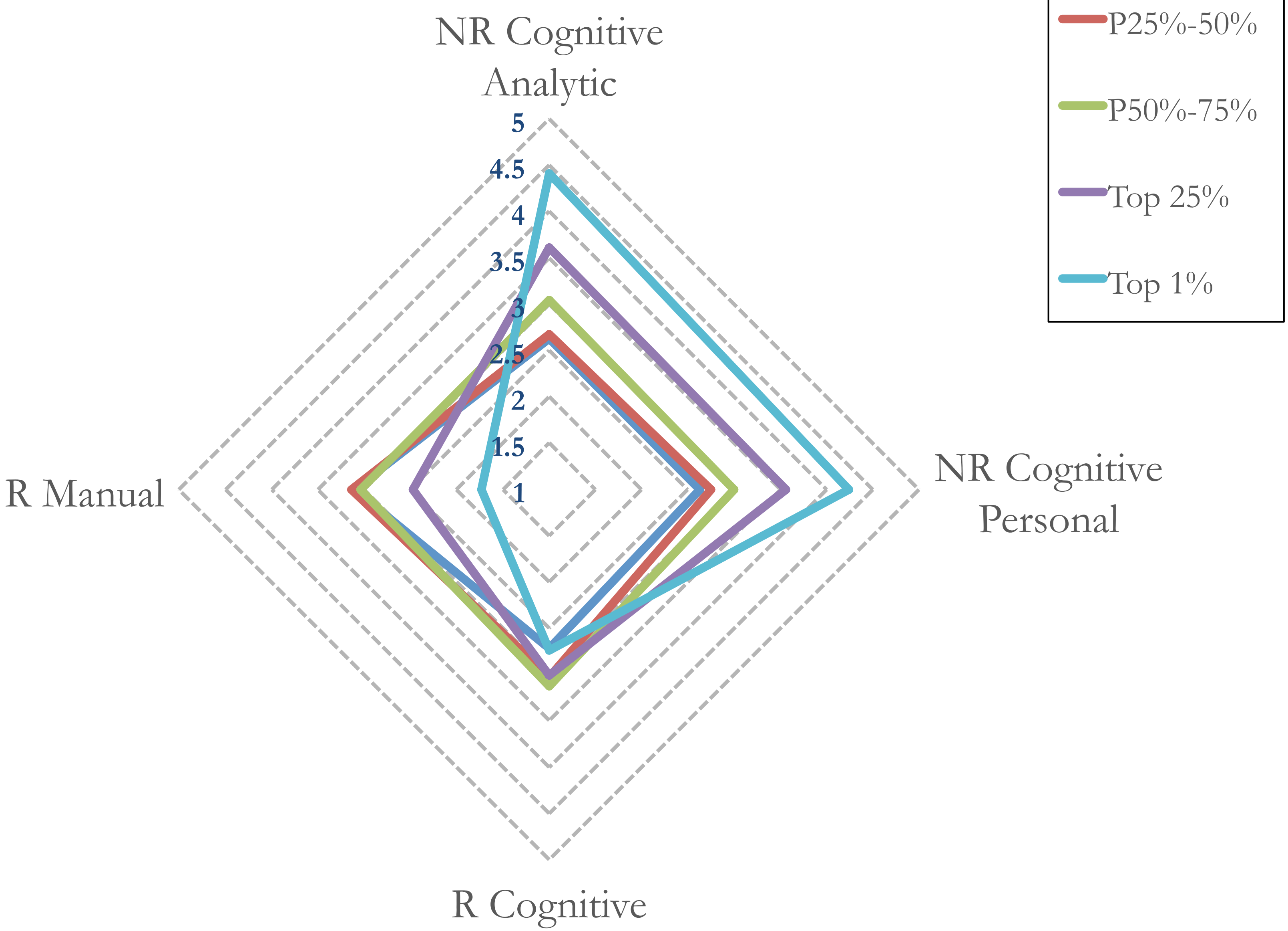


Fuente: Saltiel & Urzua (2016)

Slow growth and increasing unemployment in the region

- As the region undergoes slow growth, labor market conditions deteriorate: Layoffs.
  - Lower salaries.
  - Lower tasks on the occupational ladder.
  - Worse relative position in new firm.
  - Impact on Inequality?

- Mass layoffs in Brazil to examine the impact of involuntary layoffs:
  - Lower bound on effect.
  - May be worse during an economy-wide downturn as workers are not able to quickly re-enter.

Defining “Mass Layoffs”

- What is a mass layoff?
  - A firm originally had over 100 employees
    - Fires over half of its employees in the following years.
    - Does **not** recover its employment levels in subsequent years.
  - We recover 40,000 workers who were fired in mass layoffs in 2003-2008.

Climbing Back Up? Examining the Role of Tasks Among Displaced Workers

Felipe Benguria **Felipe Saffie** **Fernando Saltiel** **Sergio Urzua**
University of Maryland, College Park

August 13, 2018

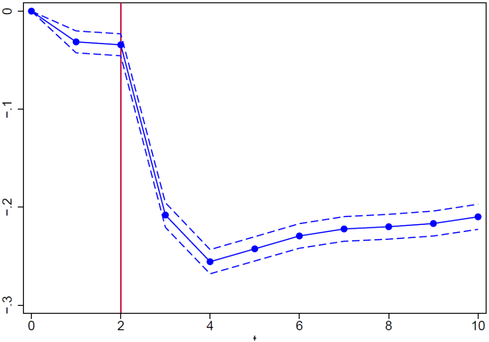
Research Design

- Matched employee-employer administrative data (RAIS) from a mandatory annual survey filled by all formal sector firms in Brazil in 2002-2012.
  - Annual information on 50 million workers and 3 million formal sector firms.
- We examine the effect of involuntary job displacement on high-tenured workers.
  - Include mass layoff and firm closure events. 50,000+ displaced workers.
  - Control group includes workers in large firms not affected by displacement.
- Estimate the impact of displacement on various outcome variables as follows:

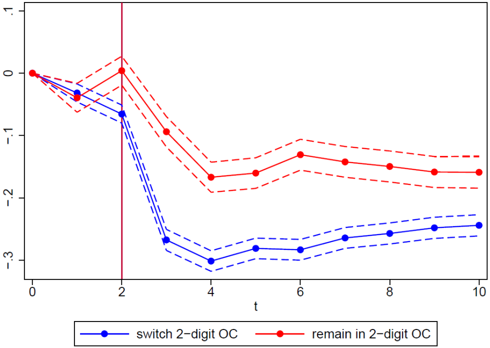
$$Y_{it} = \alpha_i + \lambda_t + X_{it}\beta + \sum_{k=-2}^{6} D_{it}^{k}\delta_k + \varepsilon_{it} \tag{1}$$

- Examine the effect on monthly earnings and occupational task content.
- Analyze heterogeneous impacts by pre-displacement occupation.

Effect on (Log) Monthly Earnings



Heterogeneity: Occupation Switchers



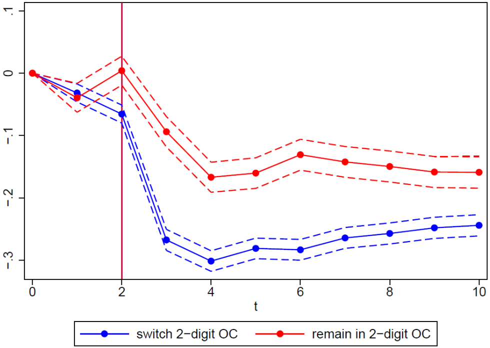
Importance of Tasks

- How to quantify direction and distance of occupational changes?
  - Occupations represent a bundle of tasks (Yamaguchi 2011).
- Crosswalk occupational data from RAIS with task content from O*NET.
  - Define occupations by their non-routine analytical, non-routine interpersonal, routine cognitive and routine manual task content.
- Follow Abowd, Kramarz and Margolis (1999) to estimate return to tasks:

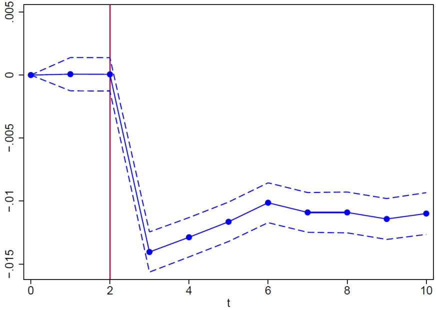
$$Y_{it} = \alpha_i + \gamma_{f(i,t)} + \delta_t + \sum_{j=1}^{4} \beta_j Task_{j(i,t)} + \epsilon_{it} \tag{2}$$

- $\hat{\beta}_j Task_{j(i,t)}$ represents the importance of each task on wages — use it to decompose observed wage impacts.

Workers in Top Non-Routine Analytical Occupations



- Loss in return to non-routine analytical task ($\hat{\beta_{NA}} Task_{NA}$) for workers in top quartile of NA task content.



- Loss in NA task content represents 5 percent of total earnings losses.
- Loss in other tasks account for an additional 5-10 percent of aggregate effect.

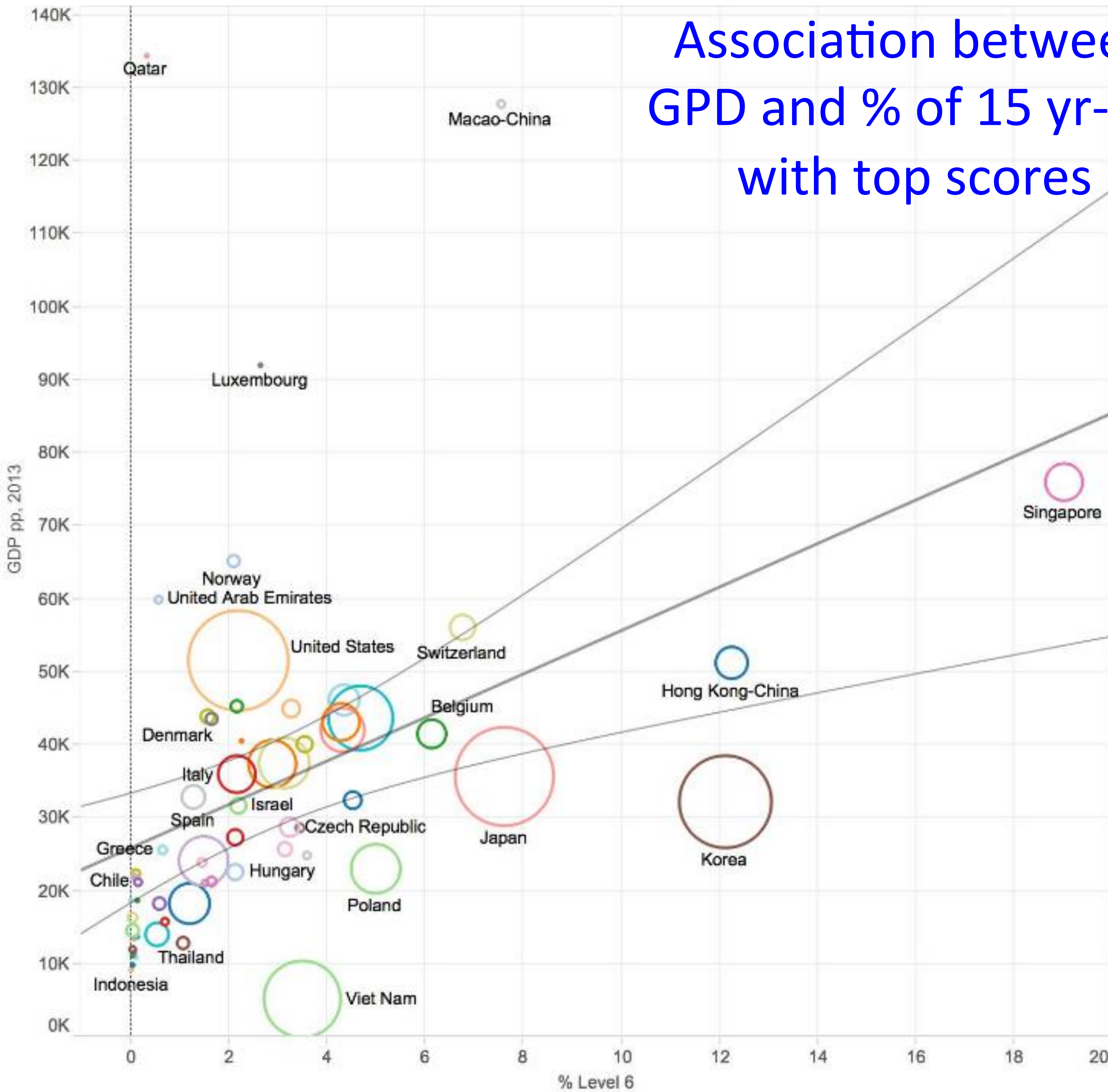
IMPLICATIONS

– Importance of active labor market policies and their role on income inequality
  - 40% of workers never re-enter the formal sector
– Role for general job training
  - Workers high on the occupational ladder in initial firm fall in the task ladder in new firm (Rucci, Prada & Urzua, 2016)
– Prepare workers to perform non-routine tasks
  - High returns in labor market

Main Future Challenge:

Promoting equal opportunities + competitiveness

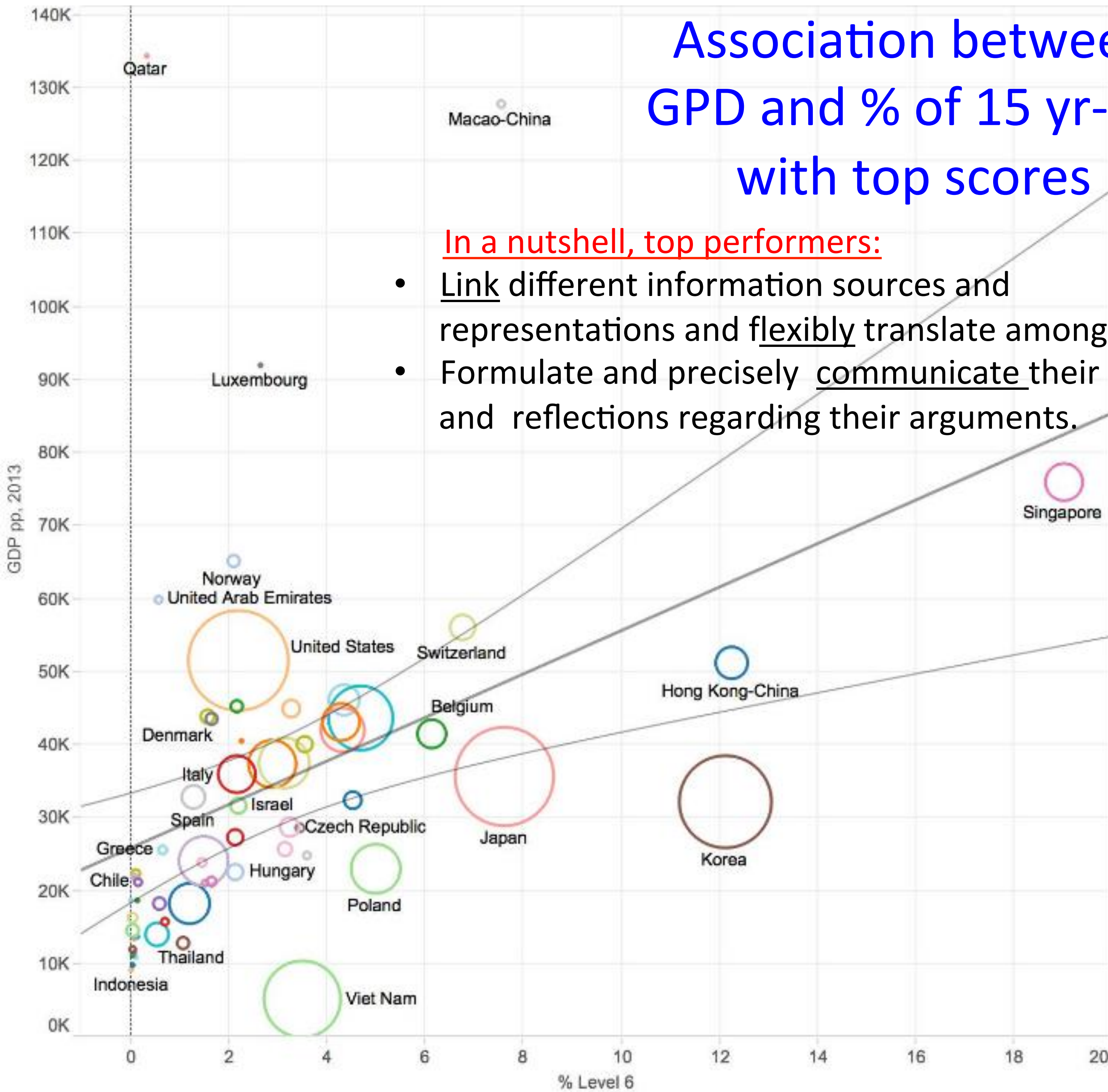
Association between GPD and % of 15 yr-old with top scores

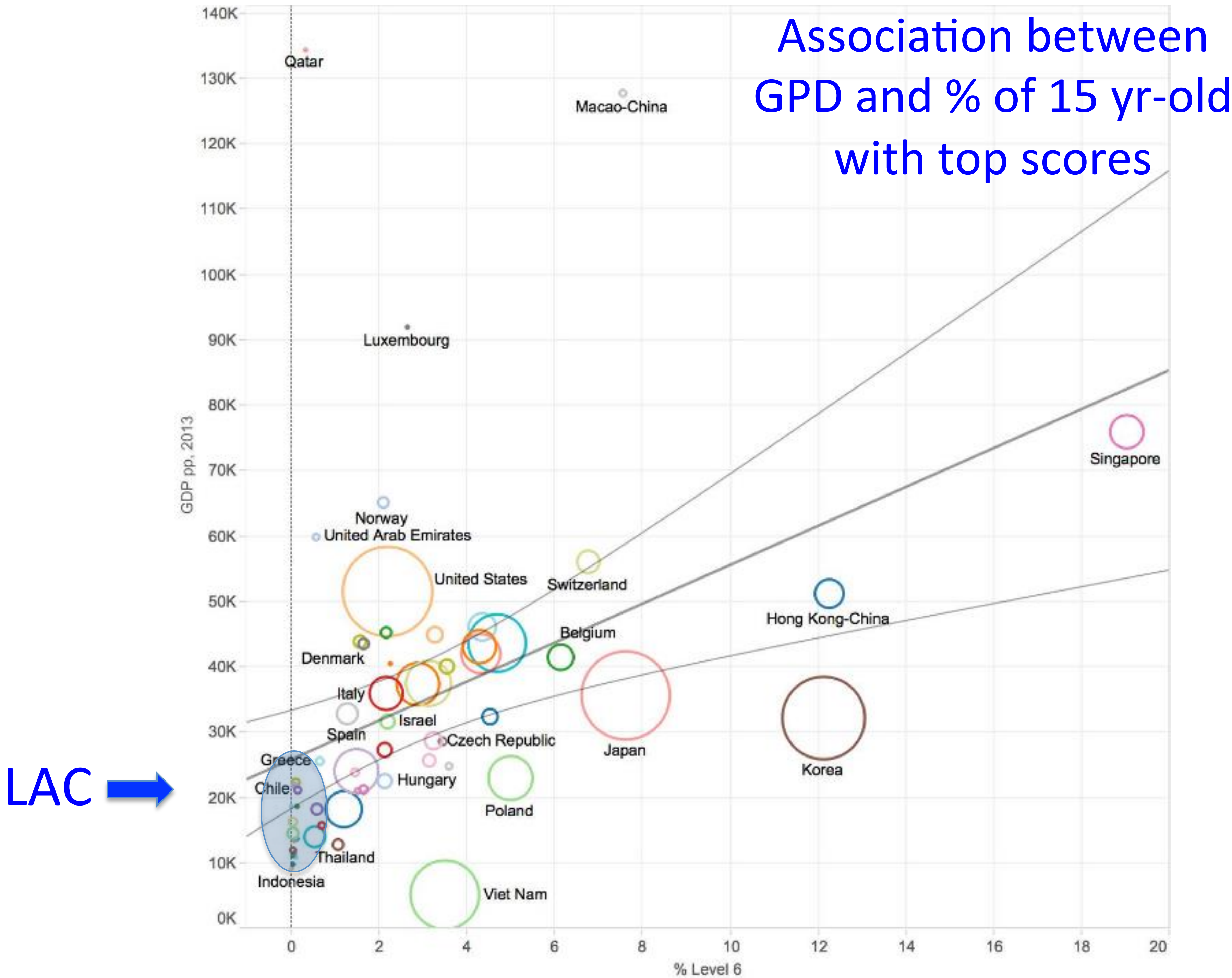


Association between GPD and % of 15 yr-old with top scores

In a nutshell, top performers:

- Link different information sources and representations and flexibly translate among them.
- Formulate and precisely communicate their actions and reflections regarding their arguments.




Association between GPD and % of 15 yr-old with top scores
LAC
GDP pp, 2013
% Level 6
Qatar
Macao-China
Luxembourg
Singapore
Norway
United Arab Emirates
United States
Switzerland
Hong Kong-China
Belgium
Denmark
Italy
Israel
Spain
Czech Republic
Japan
Korea
Greece
Chile
Hungary
Poland
Thailand
Indonesia
Viet Nam
140K
130K
120K
110K
100K
90K
80K
70K
60K
50K
40K
30K
20K
10K
0K
0
2
4
6
8
10
12
14
16
18
20

Degree of future global competitiveness:

What is the number of 15 year-old reaching top scores?

ARGENTINA (40MM)	CHILE (17MM)	HOLANDA (16.6MM)	COREA DEL SUR (48MM)

ARGENTINA
(40MM)

CHILE
(17MM)

HOLANDA
(16.6MM)

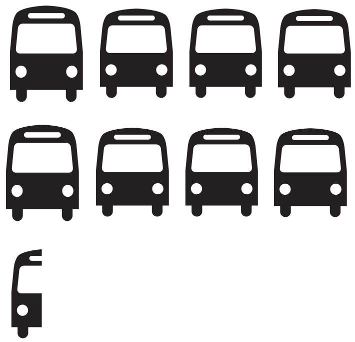
COREA DEL SUR
(48MM)

One Bus
=
44 (0.0064%)

ARGENTINA
(40MM)

One Bus
=
44 (0.0064%)

CHILE
(17MM)



Bus X 8 1/3
=
365 (0.12%)

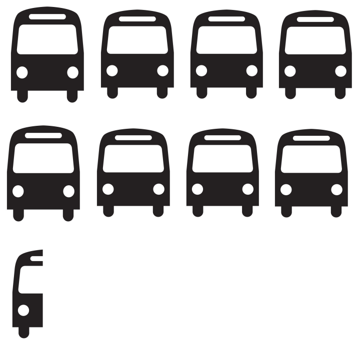
HOLANDA
(16.6MM)

COREA DEL SUR
(48MM)

ARGENTINA (40MM)

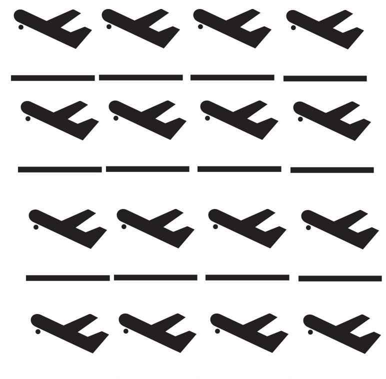
One Bus
=
44 (0.0064%)

CHILE (17MM)



Bus X 8 1/3
=
365 (0.12%)

HOLANDA (16.6MM)



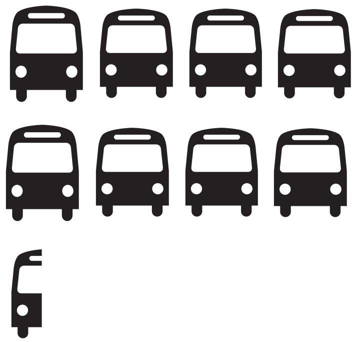
Airbus A380 x 17
=
8.735 (4.36%)

COREA DEL SUR (48MM)

ARGENTINA (40MM)

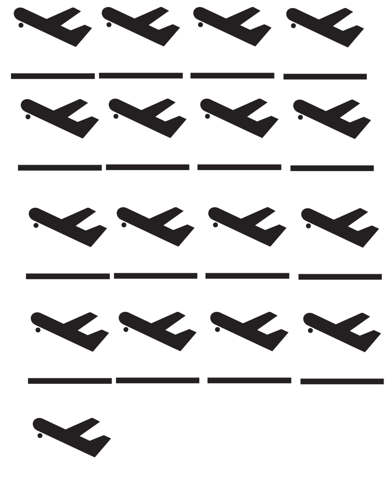
One Bus
=
44 (0.0064%)

CHILE (17MM)



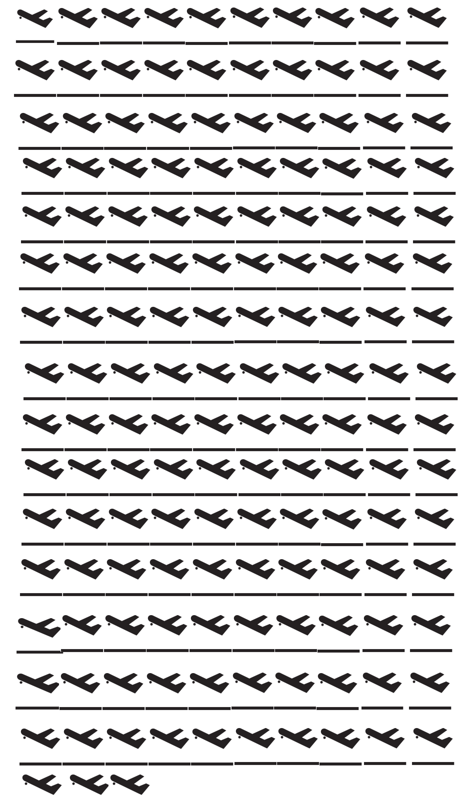
Bus X 8 1/3
=
365 (0.12%)

HOLANDA (16.6MM)



Airbus A380 x 17
=
8.735 (4.36%)

COREA DEL SUR (48MM)



Airbus A380 x 153
=
80.282 (12.1%)

SERGIO URZUA

Without structural reforms, LACs will not boost productivity, sacrificing future social and economic development

NO SINGLE BULLET

Innovation in public policies

(better data+monitoring+evaluation= better results)

Thank you