City Sophistication

Carlos Azzoni



The University of São Paulo Urban and Regional Economics Lab

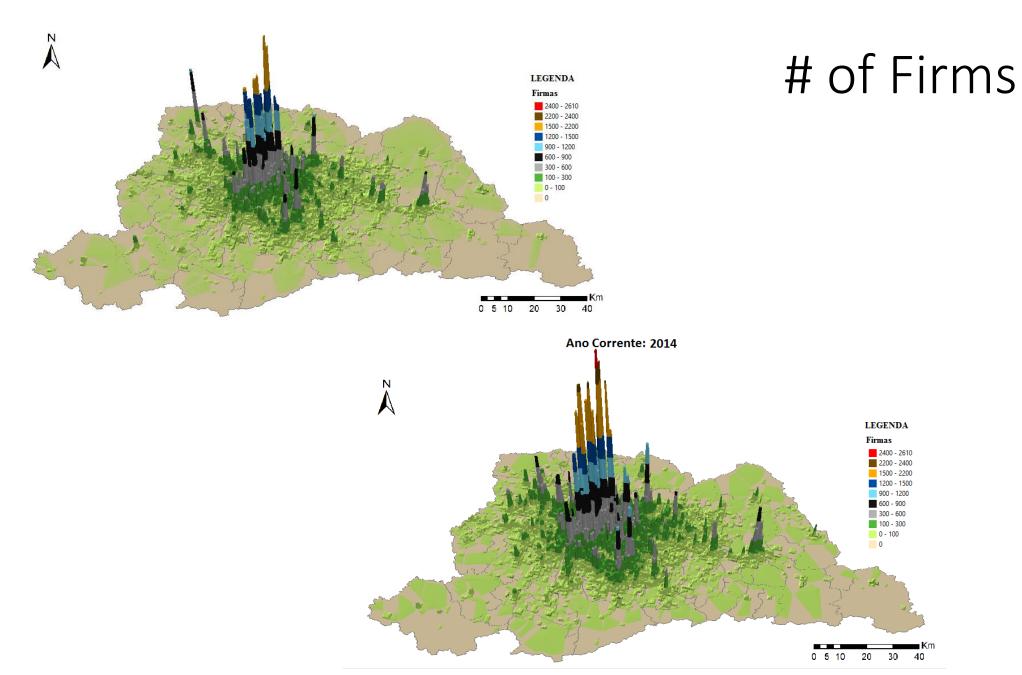
Previous results for Brazil

Urban wage premium

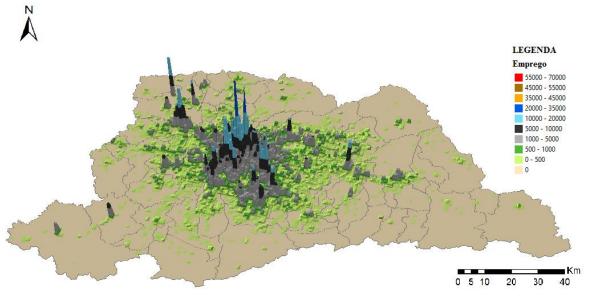
- Gonzaga and Azzoni (2019)
- Gross premium: 24% (29.5% large LMAs, 17% medium, 7.4% for small)
- With fixed effects for workers: 2.2%.
- With fixed effects for firms: 1.3%.
 - Replicate Barufi et al. (2016) and Chauvin et al. (2017).
 - Adjusted R² with just the observable effects is 60.6%;
 - Observable plus firm fixed effects, 78%;
 - Observable plus worker fixed effects, 91.7%.
 - Heterogeneity of workers is more important than the heterogeneity of firms
- Both fixed effects simultaneously premium vanishes
- Our estimation (both fixed effects, illuminated area, endogeneity):
 - Urban density 4.99%
 - Urban area 4.3%
 - Total agglomeration premium close to 10%, much higher than the previous literature

Intra-urban premium

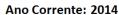
• Campos and Azzoni (2019)

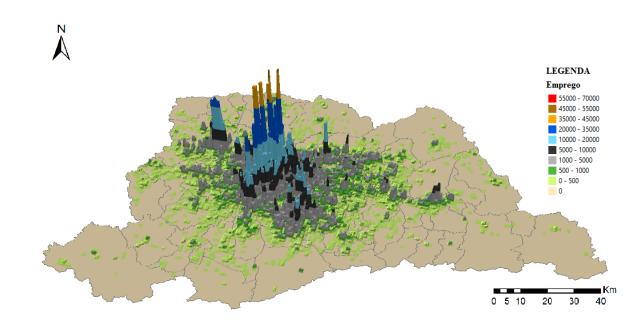


Ano Corrente: 2002

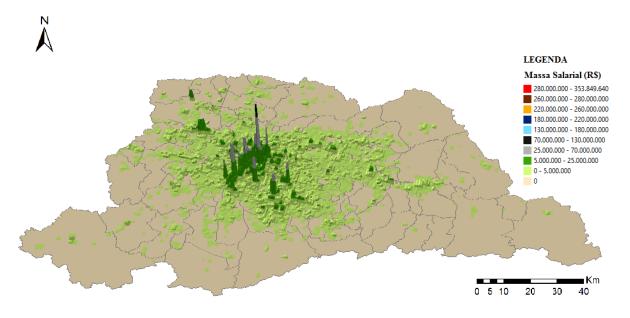


of Workers

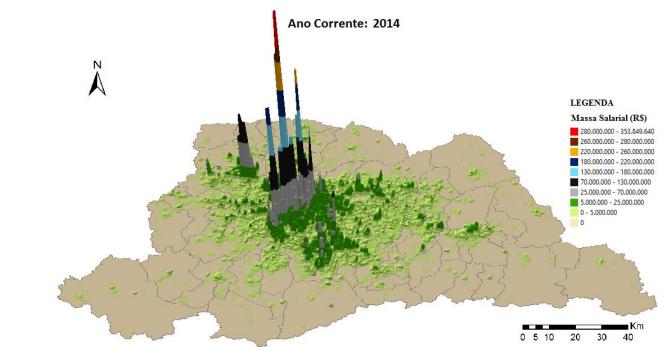




Ano Corrente: 2002



Total Wage Bill



Objective and motivation

- We assess the quality of the labor demanded by private firms in cities with different positions in the Brazilian urban network.
- The idea is that cities with more sophisticated labor demand might be more competitive, and that the observed growth in the intensity of skills in the city indicates future competitiveness.
- By looking at the skills of present workers, we deal with labor demand, which is different from considering education levels, which indicate labor supply conditions.



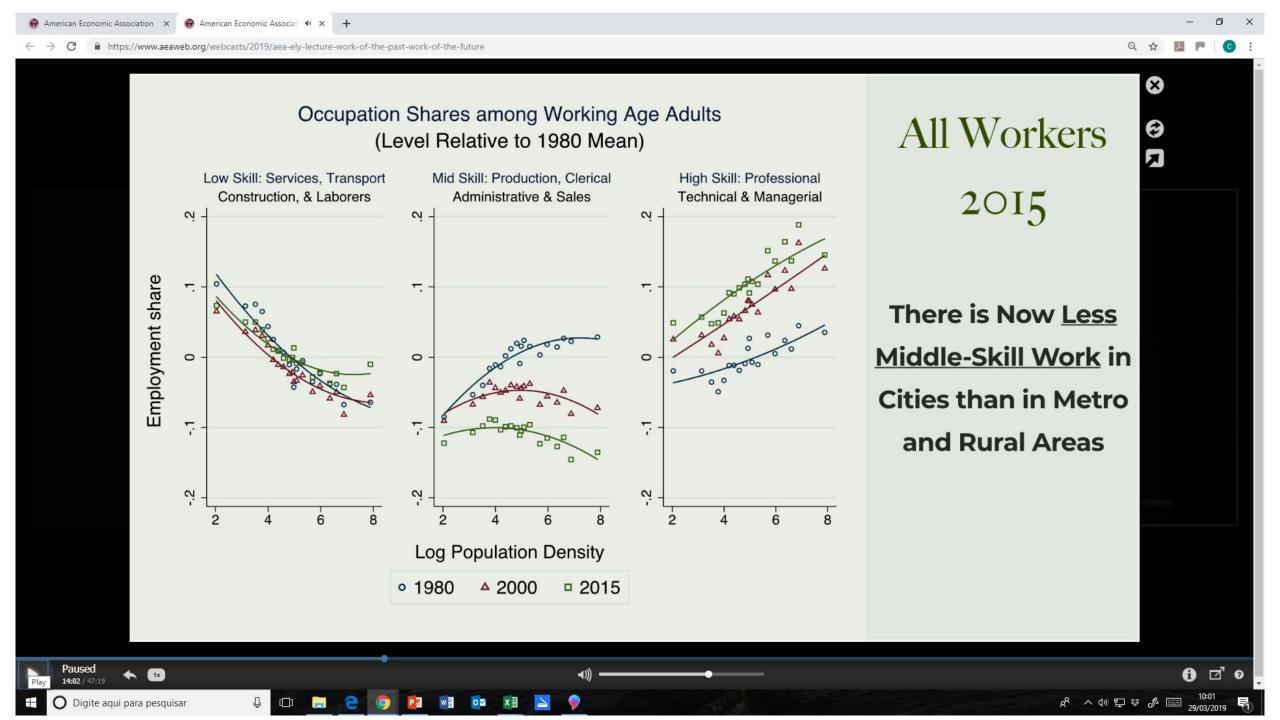
Some evidence from the USA

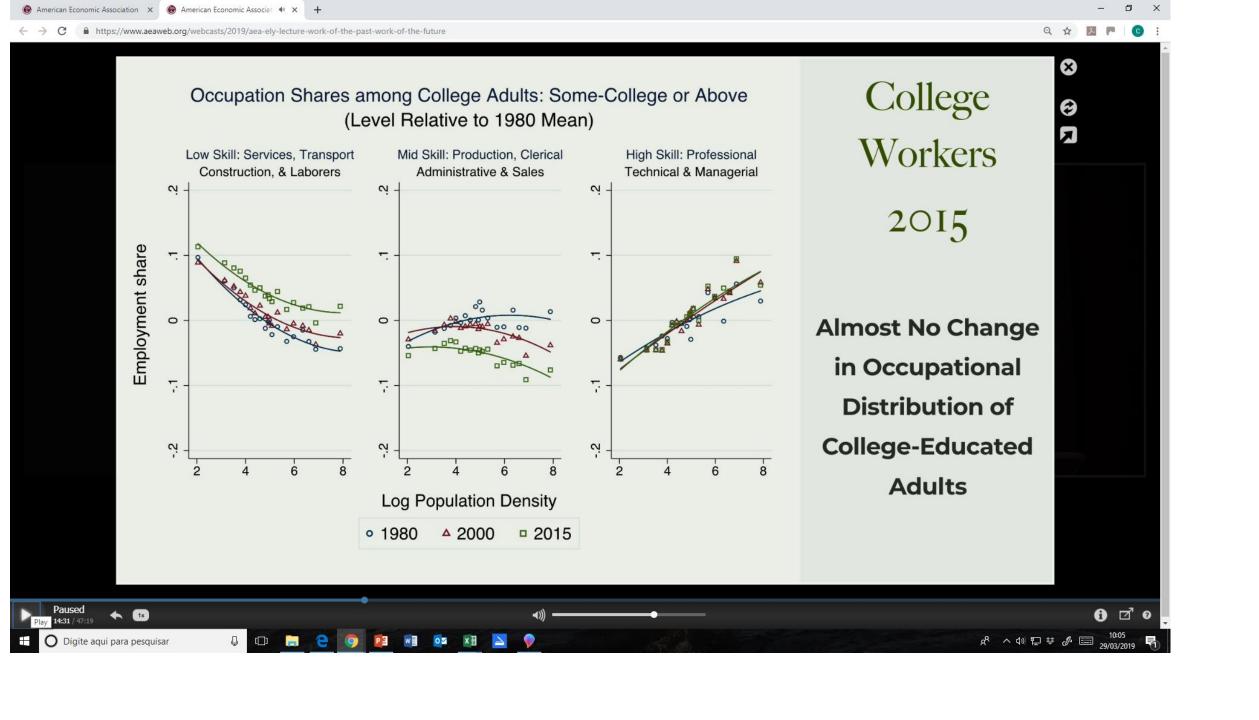
Work of the past, work of the future

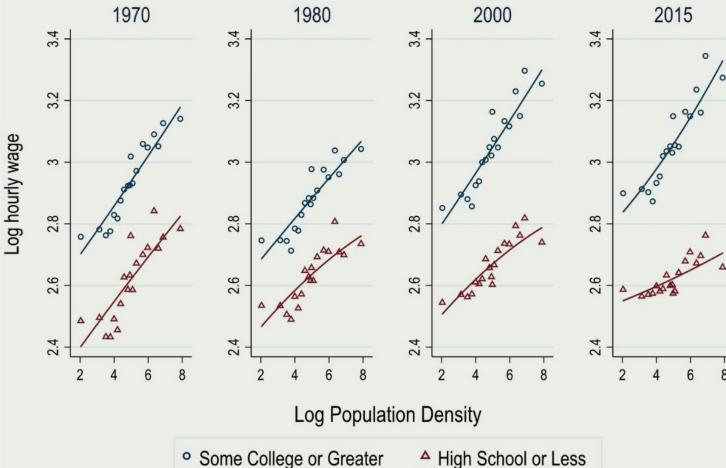
By David Autor

Keynote Speech, American Economic Association Annual Meeting, 2019

https://www.aeaweb.org/webcasts/2019/aea-ely-lecture-work-of-the-past-work-of-the-future







Wages among **Working-Age**

 Paralleling the Decline of Middle-Skill Urban Jobs

Adults

- Fall in the Urban Wage Premium for Non-**College Workers**
- **Especially pronounced** after 2000





1x







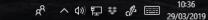




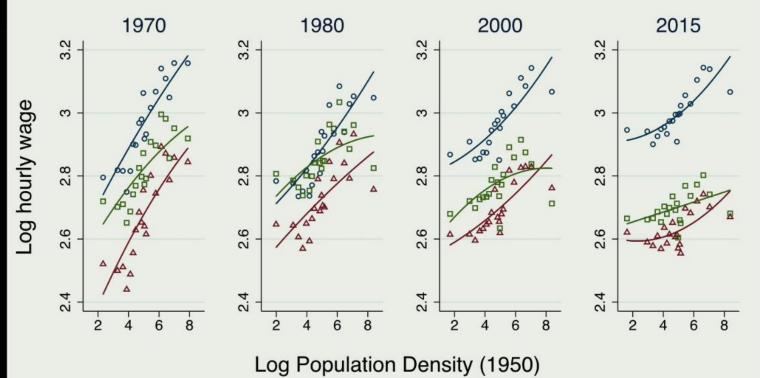








Falling Urban Wage Premium in Mid-Skill Occupations Non-College Men (High School or Less), 1970 - 2015 (\$2015)



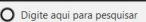
Wages of Non-College Men

High skill Low skill & Mid-skill occupations

Collapse of urban wage premium in mid-skill occupations

 High: Professional, Technical, Managerial △ Low: Services, Operatives & Laborers

Mid: Production, Admin, Sales



















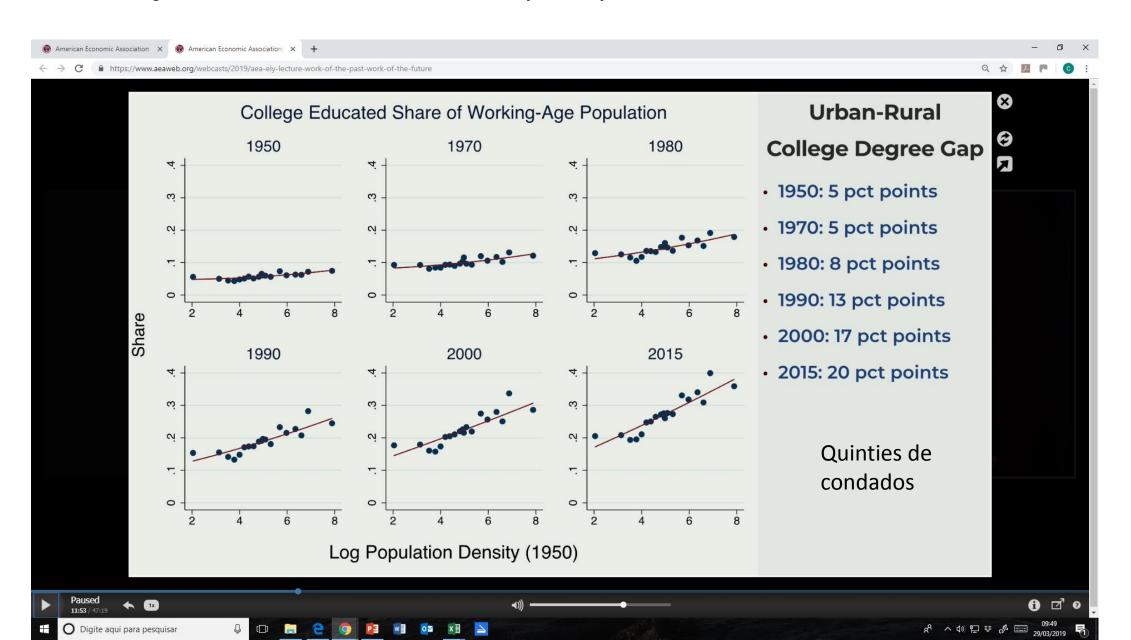


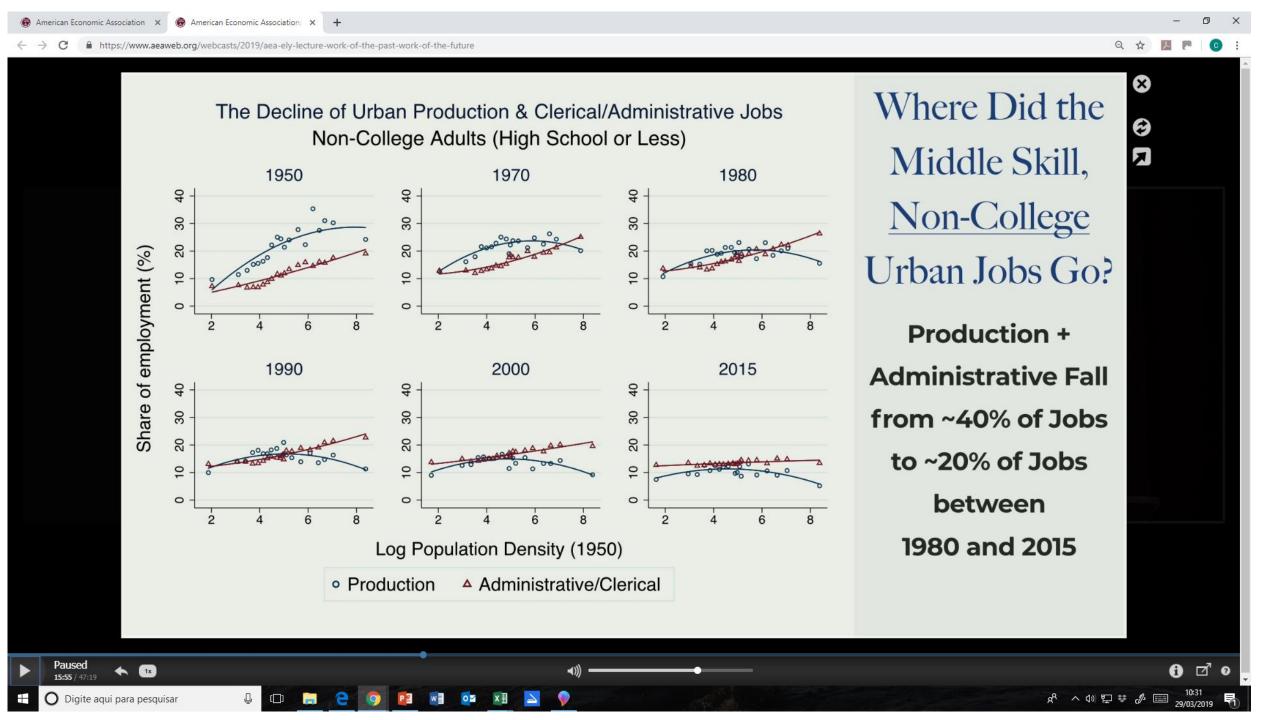


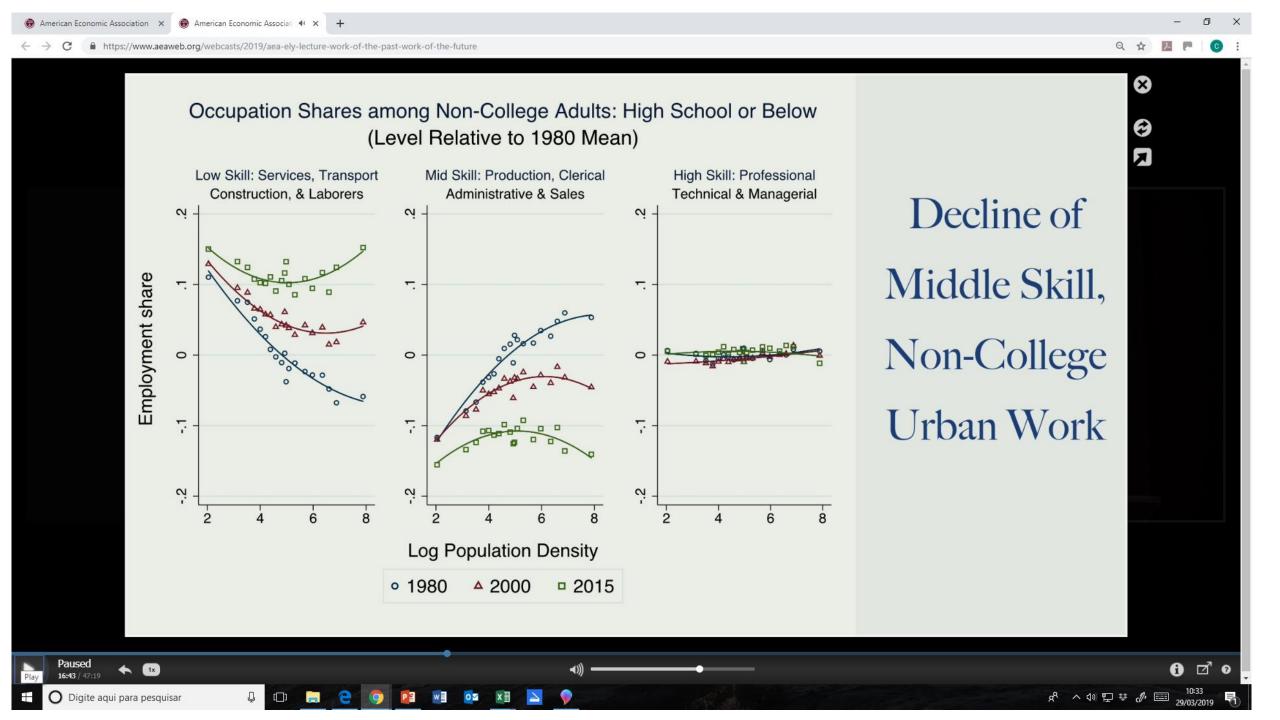
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Diferença Rural-Urbano nos USA para pessoas com nível universitário







♠ American Economic Association X
♠ American Economic Associat
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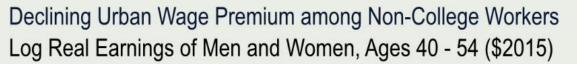
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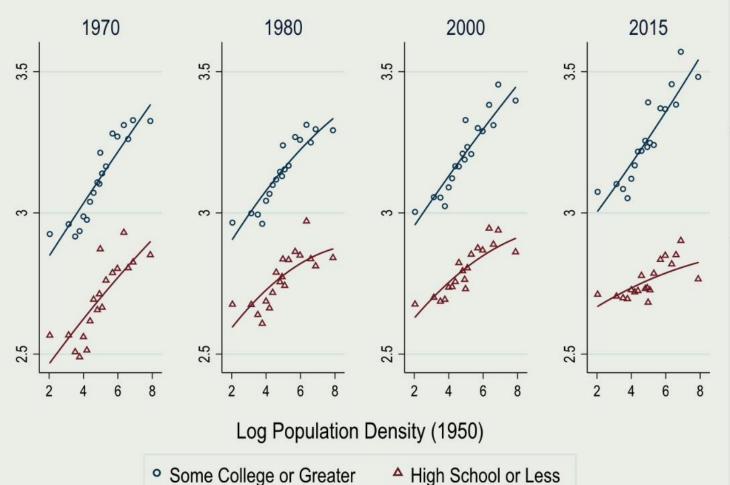
College vs.

Non-College

Wages among **Adults Ages 40-54**

- · Fall in the Urban Wage premium for noncollege workers
- Also highly visible for prime age adults, age 40 — 54









Log hourly wage

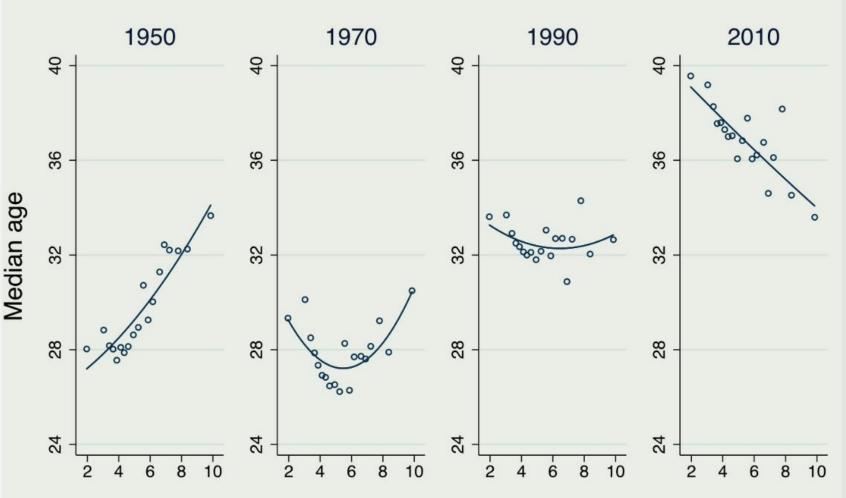






American Economic Associat 🐠 🗶

Median Age of Population by County 1950 to 2010



County population density (1950)

The Inversion of the **Age-Density Gradient, 1950-2010**

- · In 1950s, cities were five years older than rural areas
- By 1990, **no age** gradient remained
- By 2010, cities were six years younger than rural areas

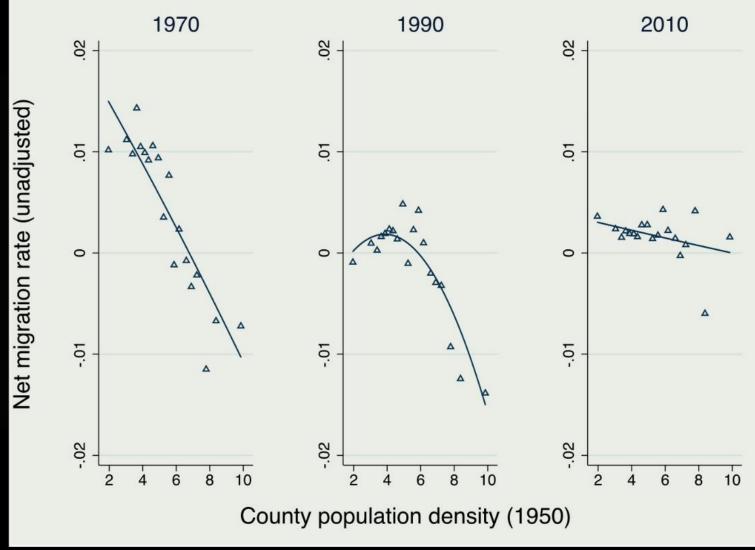
Summary, 1950 - 2010

- Rural areas aged 12 years
- Cities aged 2 yrs

♠ American Economic Associat ◆ ×

8

Net Migration Rate (Unadjusted) by County 1970 to 2010



Net Migration Rates Across Counties

Putting it All Together

- · A huge decline in net migration
- Steep fall in outflows from urban to suburban + rural areas







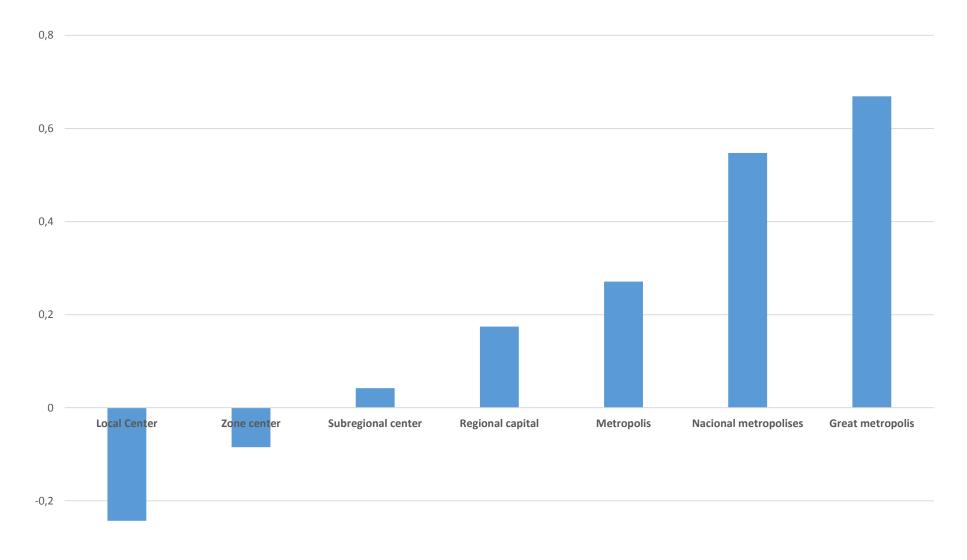
Living costs ...







Rent costs



Basic concepts

Sophistication – skill intensity of occupations – Cognitive, Social, Motor

→ Labor demand

City – Functional classification – 7 categories

Size – 351 Labor Market Areas Deciles, + 5% Top, 1% Top, Largest

Labor sophistication - Skills

- Labor demand
- Formal jobs
- Public vs. Private organizations
- Employed in December; >20 hours/week; age 18-65
- 2003-2016, matched panel of firms and workers
- Over 400 million observations
 - 5% Sample each year, proportional at the urban areas
 - Overall 21,348,669 observations
 - Private organizations 17,524,540 observations



How are skill levels measured? (For each of the 2,702 occupations)

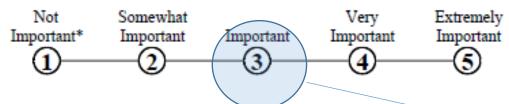
https://www.onetonline.org/

One of the 263 Skills associated with each occupation

12. Mathematical Reasoning

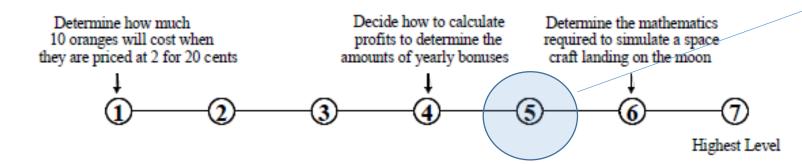
The ability to choose the right mathematical methods or formulas to solve a problem.

A. How important is MATHEMATICAL REASONING to the performance of your current job?



^{*} If you marked Not Important, skip LEVEL below and go on to the next activity.

B. What level of MATHEMATICAL REASONING is needed to perform your current job?



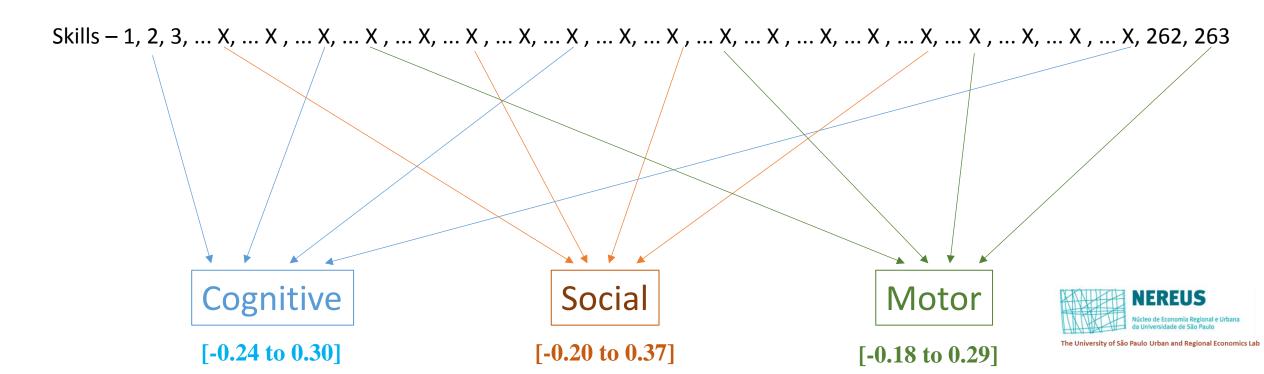
Skill level associated to the occupation 3 * 5 = 15

Range: 1 to 35 Standardized





→ 263 skills attributed to each of the =~ 6 million workers



Deductive Reasoning
Inductive Reasoning
Category Flexibility
Reading Comprehension
Writing
Critical Thinking
Complex Problem Solving
Analytical Thinking
Mathematical Reasoning

Factor Analysis → 1 variable

Social Perceptiveness
Coordination
Persuasion
Negotiation
Establishing and Maintaining
interpersonal Relationships
Selling or Influencing Others
Resolving Conflicts and
negotiating with Others

Factor Analysis → 1 variable

Manual dexterity
Control precision
Static strength
Dynamic strength
Performing general physical
activities
Handling and moving objects

Factor Analysis → 1 variable

Examples of occupations with the associated skill levels

The resulting skill indicators are continuous non-orthogonal standardized variables, with a standard deviation of 0.1, preserving a desirable relation of complementarity (Bacolod and Blum, 2010).

The value ranges are:

Cognitive [-0.24 to 0.30]

Social [-0.20 to 0.37]

Motor [-0.18 to 0.29]

Cognitive		
Low	High	
Car washer	Physicist	
Fashion model	Astronomer	
Textile fiber classifier	Spatial geophysicist	
Restaurant attendee	Neurophysiologist	
Animal killer	Surgeon	
Ma	402	

Motor	
Low	High
Operational research professor	Metal frame operator
Statistician	Mining operator
Environment economist	Airport fireman
Political scientist	Mason
Ombudsman	Car washer

Low	High
Conwechen	Ombudsman
Car washer	Media products evaluator
Cloth presser	Lawyer
Textile and leather worker	Purchases supervisor
Weaver	Commercial director
Parts washer	

Social



Skill intensity - examples

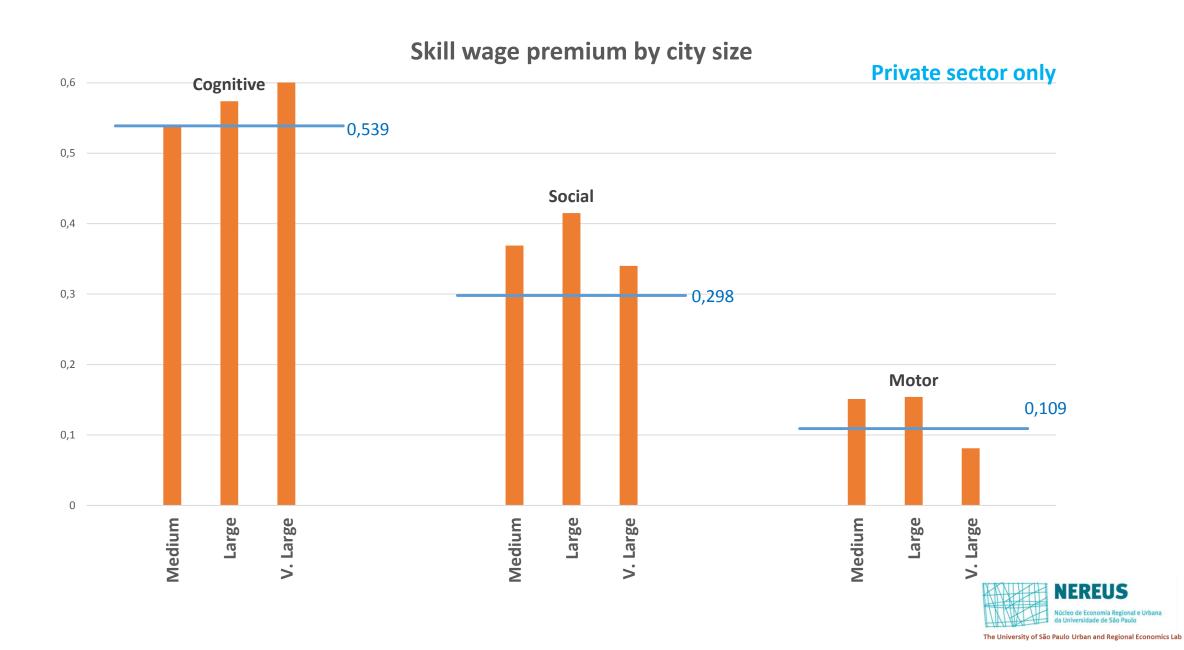
Social			
		High	Low
	High	Construction engineer (airports)	
		Cardiologist	
		Communications manager	
		Human resources director	
		Surgeon	
Cognitive		Foreign trade director	
	Low	Paper stand worker	Gardner
		Door to door vendor	Tire fixer
		Street Market vendor	Industrial sewer
		Street vendor	Paper cutter operator
		Sales assistant	Tapestry washer
		Popcorn street vendor	

Skill intensity - examples

	Motor		Motor
		High	Low
		Heart surgeon	Construction engineer (hydraulics)
		Neuro surgeon	Company lawyer
	High	Dentist surgeon	Chemical engineer
		Head and neck surgeon	Professor of sociology (college)
			Linguist
			Physicist (atomic and molecular)
Cognitive		Metal meltier	Telephone operator
		Mason	Fashion model
		Drill operator (mining)	Telemarketing operator
	Low	Concrete mounting	Mail operator
		Coal minge operator	

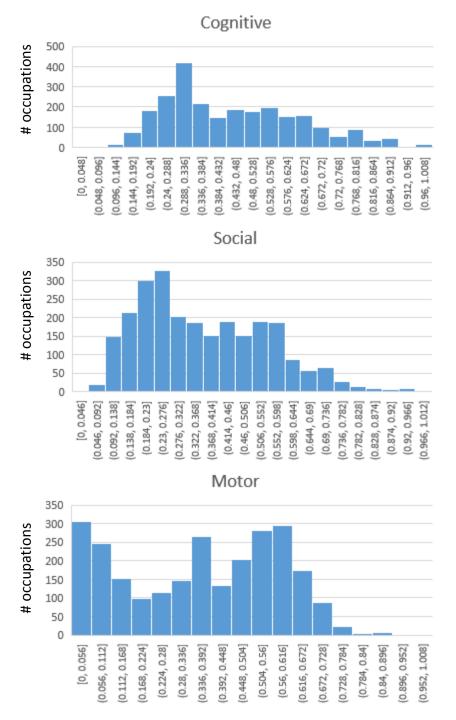
Skill intensity - examples

	Motor			
		High	Low	
		Physiotherapist	Market risk director Tourism specialist	
		Forest area supervisor	Press agent	
	High		Public relations	
			Stock market broker	
			Social Psychologist	
Social				
		Furniture assembler	Copydesk assistant	
		Train operator assistant	Advertisement model	
		Furnace assistant	Fashion model	
	Low	Machine assembler	Artistic model	
		Plastic molder		
		Wood panel operator	NEREUS Núcleo de Economia Regional e Urbana	



Distributions of skill values

Range 0 - 1 (top)



Average values	
Top 5%	0.872
Top 10%	0.819
90% lowest	0.441
Bottom 30%	0.253
Top 10%/Bottom 30%	3.2

Average values	
Top 5%	0.770
Top 10%	0.706
90% lowest	0.331
Bottom 30%	0.177
Top 10%/Bottom 30%	4.0

Average values	
Ţ	
Top 5%	0.727
Top 10%	0.685
90% lowest	0.326
Bottom 30%	0.082
Top 10%/Bottom 30%	8.4

Results - Skill Levels by City Type

Average 2003-2016



Urban Network

Great National Metropolis

2 National Metropolises

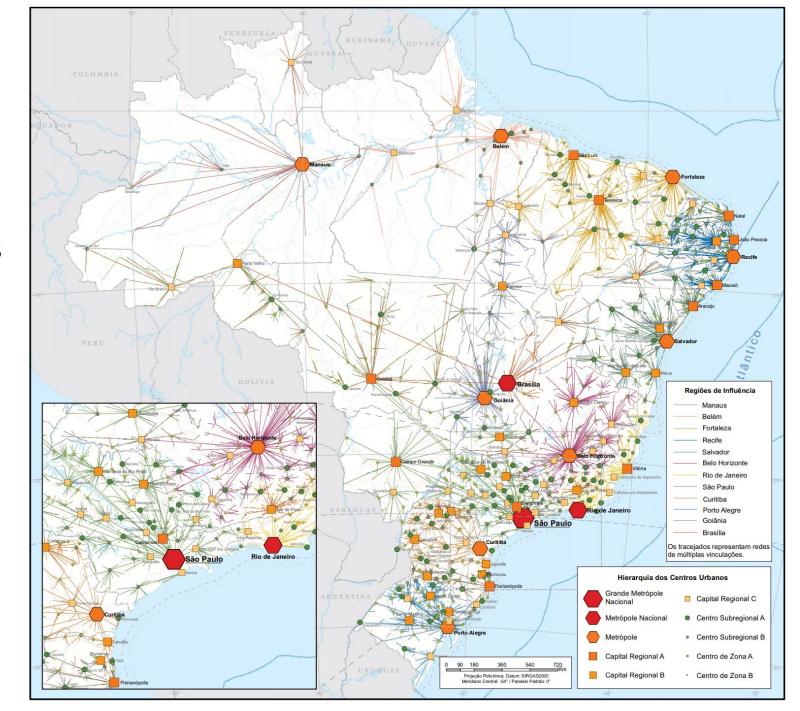
10 Metropolises

70 Regional Capitals

139 Sub-Regional Centers

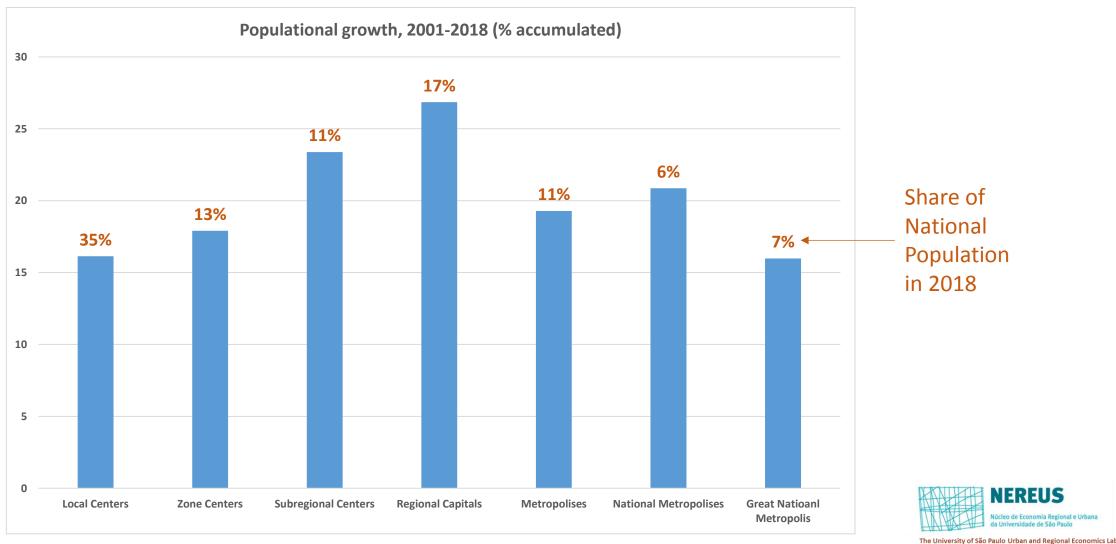
556 Zone Centers

4,473 Local Centers





Recent populational growth



Types of cities considered

- Functional classification (Official statistics office, IBGE)
 - Pop in 2018; yearly growth 2001-18
 - Great national metropolis (Sao Paulo, 12.2 K, 0.8%)
 - 2 national metropolises (Rio de Janeiro 6.7 K, 0.7%, and Brasília 2.9 K, 1.9%)
 - 10 metropolises
 - Manaus 2.1K, 2.2%; Belém- 1.5K, 0.7%; Fortaleza 2.6K, 1%; Recife 1.6K, 0.7%; Salvador 2.8K; 0.8%, Belo Horizonte 2.5K, 0.6%, Curitiba 1.9K, 0.9%; Goiânia 1.5K, 1.7%; Porto Alegre 1.5K, 0.4%
 - 70 Regional capitals (A 11, 0.9K; B 20, 0.43K; C 39, 0.25K)
 - 139 sub-regional centers (A − 85, 0.09K; B − 79, 0.07K)
 - 556 zone centers (A 192, 0.04K; B 364, 0.02K)
 - 4,473 local centers (<10K)
- 17 municipalities Pop > 1 K; Σ = 45.5 K; 21.9% of total population
- 68.2% of municipalities < 20 K; Σ = 32.2K; 15.5% of total population



Skill intensity

Skill^s =
$$\beta_0 + \beta_1$$
. Sector+ β_2 . Firm Size + β_3 . Gender + β_4 . Age + β_5 . Age²+ β_6 . Edu + β_8 . Time + β_9 . (City Type) + β_{10} . (City Type * Time) + β_9 .

Microdata - workers

14 Sector dummies (agriculture and ranching as reference)

8 Firm size dummies (<4 workers as reference)

10 Education level dummies (illiterate as reference)

6 City Type dummies (Local Centers as reference)

s – Cognitive, Social, Motor

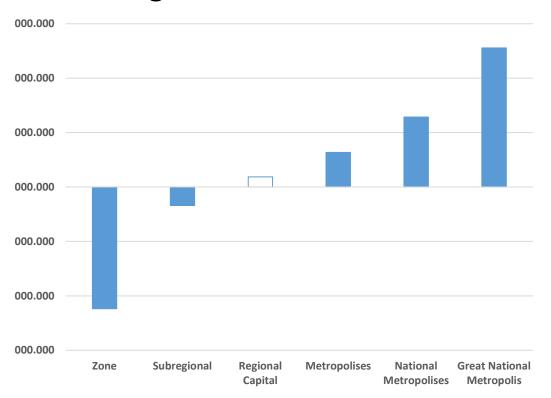
Estimation with POLS

Overall – 21,348,669 observations Private organizations – 17,524.540 observations Separate regressions for each skill type

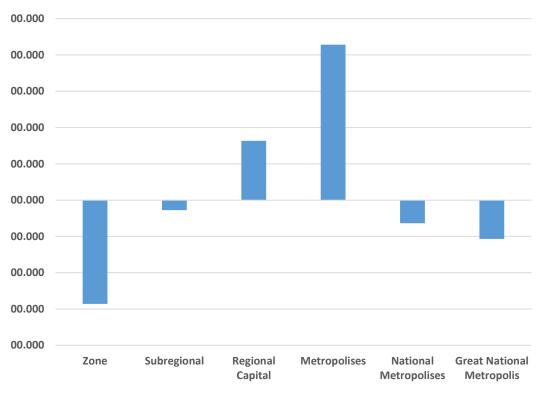


Cognitive skills

Private Organizations



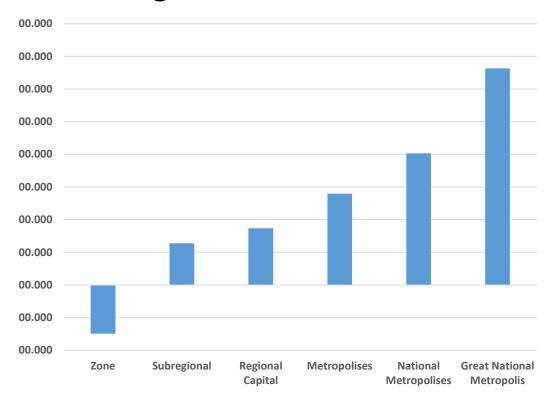
Public + Private



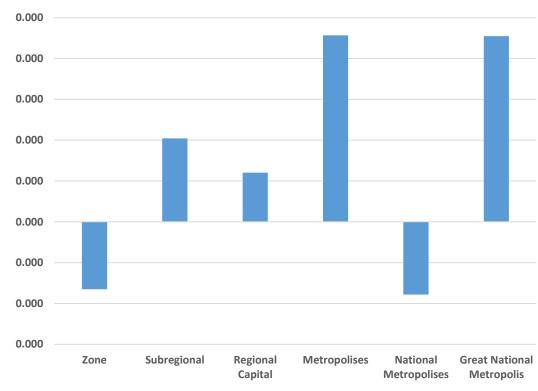


Social skills

Private Organizations



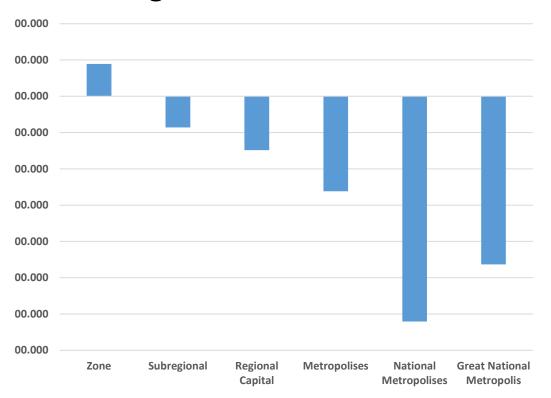
Public + Private



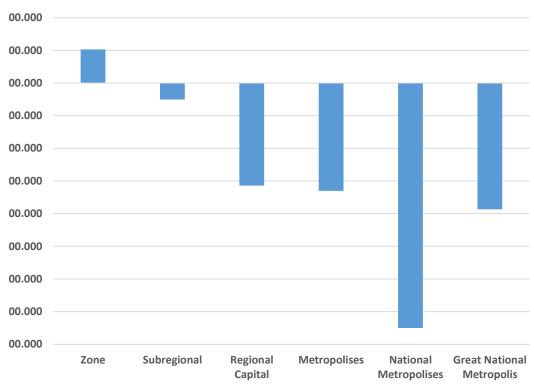


Motor skills

Private Organizations



Public + Private





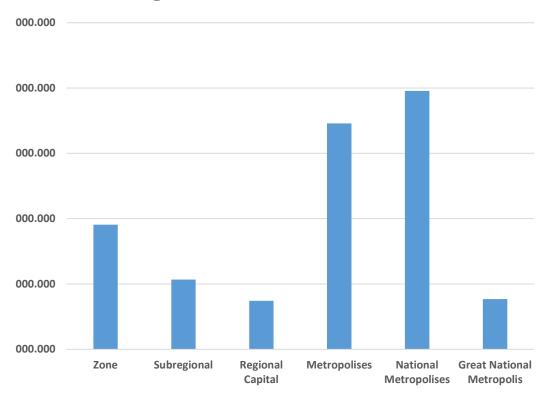
Skill Level Growth, 2003-2016



Cognitive skills – Growth 2003-16

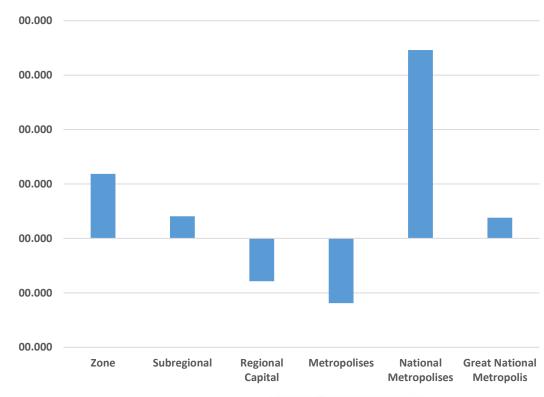


Private Organizations



Local Centers = -0,0076

Public + Private

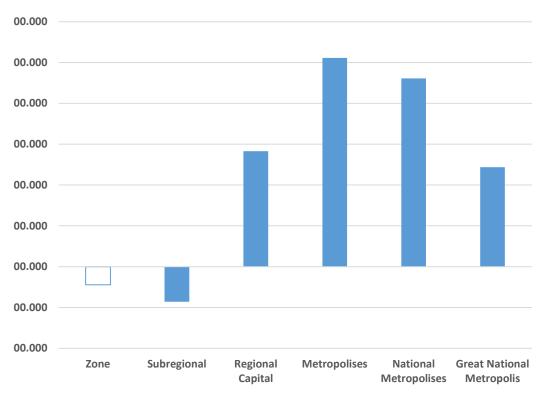




Social skills – Growth 2003-16

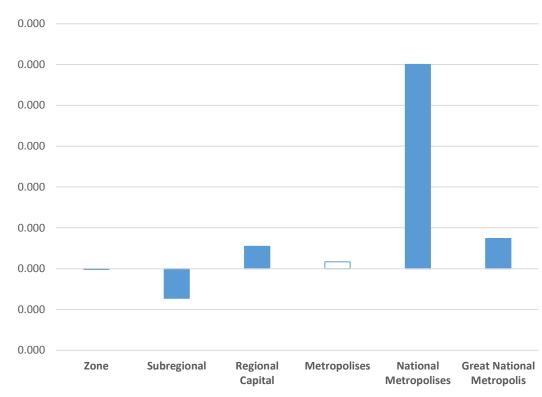


Private Organizations



Local Centers = -0,0078

Public + Private

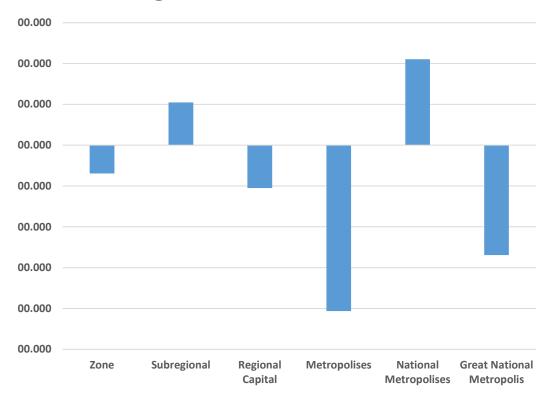




Motor skills – Growth 2003-16

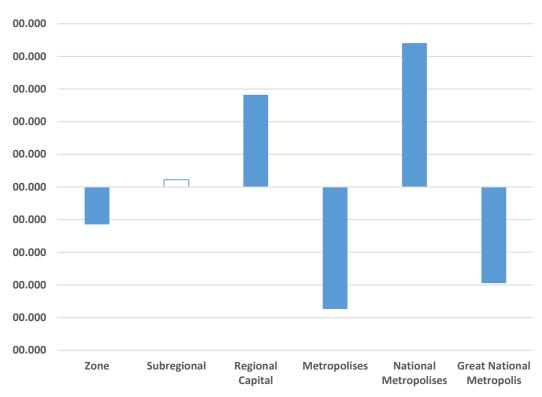
Local Centers = 0,0115

Private Organizations



Local Centers = 0,0117

Public + Private





Results - Skill Levels by City Size

Average 2003-2017

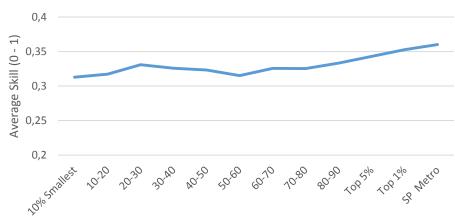


Skill Intensity: Cognitive - 2017



Urban Size - Deciles

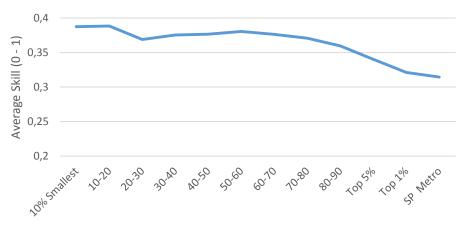
Skill Intensity: Social - 2017



Urban Size - Deciles

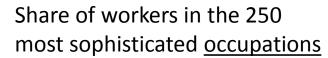
Skill Intensity by Urban Size 2017

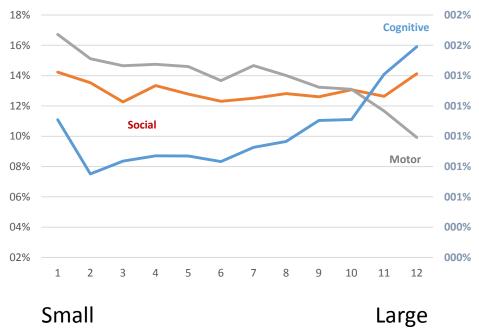
Skill Intensity: Motor - 2017



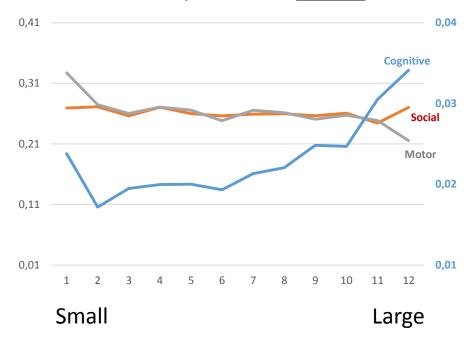
Urban Size - Deciles

Share of sophisticated work by urban size

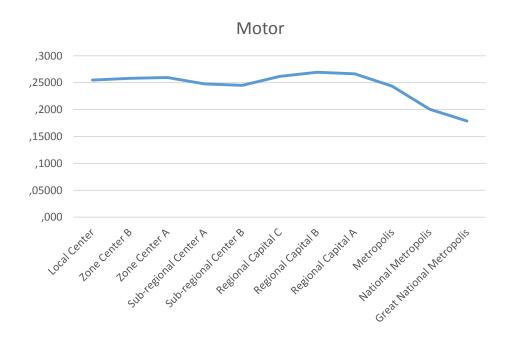




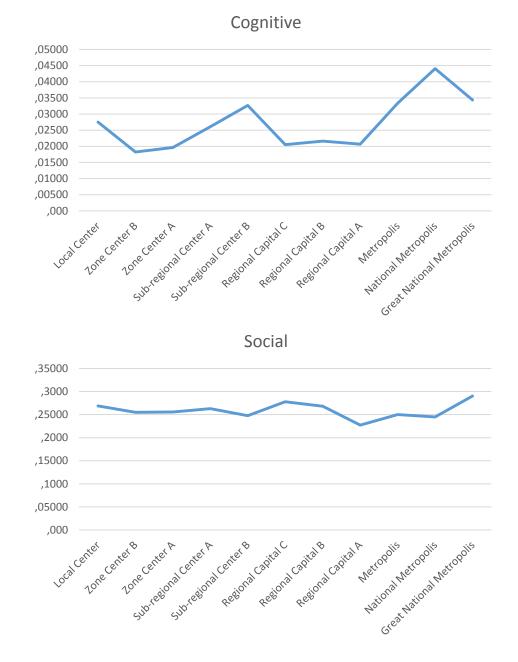
Share of workers in the 25 most sophisticated <u>sectors</u>



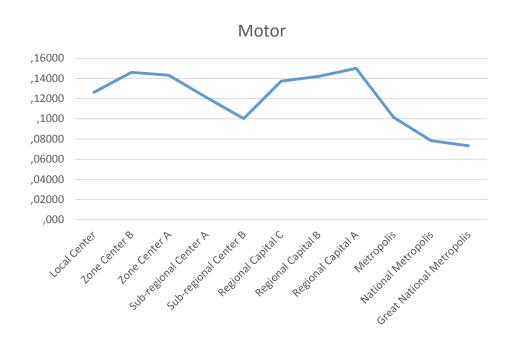
Share of <u>sum of skills</u> in top 250 occupations



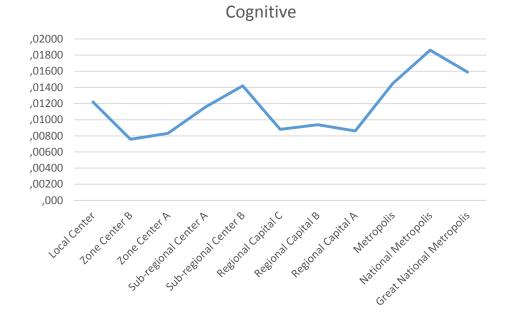


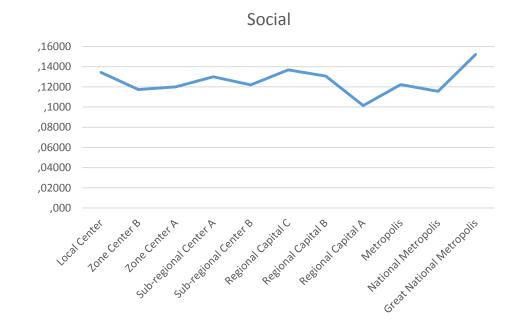


Share of <u>workers</u> in top-skill 250 occupations



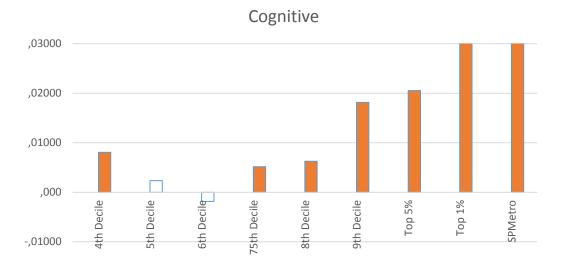
2017

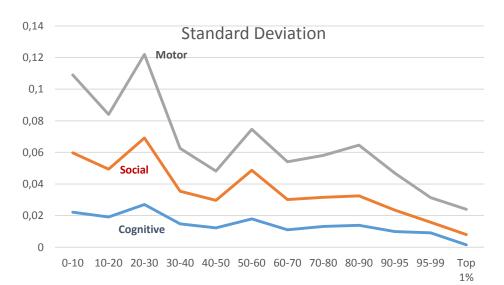




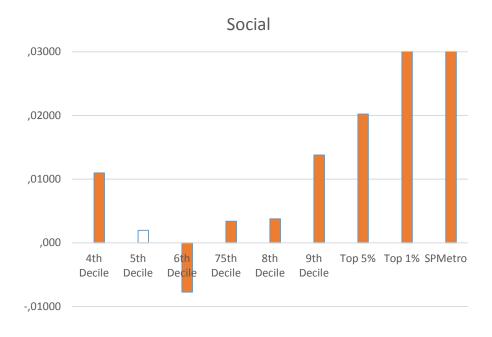
Skill levels by city size

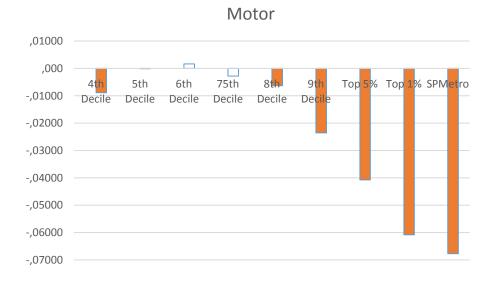
(Average 2003-2017, Intercept dummies)





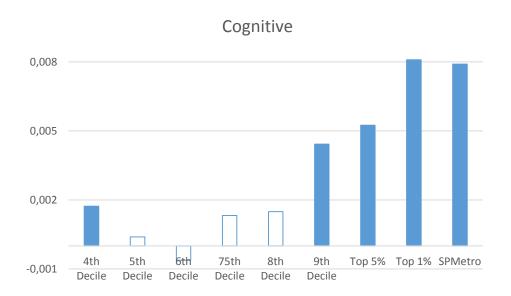
S_t = a + b*Time + c_i*(Size Dummy_i) Reference: 30% smallest LMAs





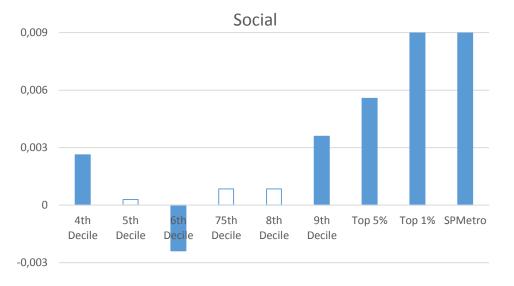
Skill growth by city size

(Average 2003-2017, Intercept dummies*Trend)



Ln $S_t = a + b*Time + c_i*(Time*Size Dummy_i)$

Reference: 30% smallest LMAs





Concluding remarks

- Cognitive and social skills more intense in centers of higher hierarchical position
- Private and public quite different
- Growth of cognitive and social skills in metropolises and national metropolises
- No consideration for the informal sector (self-employed, for example)
- Approach with good potential for regional studies



Thanks!

cazzoni@usp.br



Prof. Stan Czamanski in Brazil



ESTUDO DOS EFEITOS MULTIPLICADORES DOS INVESTIMENTOS INDUSTRIAIS E DOS PROGRAMAS GOVERNAMENTAIS

42061

Stan Czamanski Luiz Augusto de Queiroz Ablas Martin Lu Juarez Alexandre Baldini Rizzieri A study of the multiplier effects of industrial investments and governmental programs

Research Report

ESTUDO DOS EFEITOS MULTIPLICADORES DOS

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GOVERNAMENTAIS

42061

Stan Czamanski
Luiz Augusto de Queiroz Ablas
Martin Lu
Juarez Alexandre Baldini Rizzieri

SÃO PAULO 1976

molar

TABELA 4-5 EFEITO MULTIPLICADOR INTERINDUSTRIAL POR SETOR

Sample of Results from the report

CÓDIGO: FIBGE	GÊNEROS DE INDÚSTRIAS:	$i^{T}.(I-A)_{BR}^{-1}$	i ^T .(I-A) ⁻¹ 3F
00 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 99	Extração de minerais Produtos de minerais não metálicos Metalúrgica Mecânica Material elétrico e de comunicações Material de transporte Madeira Mobiliário Papel e papelão Borracha Couros e peles e produtos similares Química Produtos farmacêuticos e veterinários Perfumaria, sabões e velas Produtos de matérias plásticas Têxtil Vestuário, calçados e artefatos de tecidos Produtos alimentares Bebidas Fumo Editorial e gráfica Diversas Agricultura, extração vegetal e criação	1,1711 1,4530 1,4189 1,5748 1,6702 2,0335 1,7311 1,6481 1,4113 1,5458 1,5779 1,5268 1,4524 1,6863 1,6091 1,7841 1,9457 2,1801 1,5279 1,5805 1,5468 1,4225 2,1764	1,0498 1,3801 1,3462 1,5071 1,6154 1,9232 1,2779 1,4863 1,3983 1,4223 1,5710 1,4152 1,4258 1,4440 1,3825 1,5470 1,6644 1,9046 1,4304 1,5117 1,4771 1,3647 1,7430

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A COMPARISON OF METHODS AND FINDINGS

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TRABALHO PARA DISCUSSÃO INTERNA Nº 08/76

Nota: Circulação restrita aos professores e alunos do Instituto de Pesquisas Econômicas e do Departamento de Economia da Faculdade de Economia e Administração da Universidade de São Paulo.

Discussion paper Academic seminar



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TRABALHO PARA DISCUSSÃO INTERNA Nº 09/76

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ota: Circulação restrita aos Professores e alunos do Instituto de Pesquisas Econômicas e do Departamento de Economia da Faculdade de Economia e Administração da Universidade de São Paulo. A methodology for the computation of technical coefficients from production tax data Discussion paper, Academic seminar



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