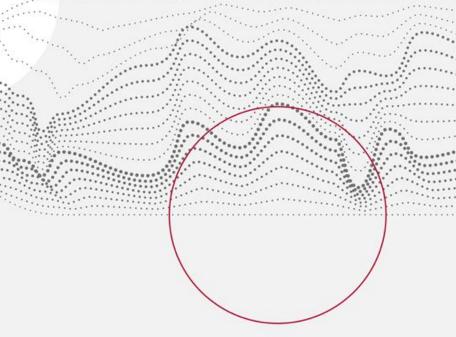


# Technology, Skills, and Globalization: Explaining International Differences in Routine and Non-Routine Work Using Survey Data

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Motivation: the shift away from routine tasks and towards non-routine tasks is a secular change on developed countries' labor markets

Worker Tasks in the EU28, 1998-2014 Worker Tasks in the U.S. Economy, 1960 – 2009: 20 Mean Task Input in Percentiles of 1960 Distribution 30 40 50 60 70 All Education Groups 15 10 5 0 -5 -10 -15 -20 2006 1998 1999 2000 2014 2001 2002 2003 2004 2005 2008 2009 2010 2013 2007 2011 2012 2010 1980 2000 1960 1970 1990 Non-Routine Interpersonal Non-Routine Analytical Non-Routine Analytical → Non-Routine Interpersonal Non-Routine Manual Routine Cognitive ----Routine Cognitive -----Non-Routine Manual Routine Manual –Routine Manual

Source: Autor, Price (2013)

Source: own calculations

Four key factors explain differences in tasks over time and across countries

- **Technological progress** (computers, ICT, robots, etc.) Autor, Levy, Murnane 2003, Spitz-Oener 2006, Autor & Dorn 2013, Michaels et al. 2013
- Globalization (FDI, trade, and global value chains)
   Oldenski, 2012, Goos et al. 2014, Reijnders & de Vries 2018
- Structural change (sectoral composition)
   Bárány & Siegel, 2018; Du & Park, 2017, Hardy et al. 2018
- **Supply of skills** (worker human capital, demographics) Salvatori, 2015; Hardy et al., 2018, Montresor, 2018

Task contents are usually measured with O\*NET, the US database on occupational demands (Autor et al. 2003, Acemoglu & Autor 2011)

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	Non-routine cognitive (analytical / interpersonal)	Routine cognitive	Routine manual	Non-routine manual
Task items	Abstract thinking, creativity, problem solving /Guiding, directing, motivating, communicating	Repeating the same tasks, being exact or accurate, structured work	Pace determined by equipment, controlling machines and processes, making repetitive motions	Operating vehicles, mechanized devices, manual dexterity, spatial orientation
Relationship b/w human tasks and ICT	Complementary	Easy to automate	Easy to automate	Automation tough or unprofitable
Occupations rich in these tasks	Specialists (e.g designers, engineers, IT developers), technicians, managers	Office clerks, sellers, administrative workers, cashiers	Production workers, e.g. machine operators, assemblers and locksmiths	Drivers, miners, construction workers, waiters and waitresses, porters, cooks

- Data: most countries lack information on worker tasks
  - Focus on occupational structure assuming the US occupation-specific tasks
- Data: tasks are measured at the level of occupation with O\*NET, the US database
  - Tasks in the same occupation may differ depending on workers' skills, tenure, etc.
- Coverage: most research focused on the US and Western Europe
  - Story may be different in the middle-income and developing countries

## The contribution of this paper

- We construct task content measures which:
  - Are measured at the worker level and country-specific
  - Are consistent with the Acemoglu & Autor (2011) measures based on O\*NET
- Data from worker surveys in 42 countries, including high, middle, and low-income
  - Previous studies using survey data examine only richer or poorer countries, and define tasks in an ad-hoc fashion (De la Rica & Gortazar 2016, Marcolin et al. 2016, Dicarlo 2016)
- We examine the contributions of technology, globalization, structural change, and skill supply to task differences across countries

- The task contents of occupations are different around the world
- The routine intensity of tasks is higher in less developed countries, also within particular occupations.
- Cross-country differences in tasks can be attributed to differences in:
  - Technology in 25%, even more for high-skilled occupations;
  - Globalization in 20%, even more for low-skilled and offshorable occupations;
  - Supply of skills in 20%.

We use three surveys which include comparable data on the skill use at work, literacy and labor market status



PIAAC (OECD)	<ul> <li>32 countries surveyed between 2011 and 2015</li> <li>sample sizes: from 4000 (Russia) to 26000 (Canada)</li> </ul>
STEP (World Bank)	<ul> <li>9 countries surveyed between 2011 and 2015</li> <li>sample sizes: from 2400 (Ukraine) to 4000 (Macedonia) urban residents</li> <li>representative for the survey areas</li> </ul>
CULS (Chinese Academy of Social Science)	<ul> <li>6 cities (Guangzhou, Shanghai, Fuzhou, Shenyang, Xian, Wuhan) in 2016</li> <li>sample size 15500</li> <li>representative for the survey area</li> </ul>

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Merge O\*NET with the US PIAAC and calculate the Autor & Acemoglu (2011) task measures: non-routine cognitive analytical and personal, routine cognitive, manual

Find combinations of PIAAC questions that approximate best the Autor & Acemoglu (2011) task measures across occupations in the US

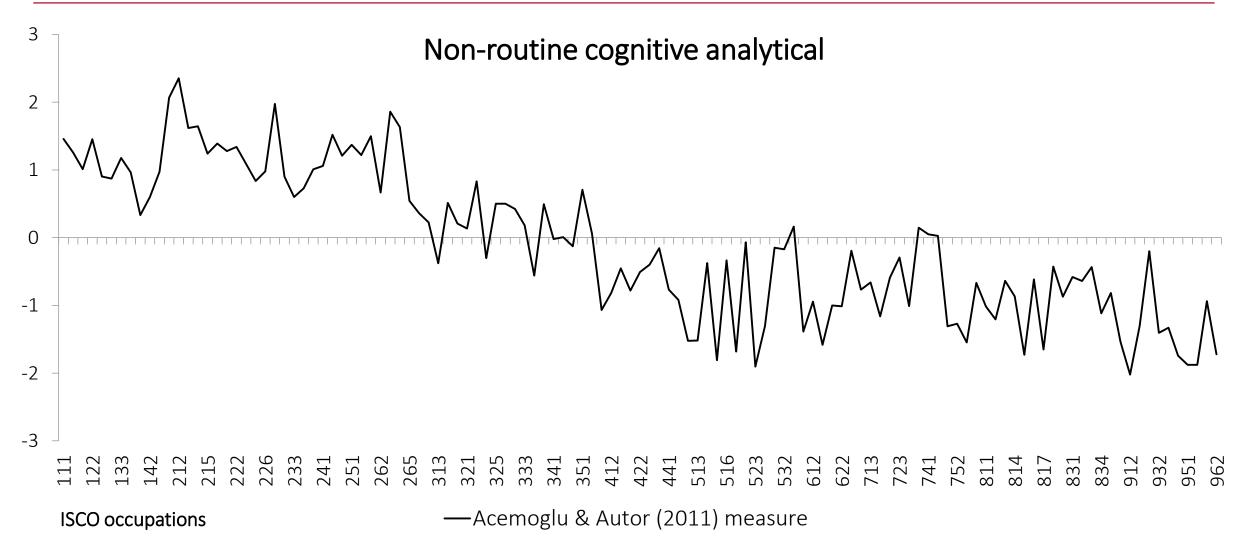
We define task contents with these PIAAC / STEP items
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	Non-routine cognitive analytical	Non-routine cognitive personal	Routine cognitive	Manual
	Reading news (at least once a month) Reading professional journals	Supervising others Presenting or making speeches (any frequence)	Changing order of tasks – reversed (not able) Filling forms (at least once a month)	Physically demanding tasks
Task items	(at least once a month) Solving problems Programming (any frequence)		Presenting – reversed (never)	
Correlation with O*NET	0.77	0.72	0.55	0.74

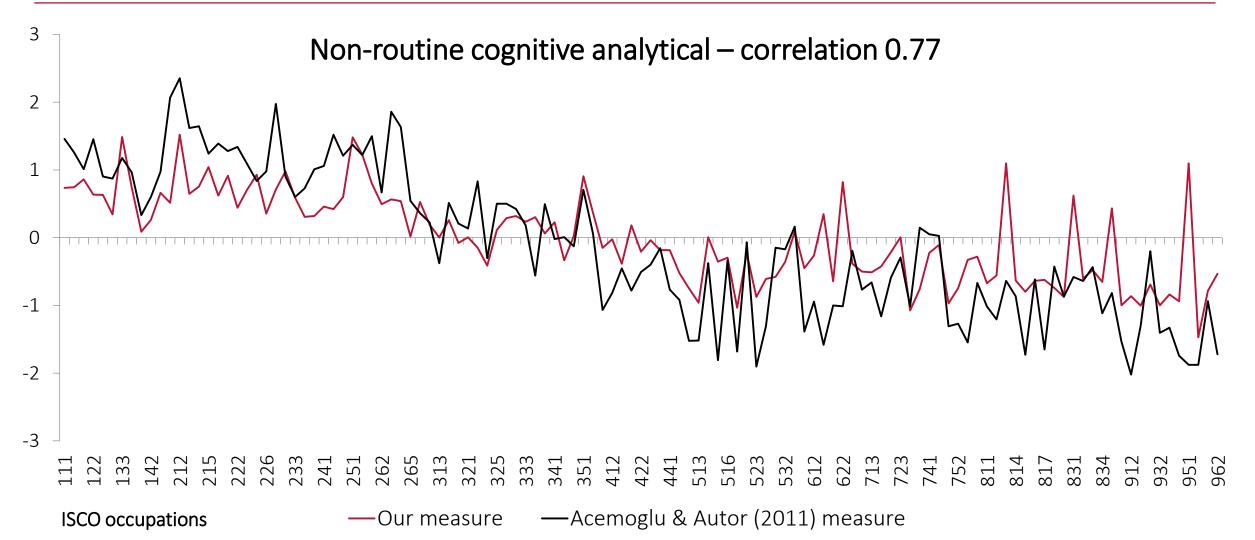
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tasks

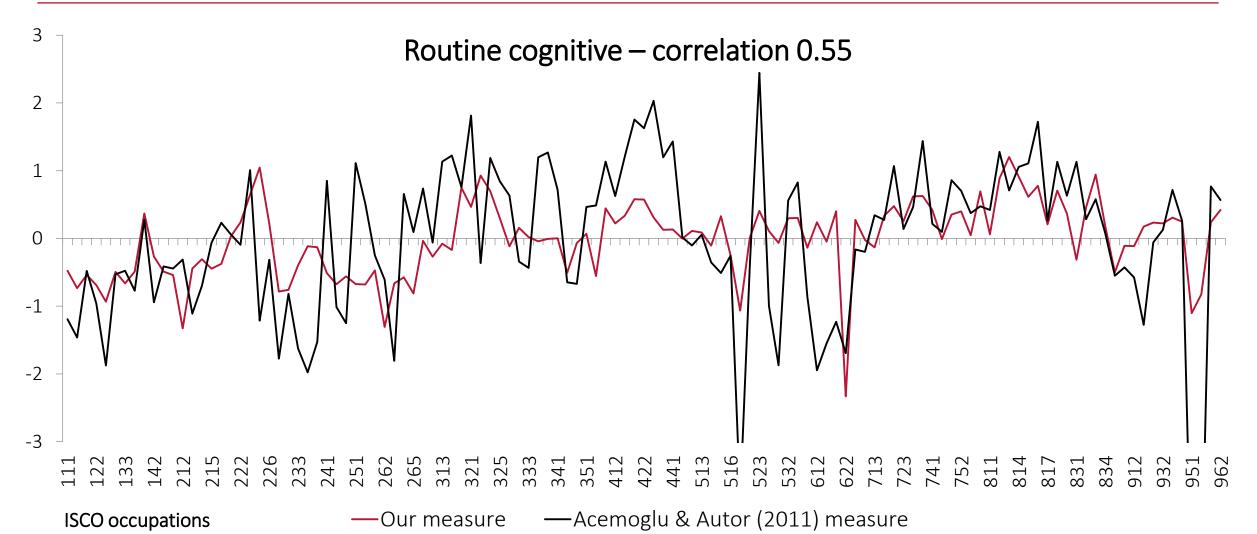
Example: the established Autor & Acemoglu (2011) measure contents calculated with O\*NET data for the US



At the 3-digit occupation level in the US, the correlations between our measures and O\*NET measures range from 0.55 to 0.77



At the 3-digit occupation level in the US, the correlations between our measures and O\*NET measures range from 0.55 to 0.77



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There is no unit of a task – we relate all countries to the US distribution:

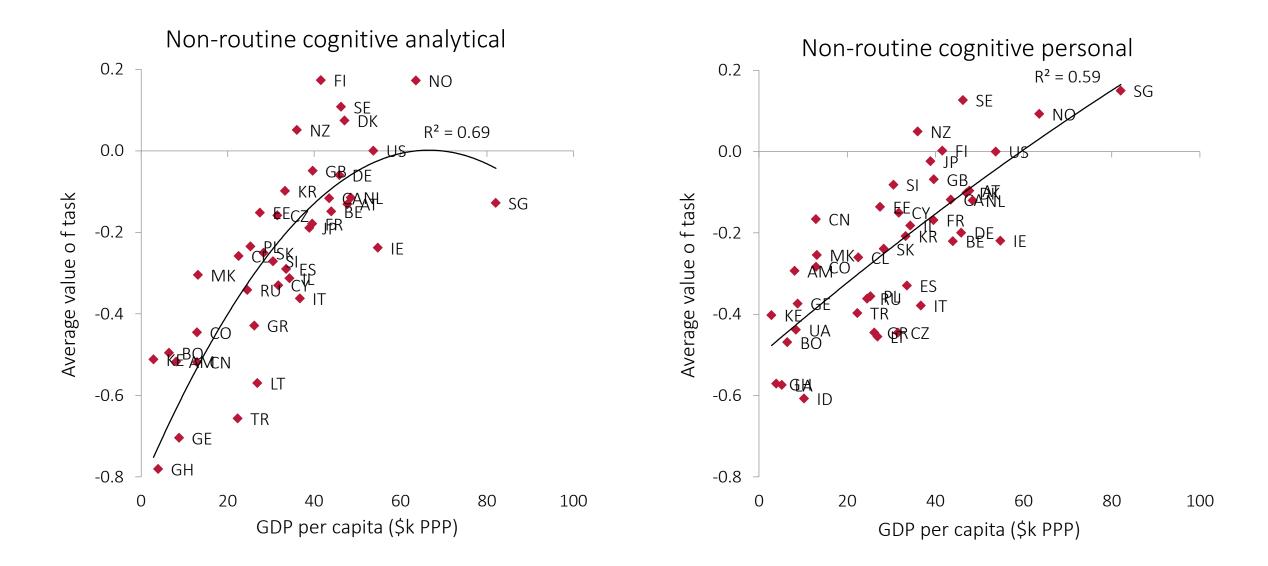
- 0 is the average level of a given task in the US
- 1 is equivalent to the standard deviation of a given task in the US

We also define routine task intensity (RTI)  $RTI = \ln(r_{cog}) - \ln\left(\frac{nr_{analytical} + nr_{personal}}{2}\right)$ 

- RTI increases with the relative importance of routine tasks,
- RTI decreases with the relative importance of non-routine tasks.

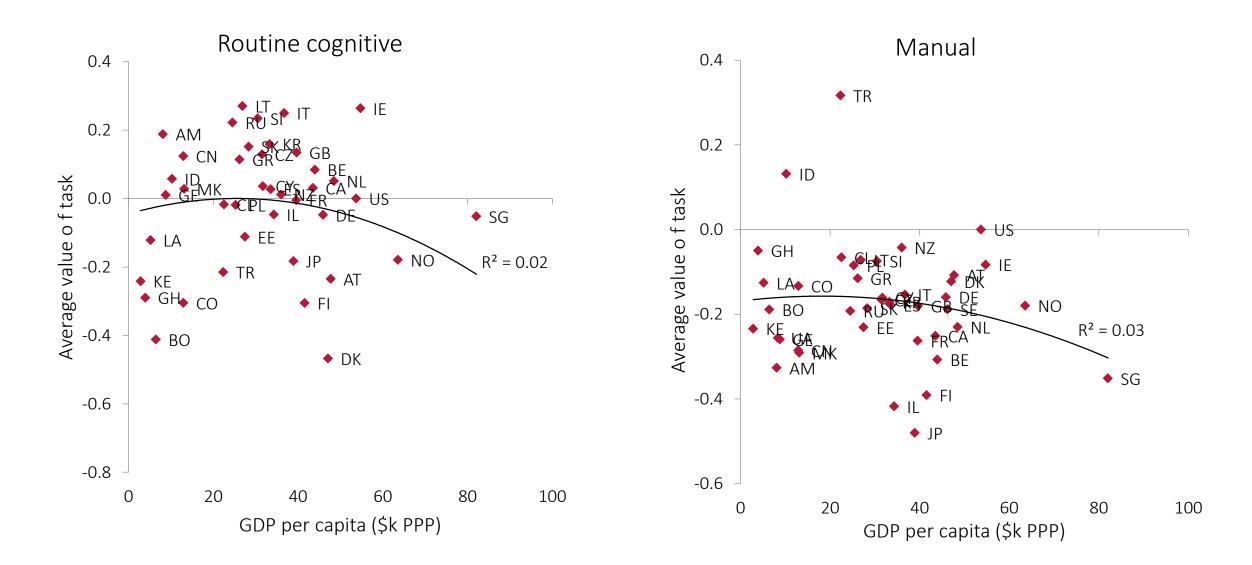
The more developed countries exhibit higher average values of non-routine tasks than the less developed countries



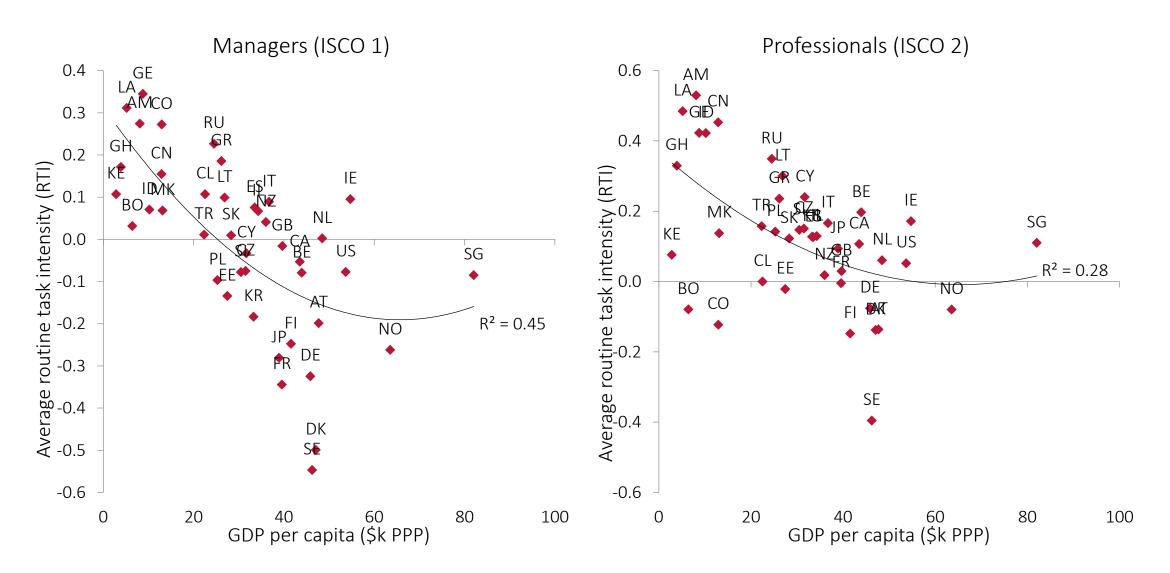


The relationship of routine cognitive and manual tasks with GDP per capita is inverse U-shaped but not significant





The differences in the routine task intensity (RTI) are most strongly related to development level among workers in the high-skilled occupations



Cross-country differences in RTI in middle- and low-skilled occupations are not systematically related to the development level

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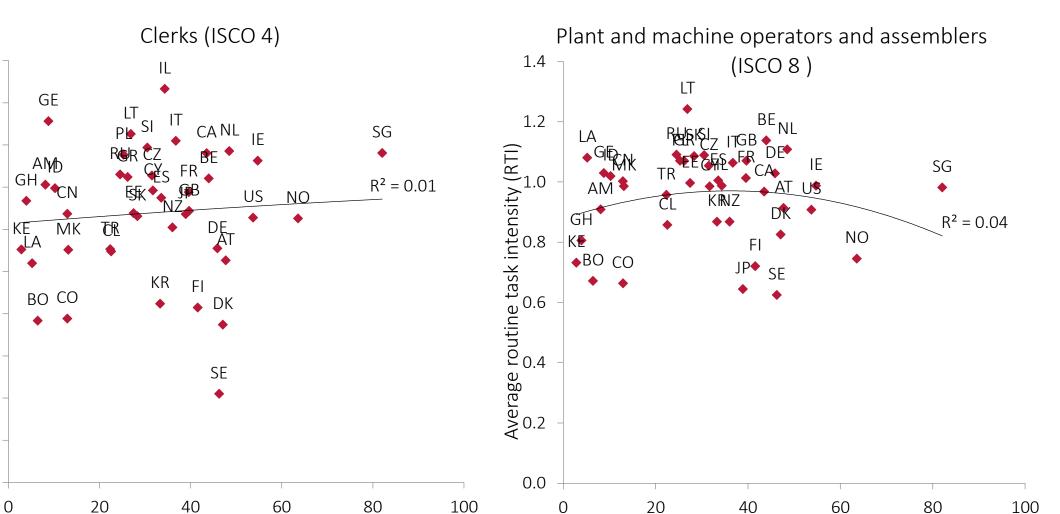
0.9

0.8

0.2

0.0

GDP per capita (\$k PPP)



0

GDP per capita (\$k PPP)

$$RTI_{ijsc} = \beta_0 + \beta_1 Z_{ijsc} + \beta_2 G_{sc} + \lambda_s + \beta_3 E_{ijsc} + \varepsilon_{ijsc}$$

 $RTI_{ijsc}$  - routine task intensity of individual *i* in occupation *j* in sector *s* in country *c*.

- $Z_{ijsc}$  technology used by individual *i* in occupation *j* in sector *s* in country *c*,
- $G_{sc}$  globalization in sector s in country c,
- $\lambda_s$  sector fixed effects,
- $E_{ijsc}$  skills and demographic characteristics of workers.

Regressions for all workers and for workers in high (ISCO 1-3), middle (ISCO 4-5) and low-skilled (ISCO 7-9) occupations

We measure the four fundamental factors with worker, sector-country and country variables

- <u>Technology</u>: sector-country share of computer use at work, \*sector-country robot stock (per worker), \*ICT capital stock per worker
- <u>Globalization</u>: foreign value added share in domestic output (FVA share, Wang et al. 2017) also interacted with GDP, FDI stock/GDP
- <u>Structural change</u>: 19 sectors, GDP per capita (log), interactions between them
- <u>Skill supply</u>: education, literacy skills, sex, age group
  - \* available for 31 countries only

Higher probablity of computer use is related to less routine tasks. Robots & ICT are insignificant if we control for computer use probability

	All workers	High-skilled occ. (ISCO 1-3)	Middle-skilled occ. (ISCO 4-5)	Low-skilled occ. (ISCO 7-9)	
Computer use	-0.501**	-0.690***	-0.353	-0.240	-

No. of obs. / R^2 148,569 / 0.22	62,907/0.13	47,373 / 0.09	38,289 / 0.08
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Globalization – specialization in global value chains – has the strongest effect among workers in low-skilled occupations

	All workers	High-skilled occ. (ISCO 1-3)	Middle-skilled occ. (ISCO 4-5)	Low-skilled occ. (ISCO 7-9)
Computer use	-0.501**	-0.690***	-0.353	-0.240
FVA share	0.266*	-0.057	0.189	0.796***
FVA* GDP pc (log, demeaned)	-0.424**	-0.216	-0.239	-0.347
FDI / GDP	0.009*	0.023***	0.010	-0.016***
GDP per capita (log, demeaned)	0.057	-0.038	0.013	0.052
No. of obs. / R^2	148,569 / 0.22	62,907 / 0.13	47,373 / 0.09	38,289 / 0.08

Higher skills are associated with less routine tasks,	
especially among workers in high-skilled occupations.	• • •

		All workers	High-skilled occ. (ISCO 1-3)	Middle-skilled occ. (ISCO 4-5)	Low-skilled occ. (ISCO 7-9)
Secondary	Primary education	0.246***	0.135***	0.223***	0.135***
Ref. Se	Tertiary education	-0.486***	-0.267***	-0.198***	-0.142***
– n vel	Low literacy skills	0.077***	0.032	0.051**	0.057**
	Upper Medium Literacy skills	-0.138***	-0.086***	-0.062***	-0.048**
<u>م</u>	High literacy skills	-0.293***	-0.190***	-0.064**	-0.174***
	No. of obs. / R^2	148,569 / 0.22	62,907 / 0.13	47,373 / 0.09	38,289 / 0.08

Female and younger workers perform more routine intensive tasks

		All workers	High-skilled occ. (ISCO 1-3)	Middle-skilled occ. (ISCO 4-5)	Low-skilled occ. (ISCO 7-9)
	Female	0.249***	0.239***	0.203***	0.346***
Ref. 25-44	Age 16-24	0.227***	0.220***	0.207***	0.147***
	Age 35-44	-0.054***	-0.062***	-0.020	-0.038*
	Age 45-54	-0.012	-0.062***	0.017	0.043*
	Age 55-64	0.020	-0.052***	0.110***	0.078***
	No. of obs. / R^2	148,569 / 0.22	62,907 / 0.13	47,373 / 0.09	38,289 / 0.08

We decompose the differences in routine task intensity between each country and the US. We present results by three classes of countries



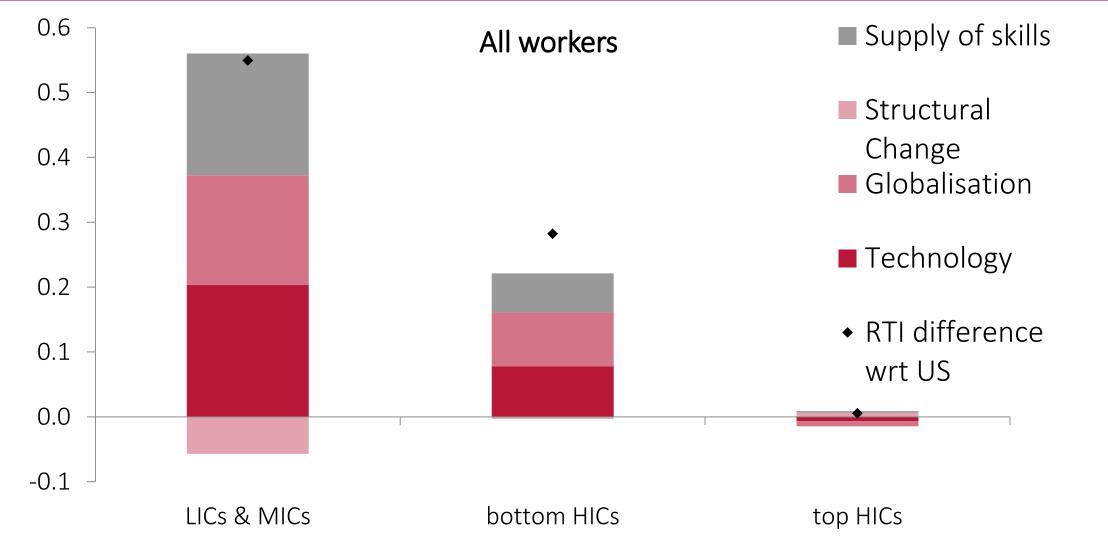
Norway

Low and Middle Income Countries	Bottom High Income Countries	Top High Income Countries	
		France	
		Israel	
Kenya	Chile	Japan	
Ghana	Poland	New Zealand	
Lao, PDR	Lithuania	United Kingdom	
Ukraine	Slovakia	Belgium	
Bolivia	Cyprus	Germany	
Indonesia	Estonia	Canada	
China	Greece	Finland	
Armenia	Czech Rep.	Austria	
Georgia	Slovenia	Netherlands	
Colombia	Spain	Sweden	
Russia	Korea, Rep.	Denmark	
Turkey	Italy	Singapore	
		Ireland	

# Average levels of RTI and explanatory variables by country groups

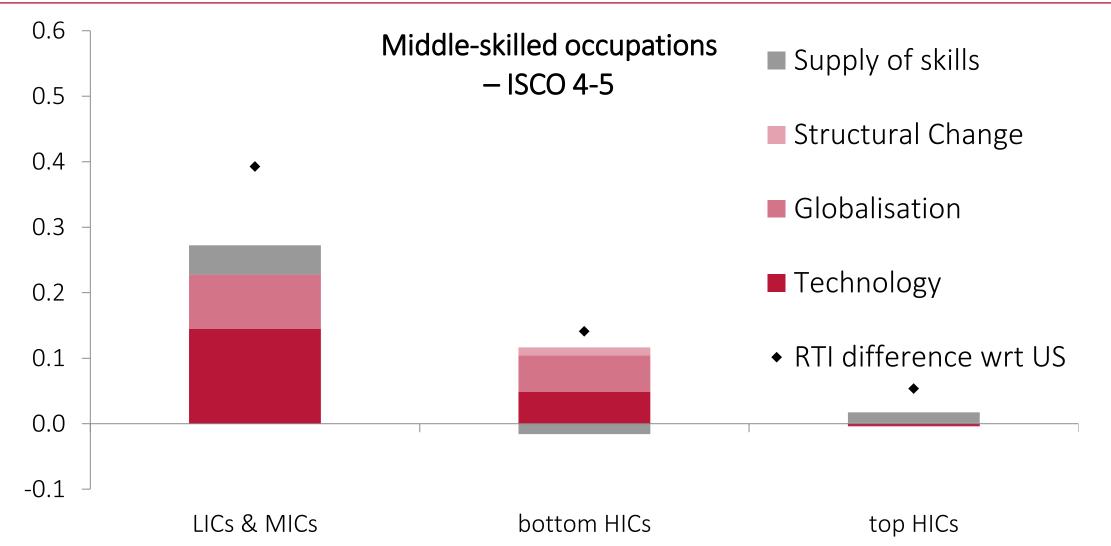
	LIHCs and MIHCs	Bottom HICs	Top HICs	US
RTI	0.54	0.28	0.01	0.00
Computer use	0.35	0.60	0.76	0.75
GDP per capita (log, demeaned)	-1.48	0.12	1.02	1.23
FDI stock/GDP	0.42	1.24	0.79	0.35
FVA Share	0.15	0.24	0.19	0.08
Education: primary	0.32	0.17	0.15	0.10
Education: tertiary	0.34	0.34	0.42	0.42
Literacy skills level: 1 or lower	0.45	0.18	0.13	0.14
Literacy skills level: 3	0.17	0.36	0.41	0.40
Literacy skills level: 4 and 5	0.02	0.08	0.15	0.15

Overall, lower supply of skills matters the most in LIHc and MIHc. In bottom HICs globalization and technology are dominant

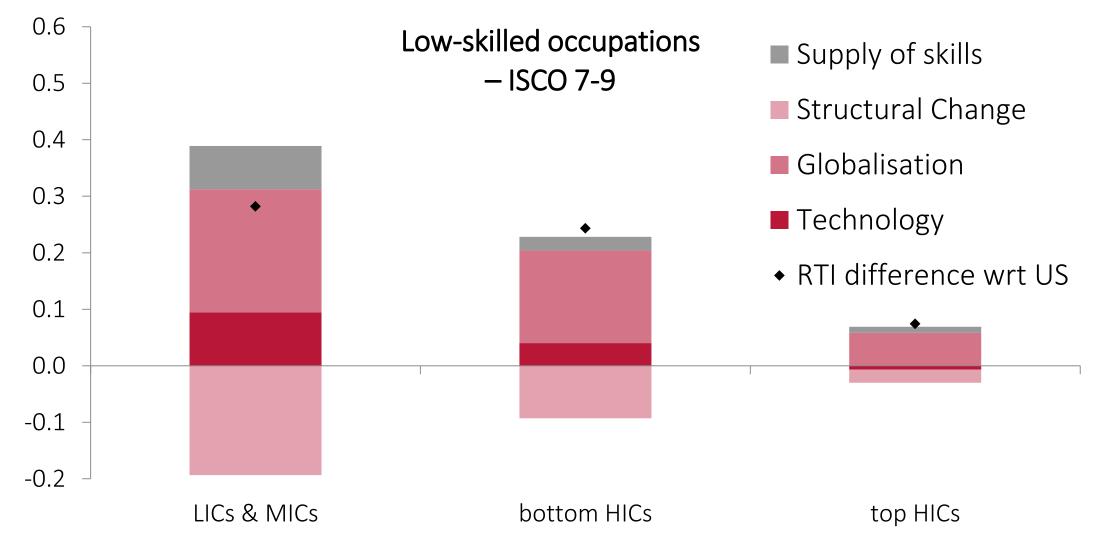


For the high-skilled occupations, technology matters the most, while skills contribute only in LICs & MICs 0.6 **High-skilled** occupations Supply of skills - ISCO 1-3 0.5 Structural Change 0.4 Globalisation 0.3 Technology 0.2 RTI difference wrt US 0.1 0.0 -0.1 LICs & MICs bottom HICs top HICs

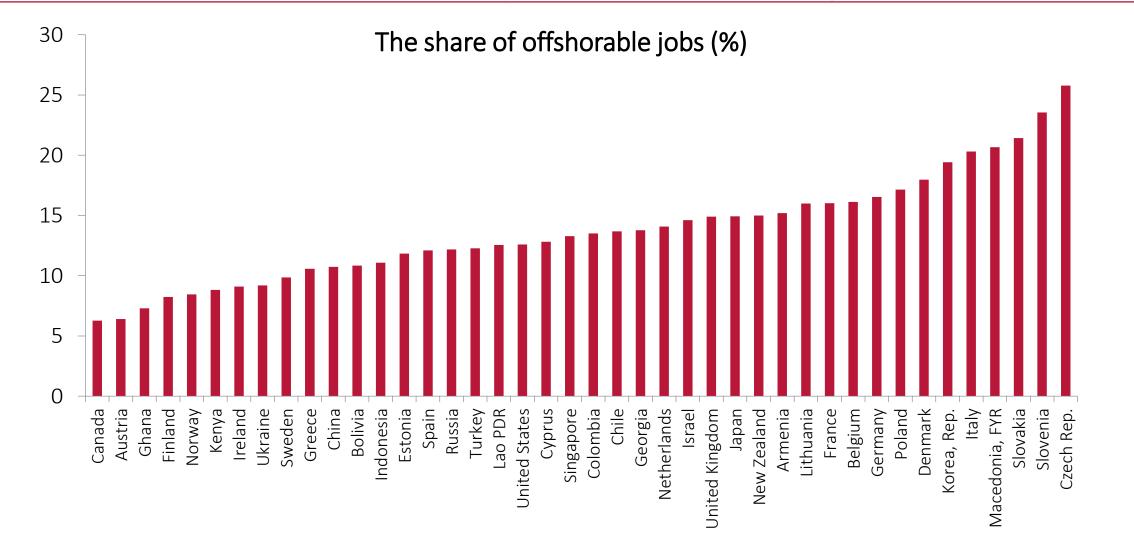
In middle-skill occupations, technology and globalization contribute the most



The contribution of globalization is the most pronounced for low-skilled occupations, for every group of countries



Next we study if the determinants of task differences are different for offshorable and non-offshorable occupations (Blinder & Krueger, 2013)

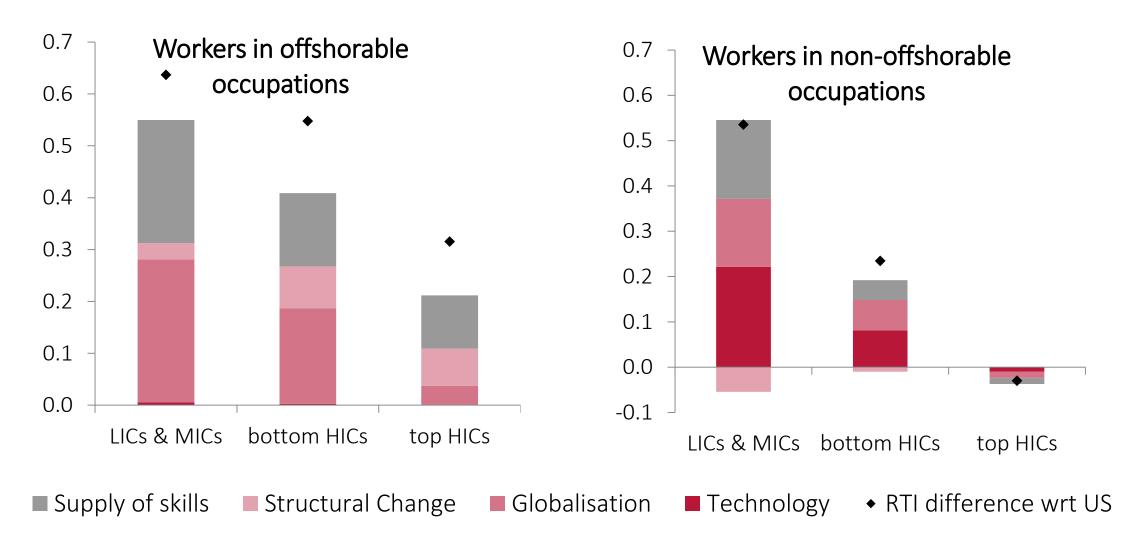


Technology matters for non-offshorable jobs.		•
Globalization matters for offshorable jobs.	•	•

#### The effects of technology and globalization on RTI in offshorable and non-offshorable occupations

	All workers	Workers in non-offshorable	Workers in offshorable	
	All WOLKETS	occupations	occupations	
Computer use	-0.508**	-0.555***	-0.012	
FVA share	0.269*	0.171	0.762***	
GDP per capita	0.060 0.062		0.015	
(log, demeaned)			0.015	
FVA share *	-0.424**	-0.396**	-0.530*	
GDP per capita (log, demeaned)	-0.424	-0.590	-0.530	
FDI / GDP	0.009*	0.012**	-0.006	
Skills and demographic			Voc	
characteristics	Yes	Yes	Yes	
Sector fixed effects	Yes	Yes	Yes	
No. of observations	148,120	129,965	18,155	
R-Squared	0.220	0.222	0.245	

Technology explains most of task differences among workers in non-offshorable occupations, but doesn't matter for offshorable occupations – globalization does

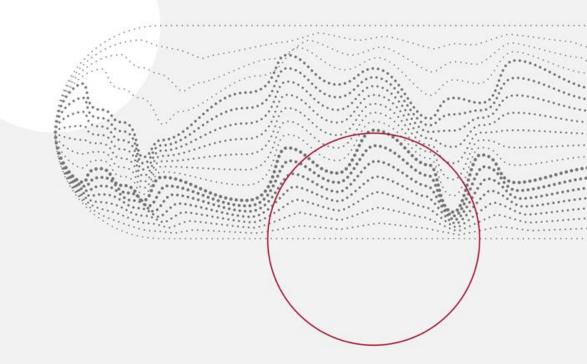


# What survey data tell us about the global differences in the nature of work .

- Occupations are indeed different around the world.
  - In high-skilled occupations differences in RTI are strongly related to the development level, but in other occupations not so much
- Technology contributes the most to the cross-country differences in tasks, especially among workers in high- and middle-skilled occupations.
- Globalization contributes the most among workers in low-skilled occupations and offshorable occupations.
- Skill supply matters more for the overall differences than for differences within occupational groups – skills determine structure of broad occupation groups.



- Thanks for listening
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Representativeness of the data is limited in some countries. Bear that in mind when looking at the results



### PIAAC

- Belgium Flanders
- Russia without Moscow municipal area
- UK England and Northern Ireland
- Indonesia Jakarta
- Singapore only permanent residents (approx. 75% of population)

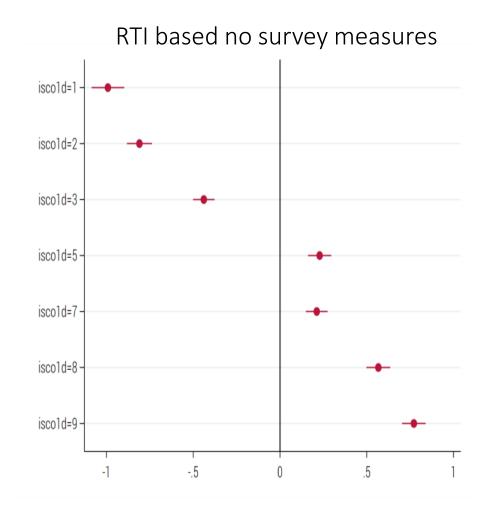
STEP – urban survey with additional limitations in some countries

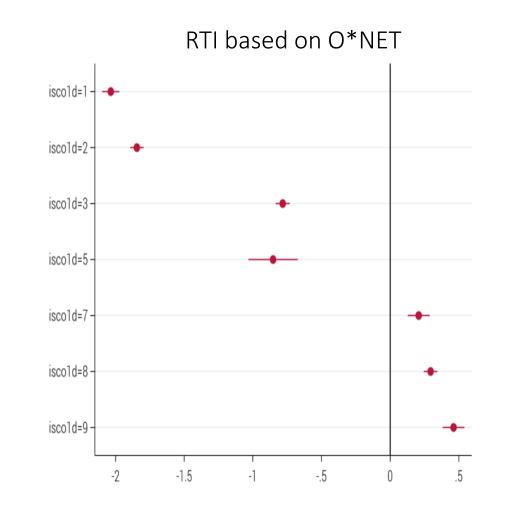
- Bolivia four main cities La Paz, El Alto, Cochabamba and Santa Cruz de la Sierra (approx. 80% of urban population)
- Colombia 13 main metropolitan areas
- Georgia no Abkhazia, South Ossetia
- Lao PDR both urban and rural, but we drop rural for consistency
- China (CULS) 6 cities

Our measures replicate the pair-wise correlations between particular task content measures across 3-digit ISCO occupations in the US

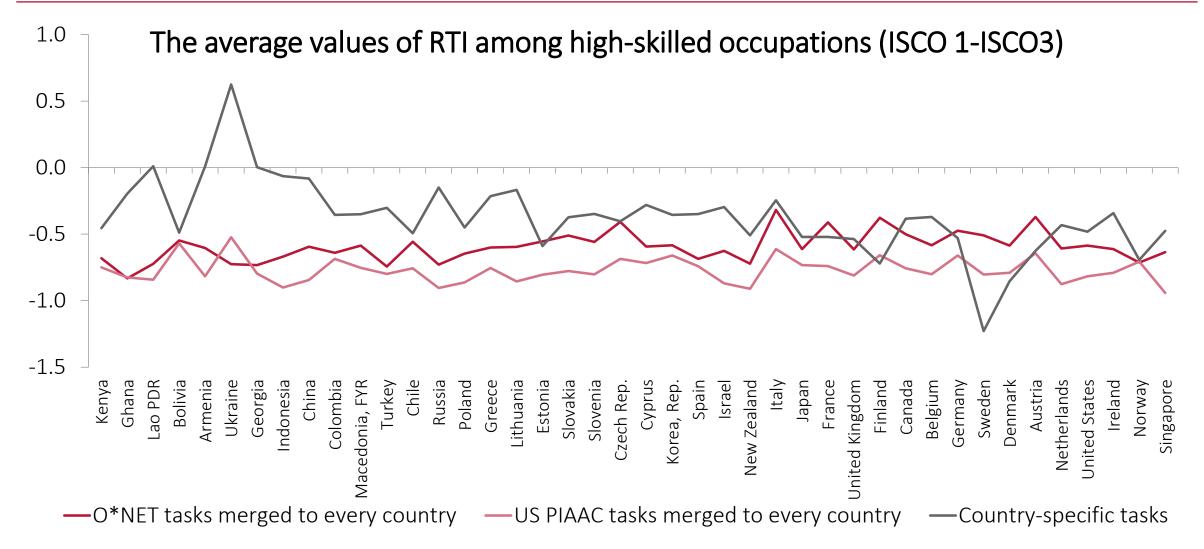
	Non-routine cognitive analytical	Non-routine cognitive personal	Routine cognitive	Manual			
	Acemoglu and Autor (2011) measures based on O*NET						
NRCA	1						
NRCP	0.71	1					
RC	-0.35	-0.54	1				
Manual	-0.64	-0.55	0.32	1			
	Survey measures based on PIAAC						
NRCA	1						
NRCP	0.64	1					
RC	-0.49	-0.57	1				
Manual	-0.57	-0.58	0.42	1			

# The distribution of survey-based RTI across occupations is consistent with the one resulting from O\*NET





Cross-country differences in particular occupations are visible only with the country-specific measurement



Once we control for GDP and literacy scores, the difference between PIAAC and STEP datasets is insignificant

	Non-routine cognitive analytical	Non-routine cognitive personal	Routine cognitive	Manual
Base model (I)	-0.22***	-0.03	-0.05	-0.38***
I+ literacy skills (II)	-0.11	-0.04	-0.20	-0.44***
ll + GDP	-0.00	0.06	-0.07	-0.18***

The reported coefficients are for a STEP dummy in a whole sample models. The base regressions include dummies for gender, 10-year age groups, education, 1-digit occupations and sectors. The standard errors are clustered at a country level. The regressions with literacy scores exclude China (CULS), Laos and Macedonia due to lack of literacy skills assessment in these countries.

Finally, we assess the role of occupations

We re-estimate our model controlling for occupations

$$RTI_{ijsc} = \beta_0 + \beta_1 Z_{ijsc} + \beta_2 G_{sc} + \lambda_s + \beta_3 E_{ijsc} + \boldsymbol{\tau_o} + \varepsilon_{ijsc}$$

 $\tau_o$  - occupational dummies (1-digit ISCO groups).

Occupations capture some of the differences otherwise attributed to fundamental factors, especially skills, but technology still explains the most

