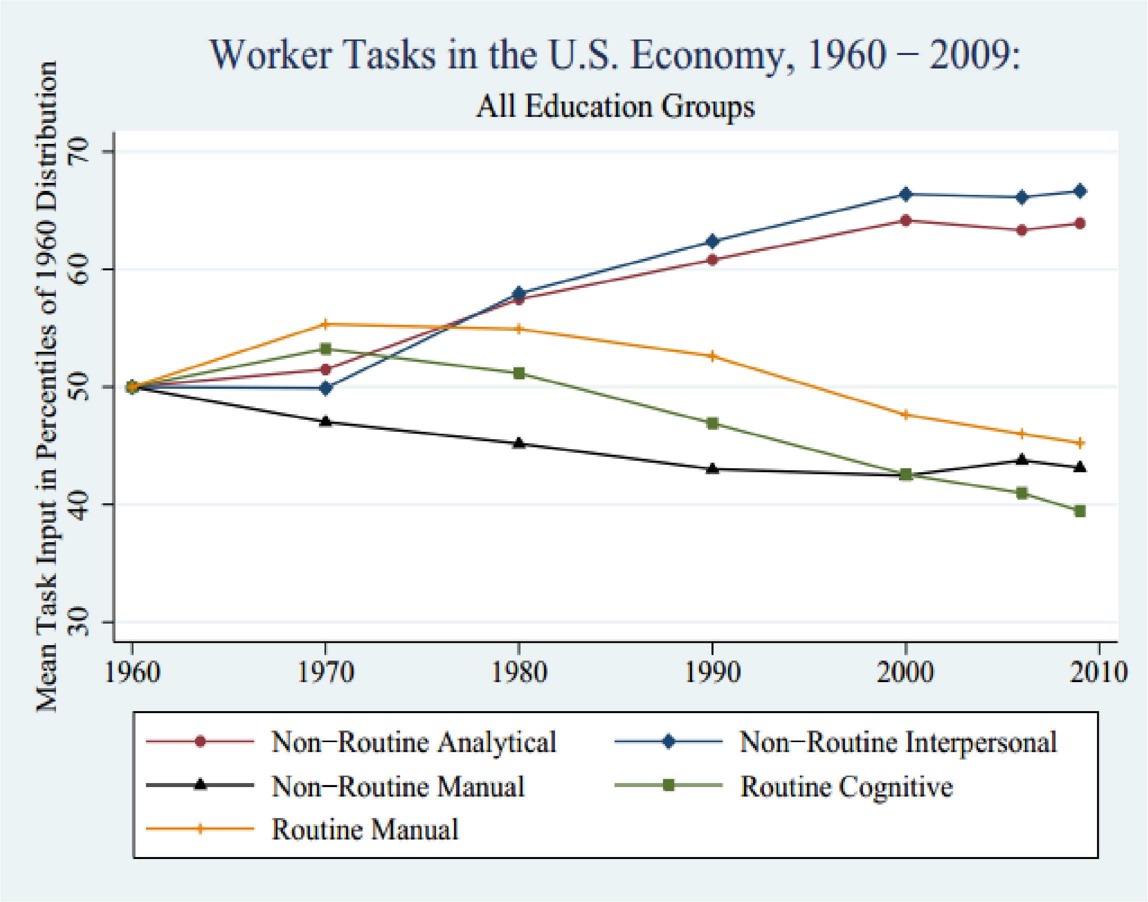
instytut badań strukturalnych

The global distribution of routine and non-routine work

Piotr Lewandowski (IBS, IZA)
Wojciech Hardy(IBS)
Albert Park (IEMS HKUST, IZA)
Du Yang (CASS)

The de-routinisation of work in the US and Western Europe can be attributed to the routine-biased technological progress and offshoring



Source: Autor, Price (2013)

- Routine cognitive and manual tasks are substituted by technology and they decline
- Non-routine cognitive tasks complement technology and they grow
- Non-routine manual tasks are typical for lousy jobs, may grow or decline depending on the general equilibrium effects

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

	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

Cross-country studies use O*NET assumming that it is a good proxy for occupational content outside of the US (occupations are identical)

- Handel (2012): high correlations between O*NET measures and results from country-specific skill surveys in some OECD countries
- Goos et al. (2014), Arias et al. (2014), Lewandowski et al. (2018): applications of O*NET to LFS data in the OECD and/or EU countries
- World Development Report 2016: the Autor (2015) typology of high-, middle-, and low-skill occupations in the US assigned to developing countries with bizzare results
- But are occupations really identical around the world?

The contribution of this paper

- We construct task content measures which:
  - Are measured at the worker level
  - Are country-specific
  - Are consistent with the Acemoglu & Autor (2011) measures based on O*NET
  - Can be applied to PIAAC and STEP datasets
- We find that the task contents of occupations are different around the world
- These differences can be attributed to differences in technology (ICT, robots), global value chain position and skills

Recent attempts to create routine/non-routine task measures using skill surveys with individual level data on job content

- De la Rica & Gortazar (2016), Marcolin et al. (2016) with PIAAC (OECD and partners)
- Dicarlo (2016) with STEP (10 developing countries)
- These papers are quite arbitrary in how they define tasks.

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- Differences wrt O*NET tasks can result from different definitions (☹) or different country-specific work patterns (☺).

- We want to minimise the former and highlight the latter

- We use PIAAC (32 countries), STEP (9 countries) and CULS (China)

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

PIAAC (OECD)

- 32 countries surveyed between 2011 and 2015
- sample sizes: from 4000 (Russia) to 26000 (Canada)

STEP (World Bank)

- 9 countries surveyed between 2011 and 2015
- sample sizes: from 2400 (Ukraine) to 4000 (Macedonia) urban residents
- representative for survey areas
- skill use at work and literacy test comparable to PIAAC

CULS (Chinese Academy of Social Science)

- 6 cities (Guangzhou, Shanghai, Fuzhou, Shenyang, Xian, Wuhan) in 2016
- sample size 15500
- representative for the survey area
- skill use at work questionnaire as in STEP

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 – without Abkhazia and South Ossetia
- Lao PDR – both urban and rural, but we drop rural for consistency
- China (CULS) – 6 cities

We construct and validate our task measures on the US PIAAC and O*NET data, and then we apply these measures to other countries

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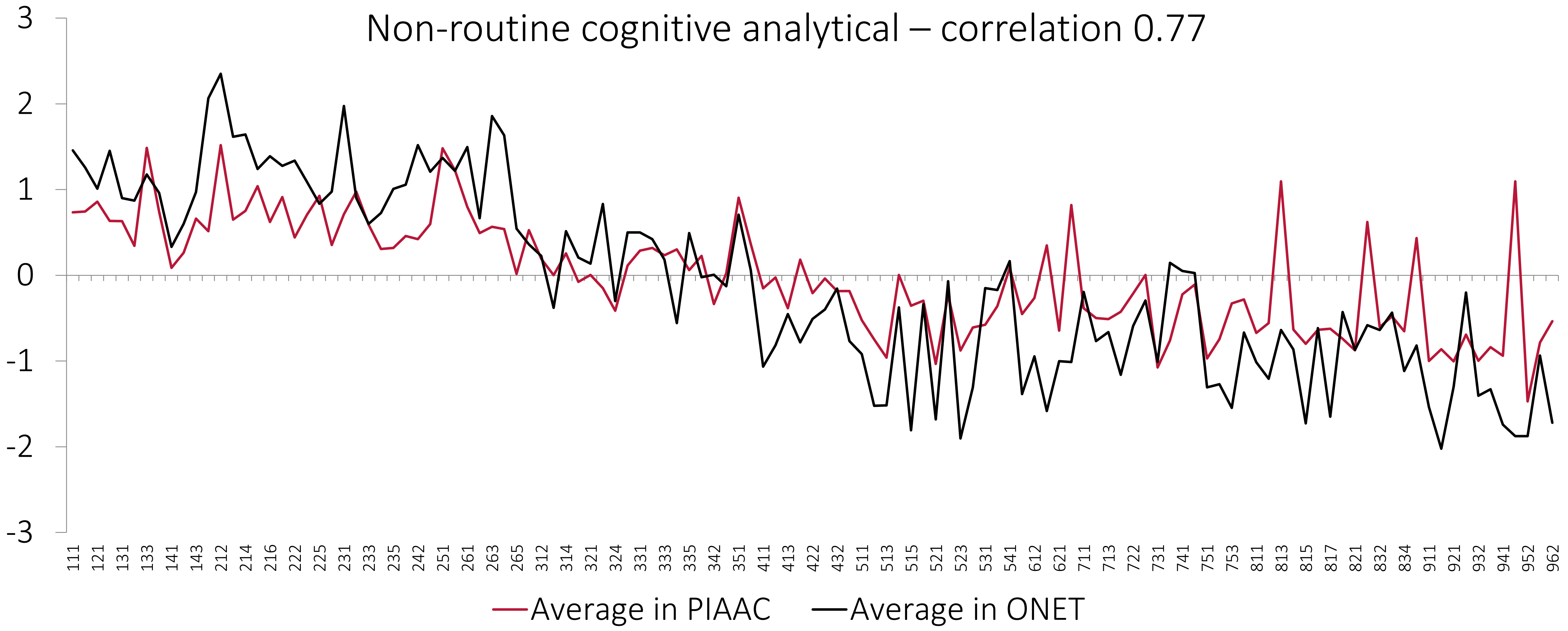
Choose the best combination for every task measure and apply them to all countries (0=US average, 1-US std)

We select the PIAAC / STEP items below and follow Autor & Acemoglu (2011) to calculate the values of tasks in all 42 countries

Task content measure	No. of item / cut-off combinations	Chosen PIAAC / STEP task items
Non-routine cognitive analytical	156 250	Reading news Reading professional titles Solving problems Programming
Non-routine cognitive interpersonal	24	Supervising Presenting
Routine cognitive	5 000	Changing order of tasks (reversed) Filling forms Presenting (reversed)
Manual	1	Physical tasks

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



Once we control for GDP and literacy scores, the difference between PIAAC and STEP datasets becomes small and 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***
II + GDP	-0.00	0.06	-0.07	-0.18***

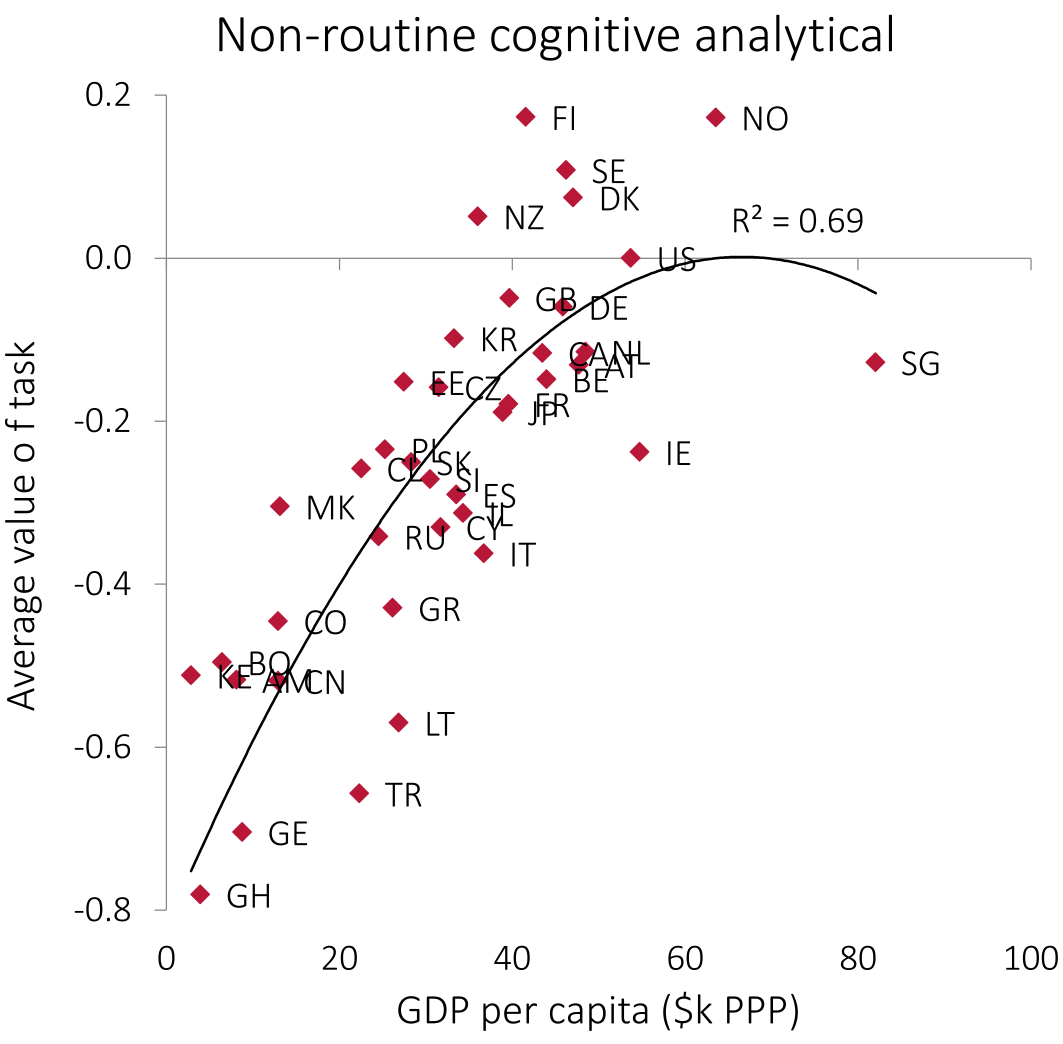
The reported coefficients are for a STEP dummy in a whole sample models. The base regressions include dummies for gender, 10-year age groups, education, 1-digit occupations and sectors. The standard errors are clustered at a country level. The regressions with literacy scores exclude China (CULS), Laos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

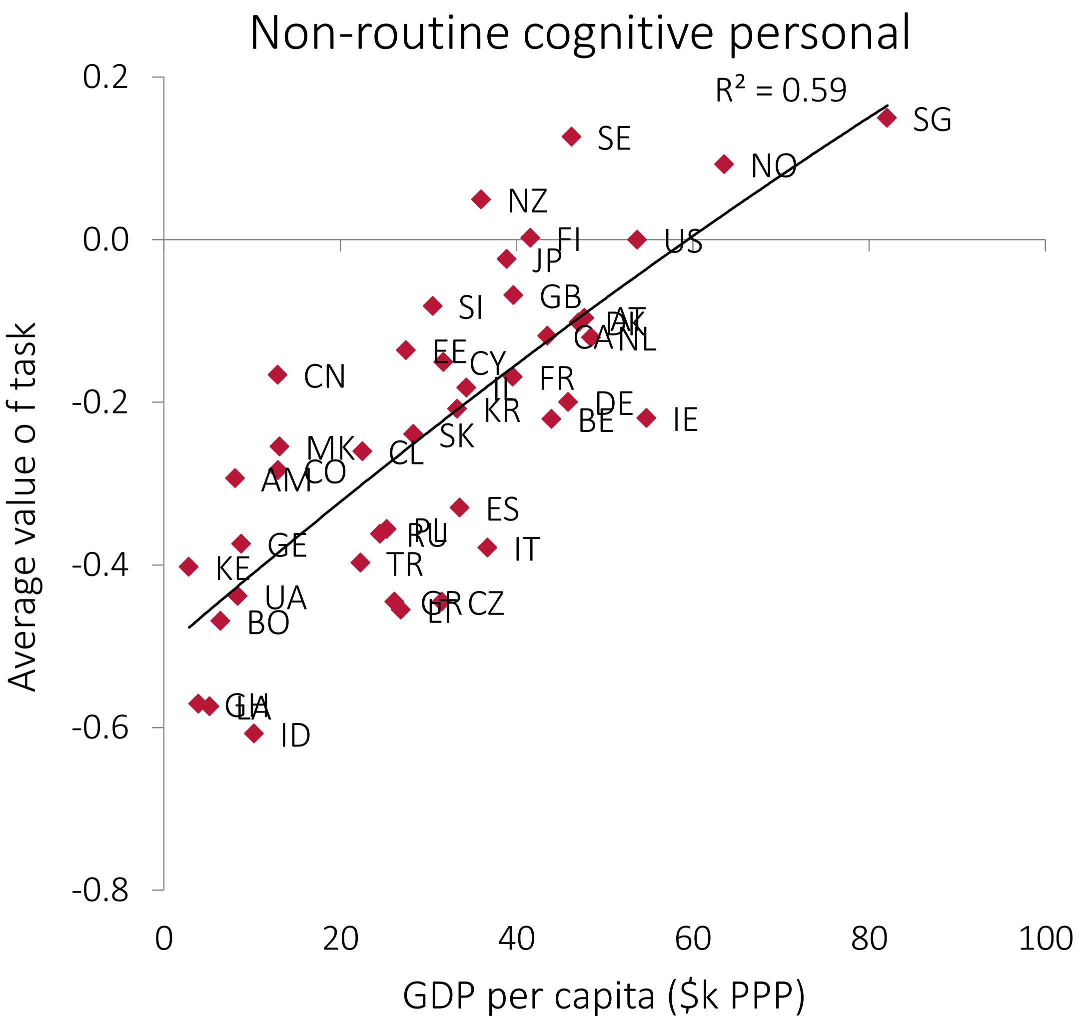
Let’s move to the results

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

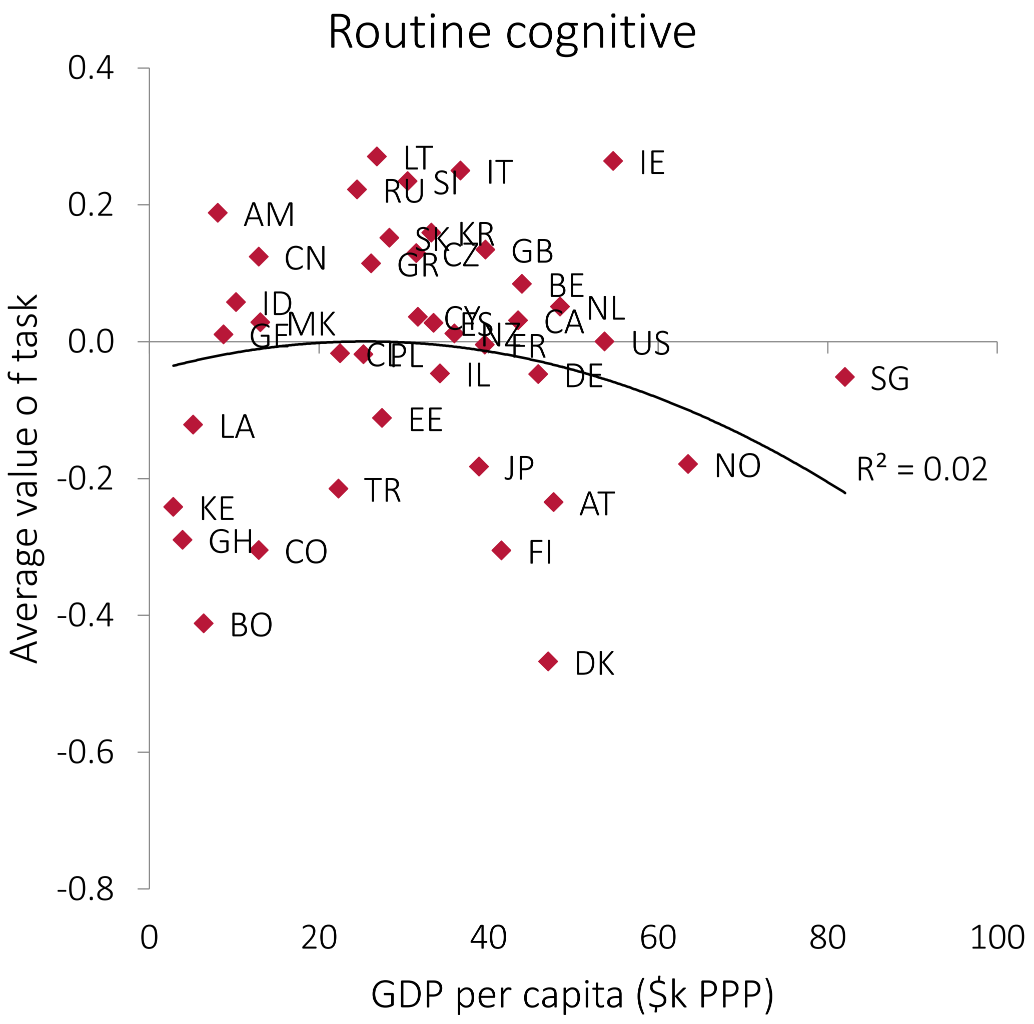
- 0 is the average level of a given task in the US
- 1 is equivalent to the standard deviation of a given task in the US

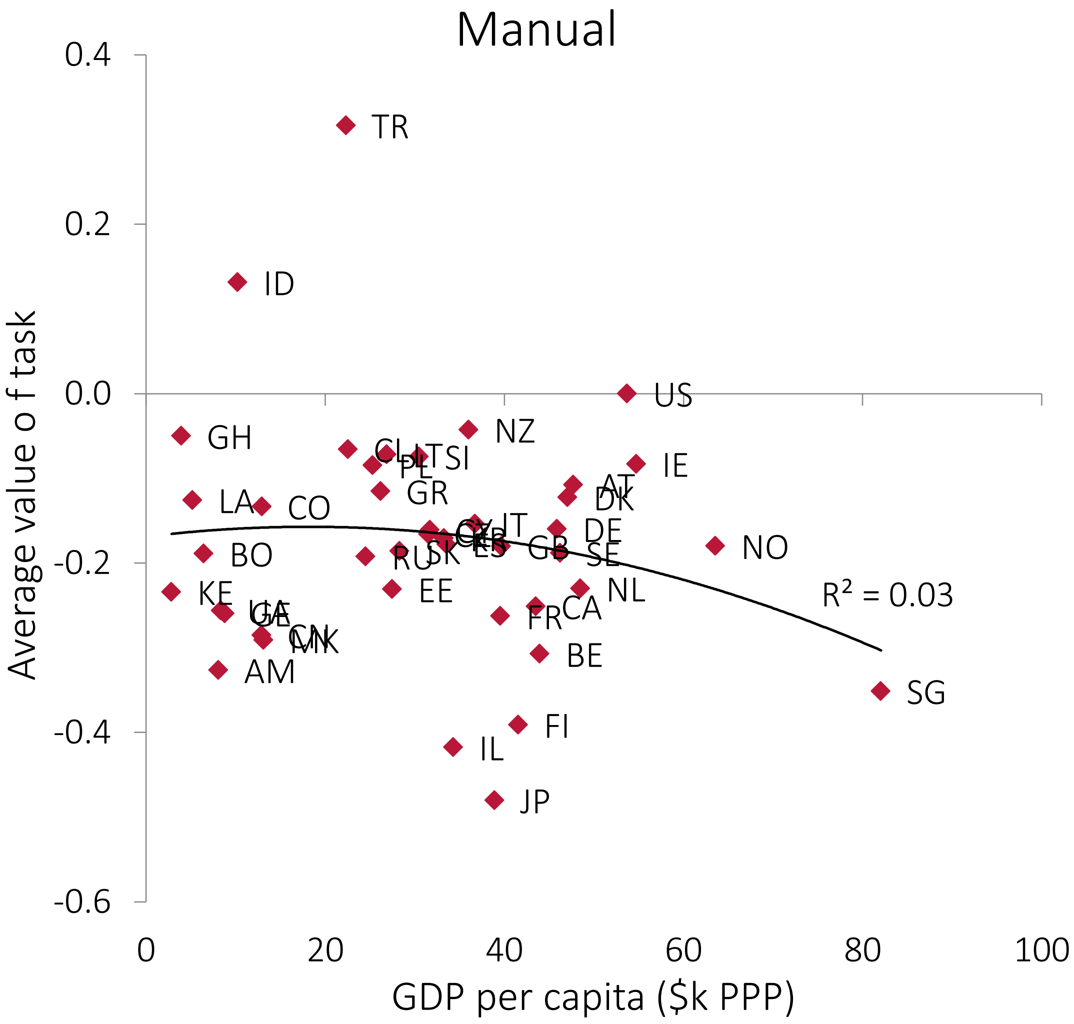
The more developed countries exhibit higher average values of non-routine tasks than the less developed countries





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





From now on I will use the relative routine task intensity (RTI)

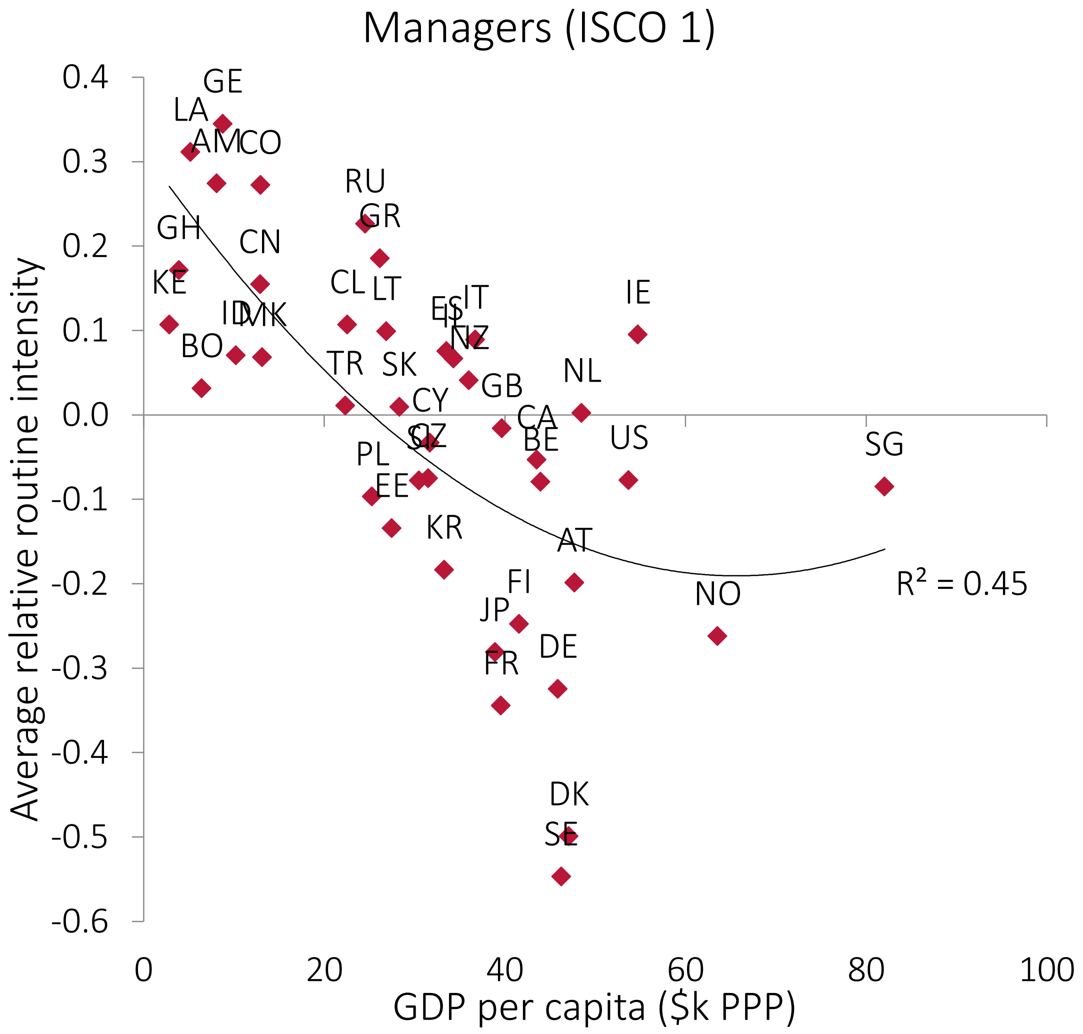
Routine task intensity (RTI) increases with the relative importance of routine tasks, decreases with the relative importance of non-routine tasks

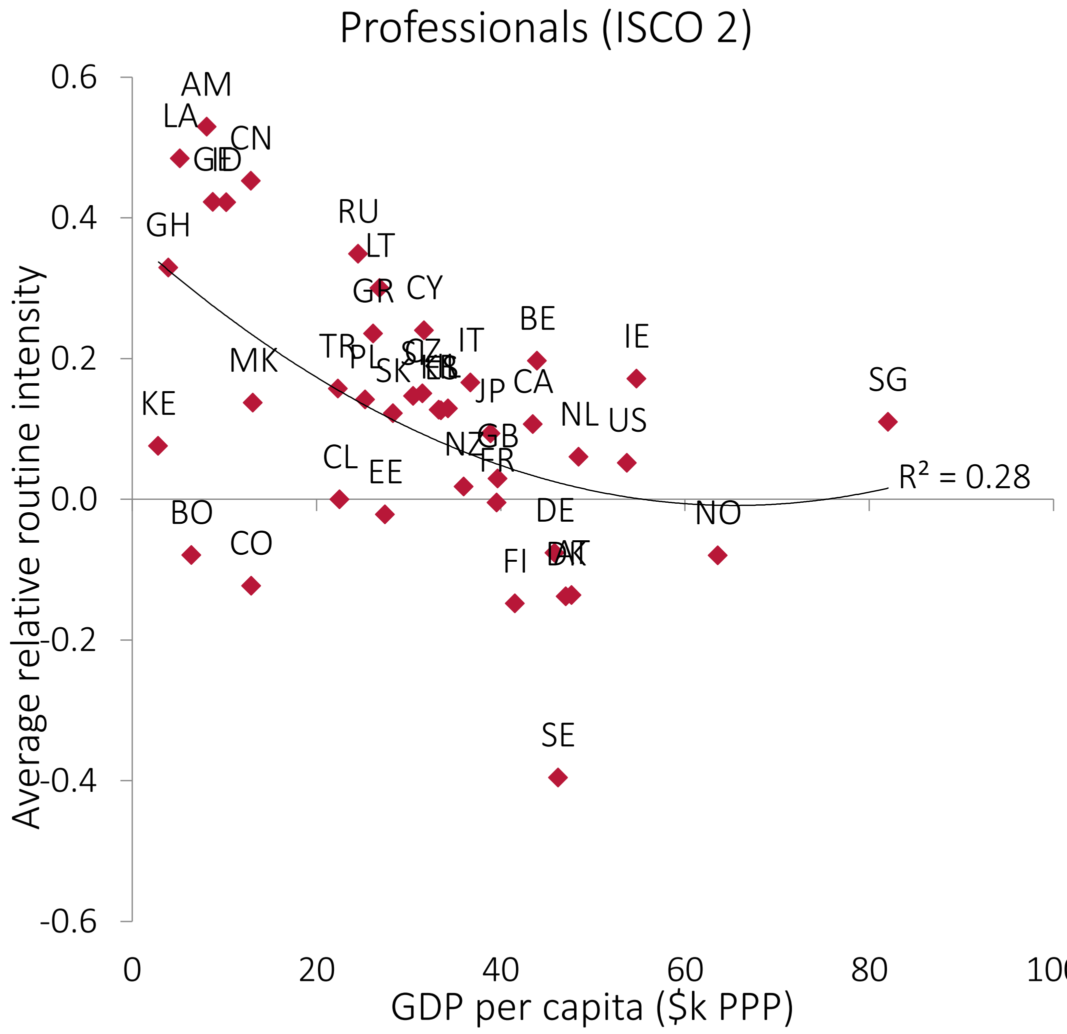
$$RTI = \ln(r_{cog}) - \ln\left(\frac{nr_{analytical} + nr_{personal}}{2}\right)$$

RTI allows

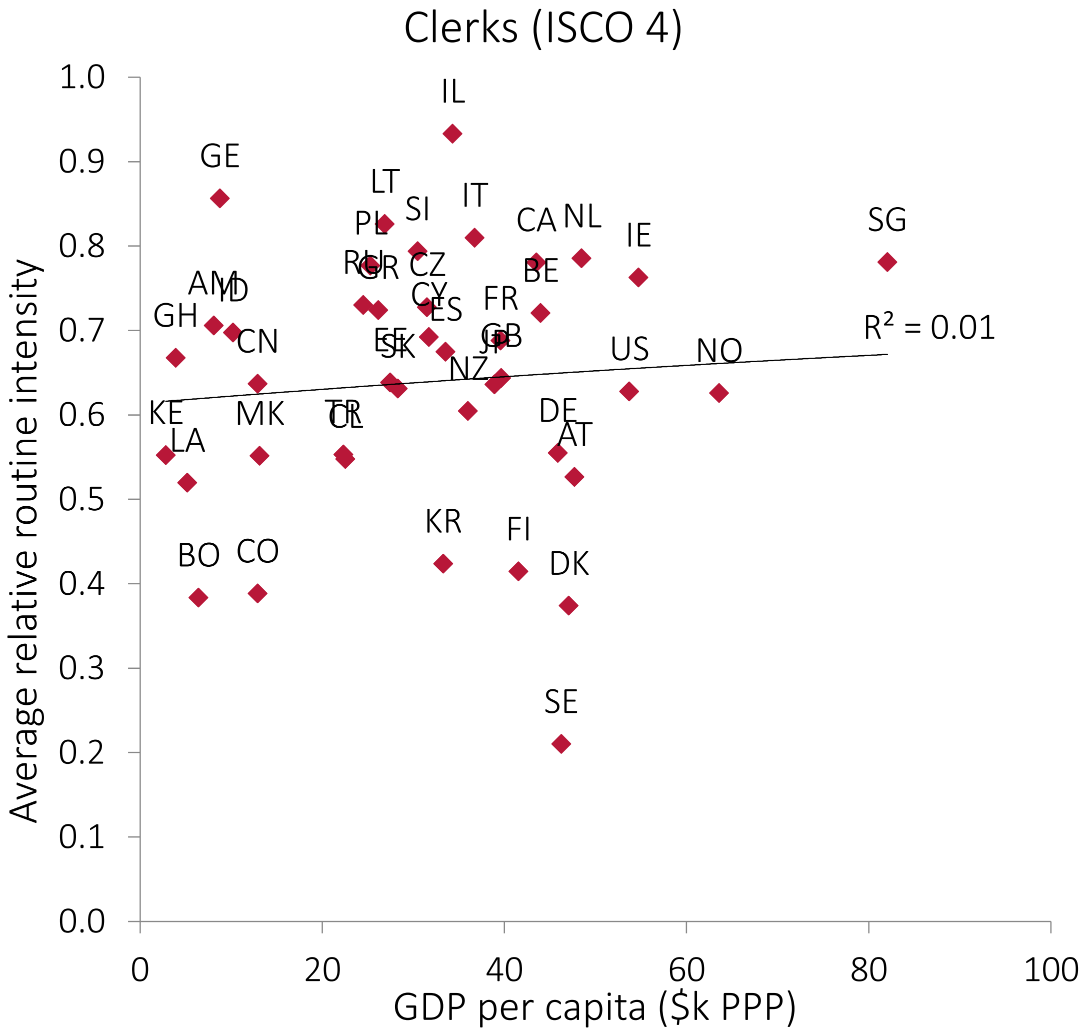
- Comparing occupations across countries
- Identifying individual-, sector-, and country-level correlates of routine intensity

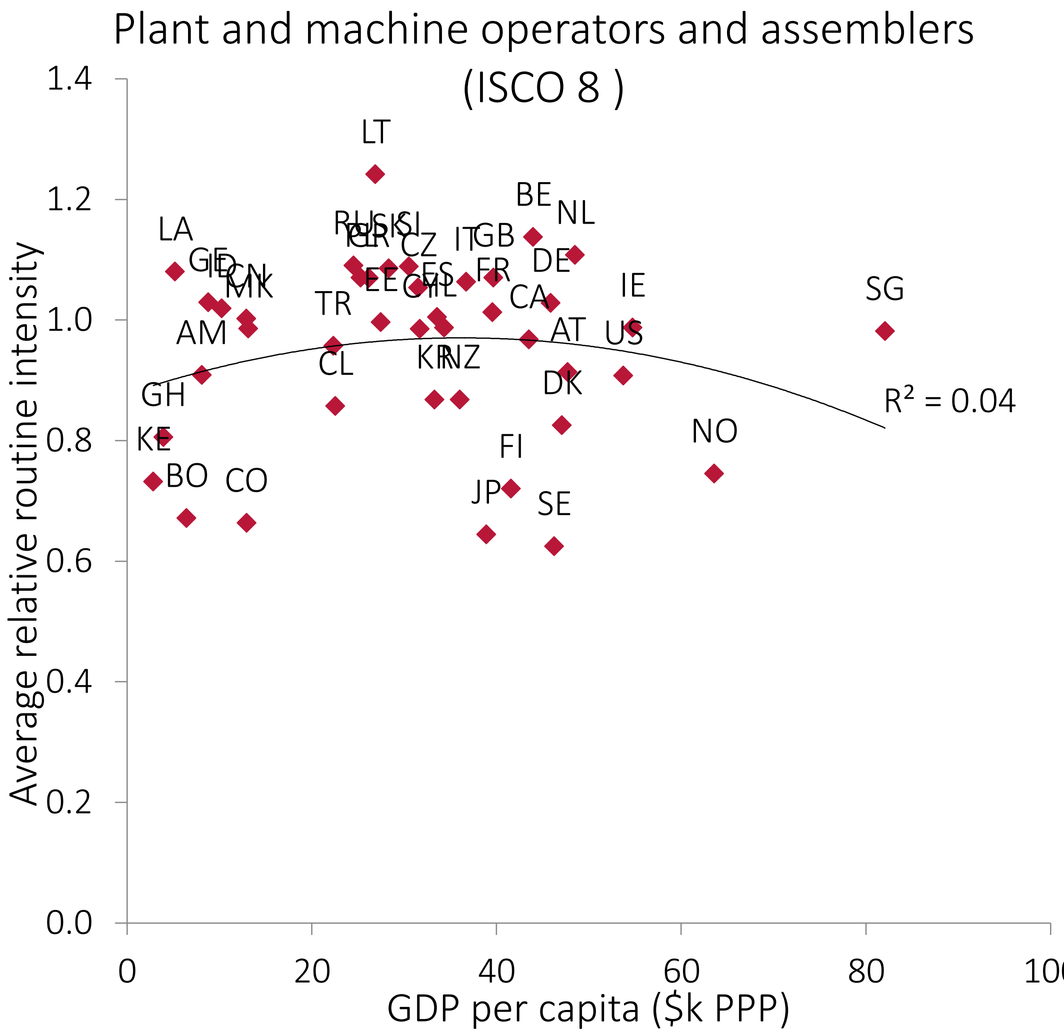
We find noticeable differences of the task content of the high-skilled occupations in the less and more developed countries





But cross-country differences in middle- and low-skilled occupations are not systematicaly related to the development level





We estimate worker-level models of routine task intensity (RTI) accounting for individual and country-sector level factors

	M1	M2	M3	M4
Primary education	0.31***	0.15***		
Tertiary education	-0.59***	-0.23***		
Literacy skills level: up to 1				
Literacy skills level: 3				
Literacy skills level: 4 and 5				
Computer use (worker)				
ICT stock per worker (country)				
Robots per worker (sector)				
Foreign VA share (sector)				
Occupation and sector controls	No	Yes		
No. of obs. / R^2	151,624 / 0.14	151,624 / 0.29		

Pooled OLS regressions. All regressions include dummies for gender, 10-year age groups. The standard errors are clustered at a country level.

Once we control for literacy skills and computer use the difference between primary and secondary educated workers turns insignificant

	M1	M2	M3	M4
Primary education	0.31***	0.15***	0.01	
Tertiary education	-0.59***	-0.23***	-0.17***	
Literacy skills level: up to 1			-0.02	
Literacy skills level: 3			-0.05***	
Literacy skills level: 4 and 5			-0.17***	
Computer use (worker)			-0.48***	
ICT stock per worker (country)				
Robots per worker (sector)				
Foreign VA share (sector)				
Occupation and sector controls	No	Yes	Yes	
No. of obs. / R^2	151,624 / 0.14	151,624 / 0.29	140,071 / 0.31	

Pooled OLS regressions. All regressions include dummies for gender, 10-year age groups. The standard errors are clustered at a country level.

ICT capital stock per worker (country level Eden, Gaggl 2015 data) and robots per worker (by sector, IFR) are negatively related to RTI

	M1	M2	M3	M4
Primary education	0.31***	0.15***	0.01	0.01
Tertiary education	-0.59***	-0.23***	-0.17***	-0.19***
Literacy skills level: up to 1			-0.02	-0.01
Literacy skills level: 3			-0.05***	-0.04***
Literacy skills level: 4 and 5			-0.17***	-0.14***
Computer use (worker)			-0.48***	-0.44***
ICT stock per worker (country)				-0.06***
Robots per worker (sector)				-0.05***
Foreign VA share (sector)				0.02
Occupation and sector controls	No	Yes	Yes	Yes
No. of obs. / R^2	151,624 / 0.14	151,624 / 0.29	140,071 / 0.31	121,109 / 0.32

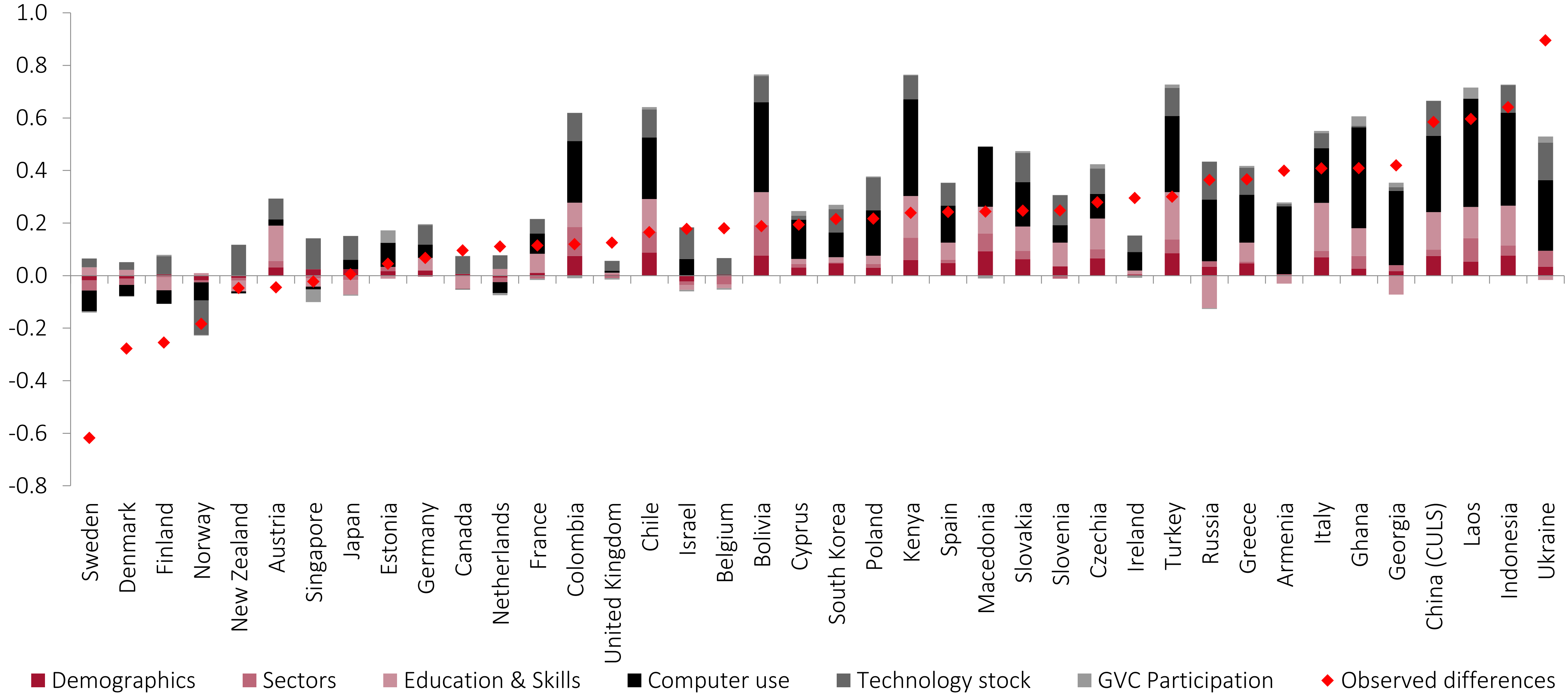
Pooled OLS regressions. All regressions include dummies for gender, 10-year age groups. The standard errors are clustered at a country level.

Next we control for selection to occupations with a two-stage multinomial treatment effects model

	high-skilled (ISCO 1-3)	low-skilled (ISCO 7-9)	RTI
Primary education	-0.20*	0.40***	0.00
Tertiary education	1.43***	-0.45***	-0.13***
Literacy skills level: up to 1	-0.21*	0.12	-0.04
Literacy skills level: 3	0.28***	-0.31***	-0.03
Literacy skills level: 4 and 5	0.70***	-0.59***	-0.19***
Computer use (worker)	1.35***	-1.54***	-0.37***
ICT stock per worker (country)			-0.03
Robots per worker (sector)			-0.04**
Foreign VA share (sector)			0.01
Sector controls	Yes	Yes	No
No. of obs. / countries		121,109 / 32	

Two-stage multinomial treatment effects model. All regressions include dummies for gender, 10-year age groups. The standard errors are clustered at a country level.

Differences in computer use, ICT stock, and education and skills contribute the most to cross-country differences in RTI



What tasks tell us about the global division of work

- We create task content measures which:
  - are worker-based and country-specific
  - but correspond with the established O*NET task content measures

- Occupations are indeed different around the world
  - Non-routine work is more common in the most advanced countries, especially among high-skilled
  - Routine cognitive work has an inverse-U shape relationship with GDP per capita

- Cross-country differences in routine intensity of jobs can be atrributed to:
  - Partly to differences in education, skills and employment structures
  - Notably to differences in computer use and ICT capital stock

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Thanks for listening

Piotr Lewandowski

piotr.lewandowski@ibs.org.pl

www.ibs.org.pl

@ibs_warsaw