

### **The Human Side of Productivity**

Preliminary results on skills with a special focus on Portugal

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#### The productivity of a typical firm lags way behind the frontier... even within the same country & industry

### Log-differences from the top 10% of firms with the highest productivity levels (VA/L) within detailed industries



- These differences are persistent and present in manufacturing and services alike
- See previous GFP and OECD work: Andrews et al (2015, 2016); Berlingieri et al (2017)
- ... and academic literature focusing on the US Bartelsman and Doms (2001); Syverson (2011);

# How do productive firms look like in terms of their *human side*?



By looking at workers and managers, we learn about

- 1. Skills (of managers and workers)
- 2. Diversity (gender, age, cultural background)
- 3. Organisation

(management layers,diversification of tasks,wage structure, workarrangements)

### How to measure the Human Side of Productivity?



# Relying on micro data about millions of firms and employees from several countries

- Universe or large representative sample of >10 employee firms in 54 private non-farm non-financial industries; from the 2000s until latest year
- Deriving two types of output:
  - 1. Aggregated **summary statistics** by detailed cells: **country x industry x year x productivity-segment**

2. **Coefficient estimates** from regressions that include several factors jointly

### Building on previous OECD experience with DMD

- DynEmp (Criscuolo, Gal, Menon, 2014, 2015; Calvino, Crisuolo, Menon, 2016; Calvino, Criscuolo, 2019)
- <u>MultiProd</u> (Berlingieri et al, 2017; 2018; 2020)
- + Complementary to
  ongoing work at the
  industry-level (Cammeraat,
  Samek and Squicciarini, 2020)

# Implementation in collaboration with our partner countries in the Global Forum

Data an	d results	available	Data available	Data being prepared					
Country	Output	Labour input	Worker info	Results coming soon	Access is in progress				
1. Costa Rica	GO, VA	L	Occ, edu	8. Belgium	11. Brazil				
2. Denmark	GO, VA	L, H	Occ, edu	9. Hungary	12. Ireland				
3. France	GO, VA	L, H	Осс	10. Sweden	13. New Zealand				
4. Germany *	GO, VA	L	Occ, edu		14. Spain				
5. Japan **	GO, VA	L, H	edu		+ Italy (ISTAT)				
6. Portugal	GO, VA	L, H	Occ, edu						
[7. Italy (INAPP)*]	GO, VA	L	Occ, edu						

Sample for our analysis: universe of firms and workers with at least 10 employees.

Exceptions: \* Representative sample, not universe

\*\* Firms with at least 50 employees

### Implementation in collaboration with our partner countries in the Global Forum

Data and results available																				
Country	Output	Labour input	Worker info	2000 (	01 02	2 03	<b>C</b> 04 (	<b>Co</b> 05	<b>ve</b> 06	rag 07	<b>ge</b> (	<b>ov</b> 09 1	er .0 :	<b>tir</b> 11 :	<b>ne</b> 12	<b>)</b> 13	14	15	16	2017
1. Costa Rica	GO, VA	L	Occ, edu						x	x	x	x	x	x	x	x	x	x	x	х
2. Denmark	GO, VA	L, H	Occ, edu								x	x	x	x	x	x	x	x	x	x
3. France	GO, VA	L, H	Осс		x	x	x	x	x	x	x	x	x	x	x	x	x	x		
4. Germany *	GO, VA	L	Occ, edu	x	x x	x	x	x	Х	Х	x	x	x	x	Х	x	x	x	x	
5. Japan **	GO, VA	L, H	edu	x	хх	X	Х	X	Х	x	x	x	x	x	х	x				
6. Portugal	GO, VA	L <i>,</i> H	Occ, edu		x	x	x	X	X	X	x	x	X	x	X	x	x	x	Х	X
[7. Italy (INAPP)*]	GO, VA	L	Occ, edu																	

Sample for our analysis: universe of firms and workers with at least 10 employees. Exceptions: \* Representative sample, not universe

\*\* Firms with at least 50 employees



- Relying on <u>occupations</u>
  - As in Acemoglu and Autor (2011, Handbook Chapter) and Goos, Manning, Salomons (2014, AER)
  - But building on the OECD Survey of Adult Skills (PIAAC) to measure abilities and the nature of tasks
- Ranking occupations along several dimensions:
  - <u>Cognitive ability</u> as a general skills measure
     = average of *literacy, numeracy* and *problem solving* scores from PIAAC
  - 2. *"Soft-skills"* or *"social skills"*: <u>Self-organisation and communications</u> Identified through factor analysis from PIAAC responses about the nature of tasks by Grundke, Jamet, Kalamova, Keslair, Squicciarini (2017)
  - 3. *"Hard-skills"*: <u>ICT intensity</u> Nedelkoska and Quintini (2018)
- Top / bottom quartile of occupations = High / low skilled segments
   → More exogenous than measures based on market outcomes (e.g. wages)
- We also use <u>educational attainment</u> as an alternative measure



### - PRELIMINARY RESULTS -

# The skill composition varies systematically along the firm productivity distribution

#### The skill composition of firms

at different segments of the productivity distribution\*



\*Based on VA / L :
Frontier: top 10%;
Medium: 40<sup>th</sup>-60<sup>th</sup> percentile;
Laggards: bottom

- Laggards: bottom 10%;

Within 2-digit industry x year x country cells, averaged across all cells

#### The skill composition varies systematically along the firm productivity distribution with key differences across sectors

Skill composition at different segment of the productivity distribution



#### The skill composition varies systematically along the firm productivity distribution with key differences across sectors in Portugal as well

Skill composition at different segment of the productivity distribution



#### The educational composition varies systematically along the firm productivity distribution in Portugal with key differences across sectors

Skill composition at different segment of the productivity distribution



## **Zooming in at** *frontier vs typical* (median) firm How the frontier differs in terms of skills?

Deviation of the **frontier** from a typical **medium performer\*** by skill groups In percentage points



#### **Zooming in at** *frontier vs typical* (median) firm How the frontier differs in terms of skills <u>by sector</u> in Portugal?

Deviation of the **frontier** from a typical **medium performer\*** by skill groups In percentage points



## **Zooming in at** *frontier vs typical* (median) firm Strong country-specific features

Deviation of the **frontier** from a typical **medium performer** 

Medium skilled workers are relatively more important for German top performers

Note: these are unweighted averages across all detailed industries and years by country



High skilled workers are most critical for top performing firms in France

Low skilled workers used the least in top firms in Costa Rica and Portugal

### A More skilled workforce a positive and robust correlate across all countries & conditional on many controls

### Firm-level regressions of **log labour productivity (VA/L)** on **skill group** shares omitted group: *medium skilled*

	Countries Variables	CRI	DEU	DNK	FRA	JPN <sup>(1)</sup>	PRT
More high (& less medium)	Share of high skilled	1.017***	1.094***	.42***	.626***	.551***	1.265***
always positive		(.104)	(.167)	(.038)	(.015)	(.044)	(.045)
more so than more medium	Share of low skilled	295***	103**	.037***	292***	.115	213***
(& less low)		(.034)	(.046)	(.014)	(.005)	(.182)	(.011)
but often with	High x high	245	-1.13***	568***	303***	368**	-1.335***
decreasing returns		(.193)	(.232)	(.061)	(.027)	(.155)	(.071)
and with complementarities	High x low	492	.314	334**	983***	.858	876***
with medium		(.329)	(.534)	(.132)	(.045)	(.64)	(.125)
	Controls	Manager an share of for	nd worker der reign); share m	mographics (si of part-time <sup>(s</sup> anager/worker	hare of old, yo <sup>2);</sup> occupation o r relative wage	oung; share liversity (H	of women; erfindahl);
Note: Standard errors clustered at	Industry x year FE	YES	YES	YES	YES	YES	YES
the firm level	Firm size categories	YES	YES	YES	YES	YES	YES
(1) Education based skill groups	R-squared	.503	.368	.689	.526	.418	.465
(2) Not available in Costa Rica	No. of observations	49,927	25,483	115,852	1,356,840	13,376	256,161

### More skilled workforce a positive and robust correlate with several variations and checks in Portugal

Firm-level regressions of log labour productivity on skill group shares (omitted : medium skilled)

	(1)	(2)	(3)	(4)	(5)
Productivity	VA/L	VA/L	VA/H	VA/L	VA/L
Skill	Baseline	Baseline	Baseline	Baseline	Education
Variables					
Share of high skilled	1.265***	1.211***	1.072***	0.871***	1.115***
	(.045)	(0.0277)	(0.0426)	(0.0528)	(0.0389)
Share of low skilled	213***	-0.262***	-0.166***	-0.226***	-0.480***
	(.011)	(0.0103)	(0.0109)	(0.0128)	(0.0141)
High x high	-1.335***		-1.157***	-1.010***	-0.608***
	(.071)		(0.0690)	(0.0836)	(0.0649)
High x low	876***		-0.935***	-1.613***	-0.312***
	(.125)		(0.121)	(0.150)	(0.0772)
Controls	Baseline	None	Baseline	Baseline + capital	Baseline
Controls	Dascinic	TUNE	Dascinic	intensity	Dasenne
Industry x year FE	YES	YES	YES	YES	YES
Firm size categories	YES	YES	YES	YES	YES
<b>R</b> -squared	0.465	0.342	0.451	0.506	0.51
Within R-squared	0.292	0.137	0.278	0.380	0.358
No. of observations	256,161	256,161	256,134	107,895	256,069

Note: Standard errors clustered at the firm level

### Firm level regressions confirm a major role for skills Key takeaways

The *human factors* are crucial for productivity:

- Skills + demographics + work organisation explain about <u>30%</u> of the total cross-firm labour productivity dispersion within industries
- 2. Controlling for <u>capital intensity</u> (K/L) raises this to <u>40%</u>
  Without affecting much the coefficients on skills
  → To investigate further how this varies by sector & country & time
  → ... and whether manager skills play a different role

Counterfactual productivity increases (in logs) from changing the skill composition of a **medium performer** firm to match that of a firm at the **frontier** 

0.25		40 ו	How can such unskilling occur?
0.2	Predicted productivity gain (left scale, log)		(i) By raising the skills of <b>existing</b>
0.2	<ul> <li>Size of high skills gap</li> </ul>	30	workers at the firm (ie by training);
0 15	(right scale, pp)		(ii) Reconcile skills needs with
0.15		20	education policies
0.1			(iii)Enabling/incentivising stronger
0.1			labour force participation (eg high
0.05		10	skilled women)
0.05			(iv)Encouraging mobility across firms
			(helps with spillovers)
0		' 0	Policies should aim for a
	JPN DNK DEU PRT FRA CRI		combination of these

Counterfactual productivity increases (in logs) from changing the skill composition of a **medium performer** firm to match that of a firm at the **frontier** 

In less knowledge intensive services, larger gains ... of which upskilling from low to medium is a substantial part in Germany



→ Note that
 this is the
 *largest segment of the economy*,
 with big
 potential gains
 from skills

Counterfactual productivity increases (in logs) from changing the skill composition of a **medium performer** firm to match that of a firm at the **frontier** 

#### **Knowledge intensive services**

Manufacturing

(ICT, prof. services, etc.)



### Summary and next steps

### Summary

- We confirm **skills** play a crucial role for the productivity of firms
- With key differences by **sectors** and **skill** levels
  - Medium skilled segment crucial for less knowledge intensive services
  - In more innovative sectors, it's mainly
     High + Low skills
- Portugal stands out in terms of the weak use of low skilled in most productive firms

#### Next steps

- More countries & link with national policy settings
- Diversity:
  - Gender / Age / Cultural background
  - Their interaction with skills
- Workforce organisation
  - Pay structure
  - Managerial structure
  - Flexible work arrangements (part time & work from home)



### Thank you

OE.CD/GFP

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### **Defining skill measures** A few examples from the general <u>cognitive</u> measure



Measure is country specific

Counterfactual productivity increases (in logs) from changing the skill composition of a **medium performer** firm to match that of a firm at the **frontier** 



Average across countries where all three periods are available (DEU, FRA, PRT) and applying the average skills gap over time as the counterfactual.