

Technology, Firms, Productivity and Employment

Selection of Some Key Findings from the GROWINPRO Project

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- 4IR and its Impact on Productivity
- **4IR and its Impact on Employment**
- Role of Entrants and Incumbents as Carriers of Productivity growth



4IR and its Impact on Productivity



Fourth Industrial Revolution (4IR)

- 4IR is the technology trend expected to reignite slowing productivity growth.
- 4IR describes a technology trend of automation and digitization that increasingly substitute human decision-making with systems of smart interconnected objects.
 - Systems build on new core digital technologies that underlie communication between objects.
 - Development of enabling technologies such as AI or 3D printing enable a wide range of new applications and encourages a feedback loop of further improvements of core technologies
- Even though 4IR build on information and communication technologies of the 3IR, it sets itself apart by the width of its scope, its system impact, the speed it is developing at, and by allowing the automation of intellectual tasks
- 4IR has the potential to drastically change production and R&D processes, business models and the organizational structure of companies in a wide range of industries.
- AI is supposed to be the next general purpose technology (Cockburn et al. 2019)

4IR & Productivity

- Developing 4IR technology is expected to be an important source for increasing productivity (Bartel2007, Brynjolfsson2011)
 - Cost and resource savings
 - Increased flexibility in production
 - Provision of better customized and personalized products & services
 - Better-informed decision making
 - Optimized delivery routes
 - More efficient flow of material and goods
 - Reduced uncertainty

Developing and incorporating the technology comes with many challenges

- Major changes in production processes (Sung2018)
- Additional investments in new and different skills, knowledge and complementary assets (Hecklau2017, Guzman2020)
- Scant empirical evidence on the impact of 4IR on productivity (Acemoglu et al (2020) on adoption of industrial robotics, Benassi et al. (2022) on 4IR patents)

Recent Trends: Strong Increase of 4IR patents



Source: Peters and Trunschke (2022), Behrens et al. (2021)

Shift Towards more Bridging Technologies

4IR Bridging Patents combine more than one technology area (core, enabling, application)



Share of bridging patents increased from 11% to 60%

Share doubled alone between 2011 and 2018.

- 20% combine core and applied tech
- 17% enabling and applied tech
- 15% core and enabling tech
- 7 % combine all three tech areas

Increase in patents combing 4IR and non-4IR technological areas → decline in the digital intensity of 4IR patents

Source: Peters and Trunschke (2022)), Behrens et al. (2021)

Productivity Impact of 4IR and Long-Run Benefits

- Dynamic discrete choice model on 4IR vs non-4IR technology
- Invest in 4IR development if long-run expected benefits > development costs
- Sample of German high-tech manufacturing firms 2008-2016

Productivity Impact



4IR innovations + 7.2% TFP



Non-4IR innovations + 5.1% TFP

Joint: +8.8% (substitutes)

Policy simulation: 25% subsidy for 4IR-innovations



2.25% 4IR innovations



-1.83% non-4IR innovations

Overall increase of innovations

Lon-run net benefits

- Dev costs higher for 4IR than non-4IR
- Dev costs higher for firms w/o 4IR experience than w/ 4IR experience
- High entry barriers for 4IR
- Long-run benefits are strongly positively skewed



■ Expected long-run benefits ■ Realized costs ■ Net realized benefits

Source: Peters and Trunschke (2021)

Productivity Increases ...

Have gained momentum



Indication that we slowly moved beyond the installation phase of the 4IR Investment in own Data bases and software are important complementary assets for benefiting from AI

Are mainly driven by enabling technologies



Source: Peters and Trunschke (2022), Blandinieres and Peters (2022)

Stronger Digitized Firms More Resilient During COVID Crisis

Covid-19 pandemic and counter measures negatively affected economies

- Revenue decline (Bloom et al., 2020)
- Disrupted supply chain (Brodeur et al., 2021)
- Uncertainty and financial restrictions (Bloom et al., 2021)
- Labor shortages (Paunov and Planes-Satorra, 2021)

Adverse environment for innovation activities

✤ But not all firms equally affected by Covid-19 → Diff-in-Diff approach using German CIS data for the period 2019-2020 (realized)/22 (expected innov. exp.)

Evidence for long Covid effecs in innovation

	ΔLog(R&D)	ΔLog(InnoExp)	ΔLog(Inv)	ΔLog(InnoExp)	ΔLog(InnoExp)	ΔLog(InnoExp)
	2019-2020	2019-2020	2019-2020	2020-2021	2021-2022	2019-2022
Negativly affected	-0.124***	-0.173***	-0.291***	-0.042***	-0.005*	-0.083***
by Covid-19	(-4.91)	(-6.29)	(-7.15)	(-3.80)	(-1.65)	(-5.83)

Stronger digitized firms have been less affected by Covid-19 shock

		ΔLog(R&D)	ΔLog(InnoExp	o) ΔLog(Inv)	
Treated & Low Digi	b1	-0.159***	-0.265***	-0.135	
Treated & High Digi	b2	-0.100***	-0.191***	-0.373***	
Non-treated & High Digi	b3	0.187***	0.102	0.012	
b1=b2		0.0731	0.0368	0.1043	
b2=b3		0.0000	0.0000	0.0004	Source: Trunschke, Peters,
b1=b3		0.0000	0.0000	0.2498	Czarnitzki und Rammer (2022)



4IR and its Impact on Employment



Automation and Dynamics in Employment and Wages

- Concern about the impact of the recent wave of innovation (automation, robots, AI, etc) on employment
- This is an old-time worry, but is this time different?
- In the contemporary economic scenario one can envisage at least two relatively new challenges:
 - The type of jobs affected is much more diffused and difficult to identify (routine-intensive rather than manual; cf. Autor 2015, Autor et al. 2013, Frey and Osborne 2017, Furman and Seamans 2018, Goos et al. 2014, Traijtenberg 2018)
 - The type of firms and sectors impacted is also much larger (general rethinking of production processes; cf. Caliendo and Rossi-Hansberg 2012)
- Evidence on direct effect of automation technologies is scarce, mixed and typically aggregate (Dauth et al. 2018, Acemoglu and Restrepo 2017, Graetz and Michaels 2018)

Automation and Dynamics in Employment and Wages

- Investment in automation *increase* firms' contemporaneous net employment growth rate, mainly due to lower separation rates, and this effect is similar across occupational categories
 - Automation spikes are identified by imports of automation-intensive capital goods
 - Different types of workers according to occupational categories and routine-intensive vs. non routine-intensive jobs
 - French firm level data for the period 2002-2015
- Spike events related to the adoption of automation- or AI-related capital goods are *not* followed by an increase in within-firm wage inequality nor in gender inequality.
 - Instead, wages increase by 1% three years after the events at different percentiles of the wage distribution
 - Most of the overall wage increase is enjoyed by newly hired workers
- Mixed evidence of adoption of automation- or AI on gender inequality: No impact on gender pay gap in France, but negative impact in Estonia.
- Overall, findings show the picture of a rather `labor friendly' effect of the latest wave of new technologies within adopting firms

Source: Domini, Grazzi, Moschella, Treibich (2019, 2021), Pavlenkova, Alfieri, Masso (2021)



Role of Entrants and Incumbents as Carriers of Productivity growth



Returns to R&D and the Heterogeneity between Entrants and Incumbents

Incumbents are more productive and spend more on innovation

However, entrants have much higher productivity returns to innovation Entrants' Return to R&D Exceeds Incumbents'

	(1)	(2)	(3)	(4)	(5)	(6)
	Entrants	Incumbents	Diff.	Entrants	Incumbents	Diff.
Log Capital	0.311*** (0.003)	0.154*** (0.000)	0.157***	0.327*** (0.001)	0.163*** (0.009)	0.164***
Log Employees	0.077*** (0.008)	0.067*** (0.000)	0.010	0.074*** (0.000)	0.067*** (0.001)	0.007**
Log R&D	0.138*** (0.001)	0.047*** (0.001)	0.091***			
Lagged Log R&D	. ,	. ,		0.070*** (0.002)	0.038*** (0.004)	0.032***
Observations	20,779	28,753		11,400	17,684	

ACF specifications including controls for firm age, industry FE, year FE, data source FE, East Germany FE. Difference in coefficients tested following Clogg et al. '95. * p < 0.10, ** p < 0.05, *** p < 0.01

 Return to innovation peaks in the first years of firm existence, then declines

Return to R&D Slowly Decays over Time

Interaction of R&D Expenditures with Firm Age



Returns to R&D Throughout the Productivity Distribution

Throughout the productivity distribution, returns to innovation much more dispersed for entrants than for incumbents



Different patterns in learning from external knowledge capital between entrants and incumbents

Source: Lubczyk and Peters (2021), Masso and Tiwari (2021)



Thank you for your attention!

