Choosing Technologies: Benefits of Developing Fourth Industrial Revolution Technologies

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ZEW

4IR: Automation of the Economy

- **Technology trend across technology fields** (Ménière et al., 2017)
  - Driven by the internet of things
  - Allowing to build systems of smart connected objects
  - Enables use of further technology, e.g. cloud computing, AI
- **Large-scale automation of task groups and *intellectual* tasks**
- **Analyze and diagnose problems via transmission and evaluation of large amounts of data without human involvement**

4IR: Application Areas

- Enterprises

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- Infrastructure

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- Products / Home and personal use

4IR: Potential Benefits and Costs

- **Developing 4IR technology is an important opportunity for increased firm performance**
  - Highly flexible production (Bartel et al., 2007)
  - More customizable/ personalized products & services (Bartel et al., 2007)
  - Better informed decision making (Brynjolfsson et al., 2011)
  - Cost savings and less uncertainty (Bresnahan et al., 2002; Arvanitis, 2005)

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- **Developing and incorporating the technology comes with many challenges**
  - Major changes in production processes (Sung (2018))
  - Need to acquire different competences/knowledge (Hecklau et al. (2017), Guzmán et al. (2020))

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  - Major changes in production processes (Sung (2018))
  - Need to acquire different competences/knowledge (Hecklau et al. (2017), Guzmán et al. (2020))
- **When deciding which technology type to develop firms have to compare expected long-run benefits and costs**

Research Question and Approach

- **What are the long-run expected benefits and costs of developing 4IR technologies (compared to non-4IR)?**

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  - Differentiate between 4IR and non-4IR technology
  - Account for dynamic nature of technology development decisions
  - Allow productivity to develop endogenously

Research Question and Approach

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- **Construct a dynamic structural model of firms' decisions to develop different technologies**
  - Differentiate between 4IR and non-4IR technology
  - Account for dynamic nature of technology development decisions
  - Allow productivity to develop endogenously
- **Estimate its parameters with a large panel data set (2008-2016)**
- **Calculate long-run benefits of both 4IR and non-4IR technology**
- **Conduct counterfactual analyses, e.g. to assess the impact of 4IR subsidies**

Main Contributions

- **Dynamic models of R&D choice** (Aw et al., 2011; Peters et al., 2017; Chen et al., 2021; Maican et al., 2020)
  - $\Rightarrow$ Differentiate between R&D for different types of technology
  - $\Rightarrow$ Calculate short- and long-run benefits and development costs

Main Contributions

- **Dynamic models of R&D choice** (Aw et al., 2011; Peters et al., 2017; Chen et al., 2021; Maican et al., 2020)
  - $\Rightarrow$ Differentiate between R&D for different types of technology
  - $\Rightarrow$ Calculate short- and long-run benefits and development costs

- **Productivity effects of digital technologies** (Brynjolfsson et al., 2011; Stiroh, 2002; Bertschek et al., 2013)
  - $\Rightarrow$ Investigate productivity effects of 4IR technology
  - $\Rightarrow$ Employ new patent classification as a measure for 4IR technology

Key Take-Aways

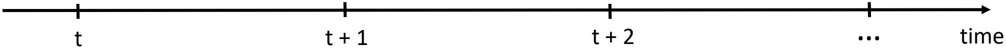
- Significant **positive productivity effects** of **4IR and non-4IR technology**
- **Productivity effect** of developing **4IR** technology is **higher**
- **Long-run benefits** are strongly **positive skewed**
- **Higher** startup and continuation **development costs** for **4IR**
- 25% **cost reduction** for **4IR** technology development **shifts** development activity **towards 4IR**
  - **overall development** activity **increases**

Theoretical Model: Overview

- **Extension of R&D choice models** (Aw et al., 2011; Peters et al., 2017, 2020)
  - Dynamic programming model
  - Links R&D/innovation $\longrightarrow$ productivity $\longrightarrow$ short-run firm profits $\longrightarrow$ long-run benefits
  - Extension allowing for R&D choice in different technology types
    - 4IR technology (d_{it})
    - Non-4IR technology (n_{it})

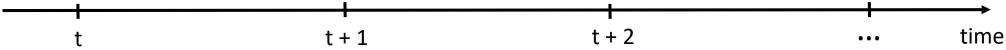
Details

Theoretical Model: Summary

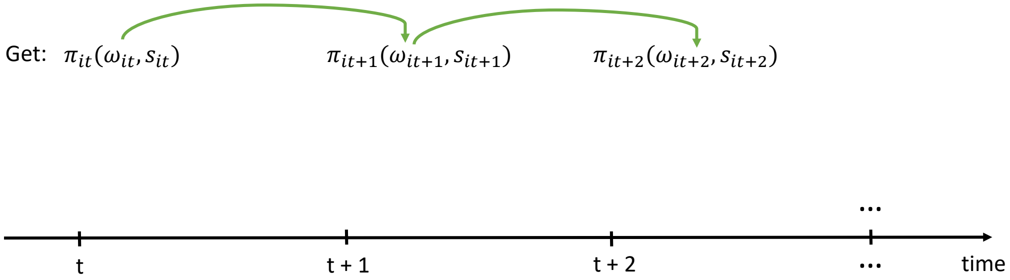


Theoretical Model: Summary

Get: $\pi_{it}(\omega_{it}, s_{it})$ $\pi_{it+1}(\omega_{it+1}, s_{it+1})$ $\pi_{it+2}(\omega_{it+2}, s_{it+2})$ …



Theoretical Model: Summary



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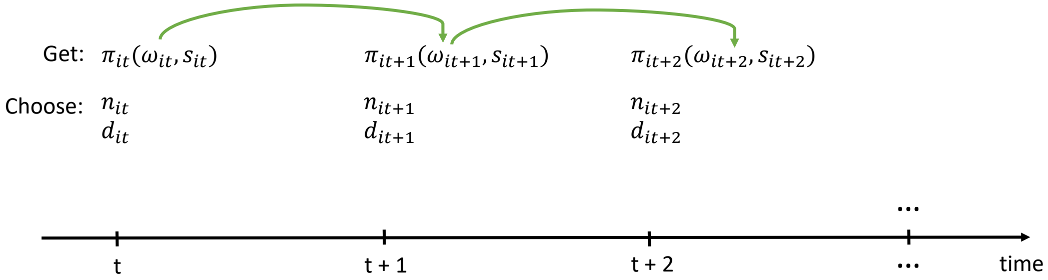
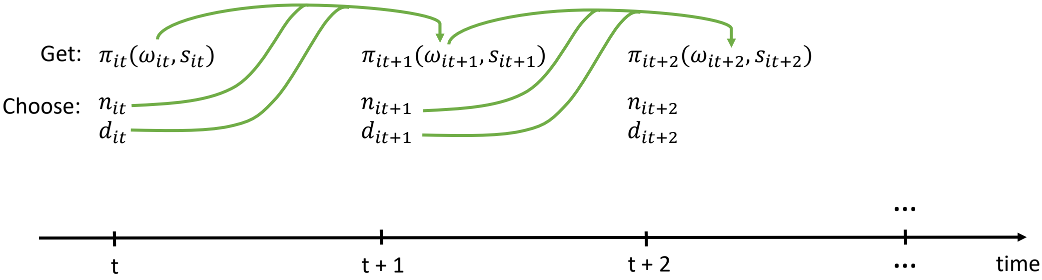
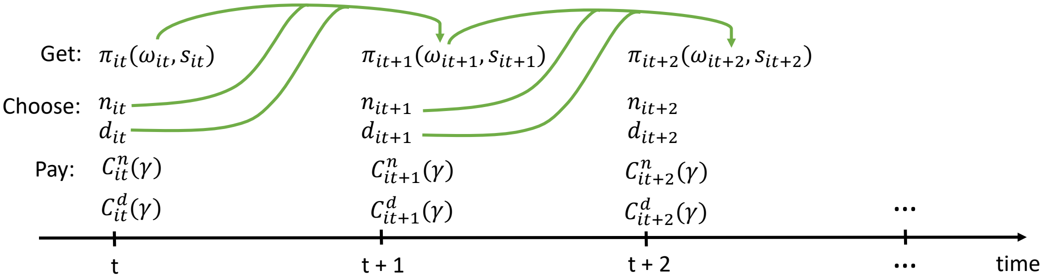


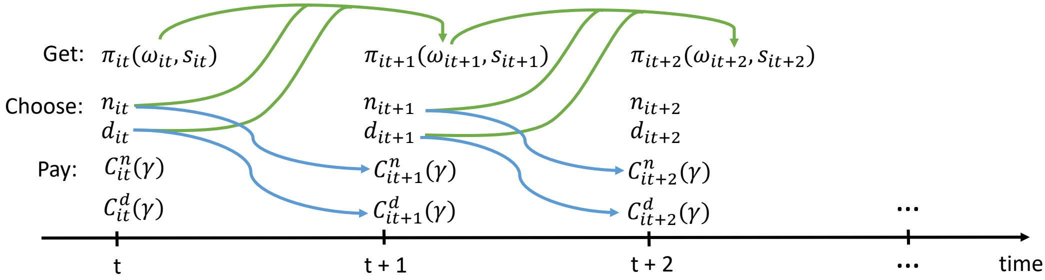
Theoretical Model: Summary



Theoretical Model: Summary



Theoretical Model: Summary



Data

- **Mannheim Innovation Panel (MIP)**
  - Representative survey of German firms with $5+$ employees in manufacturing and business services
  - Period 1993-2018
  - Information on firm variables (employees, material, capital, revenues, industry classification)

- **Patent data**
  - PATSTAT - Worldwide patent database
  - Large number of patent characteristics (CPC technology class, patent holder, patent family, citations, etc.)
  - Patent classification from EPO indicating 4IR CPC classes 4IR Classification

- **Sample restriction** to firms with 25+ employees in five high-tech sectors between 2008-2016 Summary statistics

Empirical Model: Overview

- We estimate all model parameters in two stages
- **1st stage**
  - Estimate demand elasticity η_j Details
  - Estimate revenue function to get all static parameters
    - Deal with simultaneity issue
    - Calculate productivity (ω_{it})
- **2nd stage**
  - Estimating dynamic parameters (cost parameters, value function and expected value function)

Estimation: 1st stage

- Static Parameters
  - Estimate the revenue function from the theoretic model

$$r_{it} = \lambda_{jt} + (1+\eta_j)(\beta_0 + \beta_k k_{it} + \sum_{z=1}^{Z} \beta_{a_z} A_{it}^z + \beta_e E_{it}$$
$$- (\alpha_1 \omega_{it\text{-}1} + \alpha_2 \omega_{it\text{-}1}^2 + \alpha_3 \omega_{it\text{-}1}^3 + \alpha_4 d_{it\text{-}1} + \alpha_5 n_{it\text{-}1} + \alpha_6 d_{it\text{-}1} \cdot n_{it\text{-}1}) + \epsilon_{it}$$

  - Follow idea from Olley and Pakes (1996) to account for simultaneity bias

    $\Rightarrow$ Define ω_{it} as a function of observables and replace it in the equation
  - Estimate revenue equation using NLLS
  - Calculate productivity (ω_{it}) and profits for second stage

Estimation: 2[nd] stage

- Dynamic Parameters
  - Estimate development cost distribution parameters γ and benefits
  - Based on nested fixed point algorithm
  - Likelihood function details

$$\mathcal{L}(\gamma | d_{it}, n_{it}, s_{it}) = \prod_i \prod_t P(d_{it}, n_{it} | s_{it}, \gamma)$$

  - Problem: Likelihood function is very complex $\Rightarrow$ local maxima problem when using maximum likelihood
  - Use Bayesian Markov Chain Monte Carlo estimation

details

Results Stage 1: Productivity Evolution Parameters

Variable	Coef	SE
ω_{it-1}	0.403^{***}	0.041
ω_{it-1}^2	0.342^{***}	0.007
ω_{it-1}^3	-0.069^{***}	0.003
d_{it-1}	0.072^{***}	0.022
n_{it-1}	0.051^{***}	0.007
$n_{it-1} \cdot d_{it-1}$	-0.035	0.024
SE($\hat{\xi}$)	0.098	
Observations	3472	

Notes: Significance at the * 5% level, ** 1% level, *** 0.1% level. Time dummy variables are included in estimation but not reported. Chemical industry dummy is excluded as reference category.

Results Stage 1: Cost Function Parameters

Variable	Coef	SE
Capital	-0.094^{***}	0.003
A2: $10-19$	0.051	0.029
A3: $20-49$	0.028	0.027
A4: $50+$	-0.08^{***}	0.03
Export	-0.001	0.016
Observations	3472	

Notes: Significance at the * 5% level, ** 1% level, *** 0.1% level. Time dummy variables are included in estimation but not reported. Chemical industry dummy is excluded as reference category.

Results Stage 2: Development Cost Parameters

		Parameter(γ) Mean	Parameter(γ) SD	Realized cost[1] Mean	Realized cost[1] SD
Non-4IR technology	γ^{sn}	30.279	2.345	40.790	40.977
	γ^{cn}	3.296	0.143	40.513	52.427
4IR technology	γ^{sd}	70.442	6.907	71.189	75.163
	γ^{cd}	7.308	0.530	47.359	68.244

[1] Realized costs from simulations

Results Stage 2: Marginal Long-run Benefits

	Mean	Median	SD	Min	Max
$\Delta EV(n_{it}\|s_{it})$	70.648	23.460	108.508	0.478	697.547
$\Delta EV(d_{it}\|s_{it})$	118.698	27.565	233.352	0.650	1877.031
Observations	3,472				

Results Stage 2: Marginal Long-run Benefits

	Mean	Median	SD	Min	Max
$\Delta\ EV(n_{it} \mid n_{it-1} = 0, s_{it})$	55.318	16.226	96.051	0.478	637.402
$\Delta\ EV(n_{it} \mid n_{it-1} = 1, s_{it})$	110.761	59.093	127.407	0.775	697.547
$\Delta\ EV(d_{it} \mid d_{it-1} = 0, s_{it})$	95.783	24.659	187.450	0.650	1702.660
$\Delta\ EV(d_{it} \mid d_{it-1} = 1, s_{it})$	288.421	155.681	359.493	3.986	1877.031
Observations	3,472				

Simulations: Cost Reduction

- Simulation of a 25% R&D subsidy for 4IR technology development

	Year 2	Year 5	Year 7	Year 10
Δ 4IR rate	0.0157	0.0249	0.0255	0.0237
Δ non-4IR rate	-0.0143	-0.0185	-0.0198	-0.0205
Δ productivity	-0.0061	-0.0059	-0.0041	0.0011

Notes: Numbers represent average differences over 50 simulations with and without the policy change.

Conclusion and Outlook

- Constructed a structural model of firm’s technology development choice
- Positive productivity effects of developing 4IR
- Higher productivity effect for 4IR than for non-4IR technology
- Substantially higher startup costs for developing either technologies
- Development costs for 4IR technology are more than double the costs for non-4IR technology
- Expected benefits for 4IR technology are higher
- Experienced developers have higher expected benefits
- 25% 4IR subsidy substantially increases 4IR development (+2.3 PP) and reduces non-4IR development (-2.1 PP), but overall effect still positive
- Outlook: Further policy simulations

Thanks for your attention!

Appendix: Theoretical Model: Part 1 - Consumer Demand

- Assume monopolistic competition (Dixit and Stiglitz, 1977)

- **Demand** for each firm *i*'s

$$q_{it} = \left(\frac{p_{it}}{P_{jt}}\right)^{\eta_j} \frac{I_{jt}}{P_{jt}} e^{\phi_{it}} = \Phi_{jt} p_{it}^{\eta_j} e^{\phi_{it}},$$

  - P_{jt} : Industry *j*'s price index
  - I_{jt} : Market size
  - η_j : Demand elasticity
  - ϕ_{it} : Demand shifter

Appendix: Theoretical Model: Part 1 - Price Setting

- **Marginal costs**

$$C_{it}^{M} = \frac{C\left(K_{it}, W_{it}, A_{it}, E_{it}\right)}{e^{\psi_{it}}}$$

  - K_{it} : Capital stock
  - W_{it}: Input market prices
  - A_{it} : Firm age
  - E_{it} : Export status
  - ψ_{it} : Production efficiency

Appendix: Theoretical Model: Part 1 - Price Setting

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- **Price setting rule** given by profit maximization

$$p_{it} = \frac{\eta_j}{1+\eta_j} C_{it}^{M}$$

Appendix: Theoretical Model: Part 1 - Firm Profits

- **Revenues**

$$R_{it} = \left(\frac{\eta_j}{1+\eta_j}\right)^{1+\eta_j} \Phi_{jt} C\left(\cdot\right)^{1+\eta_j} e^{-(1+\eta_j)\,\omega_{it}}$$

  - ω_{it} : Revenue productivity
    (combined production efficiency and demand shifter)

Appendix: Theoretical Model: Part 1 - Firm Profits

- **Revenues**

$$R_{it} = \left(\frac{\eta_j}{1+\eta_j}\right)^{1+\eta_j} \Phi_{jt} C\left(\cdot\right)^{1+\eta_j} e^{-(1+\eta_j)\,\omega_{it}}$$

  - ω_{it} : Revenue productivity
    (combined production efficiency and demand shifter)

- **Short-run profits**

$$\pi(\omega_{it}) = -\frac{1}{\eta_j} R_{it}$$

Appendix: Theoretical Model: Part 2 - Productivity Development

- Technology development decision affects firm's future productivity
- Productivity ω_{it} evolves as an endogenous Markov process

$$\omega_{it+1} = g(\omega_{it}, d_{it}, n_{it}) + \xi_{it+1}, \; with \; \xi_{it+1} \sim f(0, \sigma_{\xi}^{2})$$

Appendix: Theoretical Model: Part 3 - Dynamic Development Decision

- Technology development is costly
- **Development costs** unobserved
- Model as draw from an exponential distribution

$$C_{it}^{d} \sim exp(\gamma^{d}(K_{it}, d_{it-1})),$$
$$C_{it}^{n} \sim exp(\gamma^{n}(K_{it}, n_{it-1})).$$

  - γ^{d}, γ^{n} : Technology development cost parameter for 4IR- and non-4IR innovation cost distributions

Appendix: Theoretical Model: Part 3 - Dynamic Development Decision

- Firms choose to develop d or n to maximize their discounted future value

- **Value function**

$$V(s_{it}) = \pi(\omega_{it}) + \max_{d,n\in\{0,1\}} \left\{ \delta E[V(s_{it+1}|\omega_{it}, d_{it}, n_{it})] - C^d_{it} \cdot d_{it} - C^n_{it} \cdot n_{it} \right\},$$

  - $s_{it} = (\omega_{it}, K_{it}, d_{it-1}, n_{it-1})$
  - δ : Discount factor

Appendix: Theoretical Model: Part 3 - Dynamic Development Decision

- Assume: Sequential decision making:
  - First, non-4IR development

$$E[V(s_{it+1}|\omega_{it}, d_{it}, n_{it})] = \int_{\omega} \left\{ \begin{array}{l} V(s_{it+1}|n_{it} = 1; \omega_{it}) - C^{n}_{it}, \\ V(s_{it+1}|n_{it} = 0; \omega_{it}) \end{array} \right\} dG\left(\omega_{it+1}|\omega_{it}, d_{it}, n_{it}\right)$$

  - Second, 4IR development

$$V(s_{it+1}|n_{it}; \omega_{it}) = \int_{\omega} \left\{ \begin{array}{l} E[V(s_{it+1}|d_{it} = 1, n_{it}, \omega_{it})] - C^{d}_{it}, \\ E[V(s_{it+1}|d_{it} = 0, n_{it}, \omega_{it})] \end{array} \right\} dG\left(\omega_{it+1}|\omega_{it}, d_{it}, \right)$$

Appendix: Theoretical Model: Part 3 - Benefit of Developing 4IR Technology

- **Marginal benefit** of technology development investment is given by the difference in expected future value of the firm:
  - **Developing 4IR technology**

$$\Delta_d E_t[V(s_{it+1})] = \delta E_t[V(s_{it+1}|\omega_{it}, n_{it}; d_{it} = 1)] - \delta E_t[V(s_{it+1}|\omega_{it}, n_{it}; d_{it} = 0)]$$

  - **Developing non-4IR technology**

$$\Delta_n E_t[V(s_{it+1})] = \delta E_t[V(s_{it+1}|\omega_{it}, d_{it}; n_{it} = 1)] - \delta E_t[V(s_{it+1}|\omega_{it}, d_{it}; n_{it} = 0)]$$

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Appendix: Demand Elasticities - Estimation

- Using profit equation 24

$$\pi_{it} = \pi(\omega_{it}) = -\frac{1}{\eta_j} R_{it} \Leftrightarrow \frac{C_{it}^M q_{it}}{R_{it}} = 1 + \frac{1}{\eta_j}$$

- Regress total variable cost - revenue ration on industry-specific constants
- Back out industry demand elasticity η_j Results

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Appendix: Demand Elasticities - Results

Industry	Obs.	η
Chemicals	1,164	-3.11
Machinery	1,824	-3.9
Electrical engineering	1,317	-3.99
Instruments	922	-3.34
Vehicles	905	-4.29
Observations	6132	

Notes: Industry demand elasticity estimates are based on a larger sample as we only require total variables costs and revenues to be non-missing and also include firms that are observed only once or with gaps.

Appendix: Summary Statistics

Variable	Model	Unit	mean	med	sd	min	max
Revenues	R	mio €	409.237	30.125	995.27	0	9978
Fixed capital	K	mio €	229.12	6.209	715.277	0	10284.11
Material cost	M	mio €	228.201	13.699	620.883	0	8700.333
Labor cost		mio €	76.918	7.578	193.104	0	2295.061
Total variable cost	$C^M q$	mio €	305.119	22.054	772.844	0	8861.522
Firm age							
0-9	A^1	0/1	.132	0	.338	0	1
10-19	A^2	0/1	.256	0	.436	0	1
20-49	A^3	0/1	.358	0	.479	0	1
50+	A^4	0/1	.24	0	.427	0	1
Exporter	E	0/1	0.917	1	0.277	0	1
Non-digital tech	n	0/1	0.227	0	0.419	0	1
Digital tech	d	0/1	0.085	0	0.278	0	1

Notes: Number of observations: 45589. Sample period: 1993-2016. For ease of representation, all monetary variables are in million euro, for estimation we use their log values.

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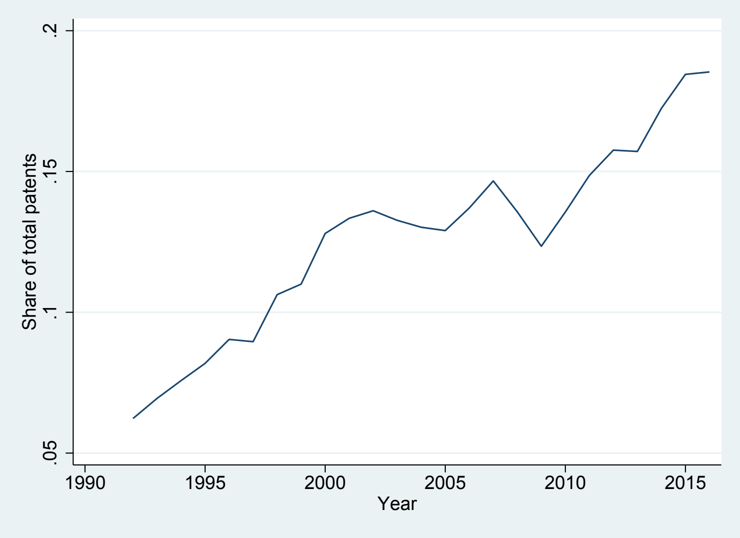
Appendix: 4IR Patent classification

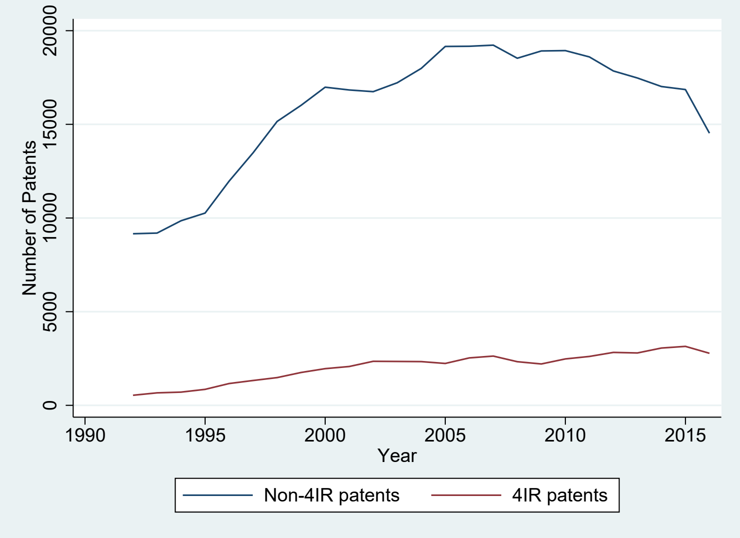
- Developed by the European Patent Office in 2017
- Patent examiners from all technology fields identified 320 CPC fields they relate to building blocks of 4IR
- Three building blocks

Technologies	Description	Examples
Core technologies	Basic technologies to build 4IR technology on	sensors, cloud storage, adaptive databases
Enabling technologies	Build on core technologies and allow a variety of application domains	big data diagnostics, virtual reality, position determination sys.
Application domains	Applications using core- and enabling technologies	intelligent robotics, smart home sys., wearables

Appendix: Increasing Share of 4IR Patents over Time



Appendix: Development of 4IR and Non-4IR Patents over Time



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Appendix: Data: Patents per Industry

Industry	Non-4IR Patents	4IR Patents	% 4IR Patents	Total Patents
Food	474	9	.0186	483
Textiles	1,117	89	.0738	1,206
Paper/Wood	2,564	600	.1896	3,164
Chemicals	52,432	1,203	.0224	53,635
Plastic	4,616	130	.0274	4,746
Minerals	2,068	67	.0314	2,135
Metal	5,156	214	.0399	5,370
Machinery	38,392	3,318	.0795	41,710
Electronics	46,763	14,407	.2355	61,170
Instruments	11,421	2,936	.2045	14,357
Vehicles	26,518	7,658	.2241	34,176
Misc. manuf.	890	98	.0992	988
Total/Average	200,852	34,475	.1465	235,327

Appendix: Empirical Model: Overview

- We estimate all model parameters in two stages
- **1st stage**
  - Estimate demand elasticity η_j Details
  - Estimate revenue function to get all static parameters
    - Deal with simultaneity issue
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- **2nd stage**
  - Estimating dynamic parameters (cost parameters, value function and expected value function)

Appendix: Empirical Model: Stage 1 - Static Parameters

- Assume Cobb-Douglas type functional form of cost function
  - Assume input prices W do not differ between firms (so $W_{it} = W_t$)

$$C(K_{it}, W_{it}, A_{it}, E_{it}) = K_{it}^{\beta_k} W_t^{\beta_w} e^{\beta_0 + \sum_{z=1}^{Z} \beta_{a_z} A_{it}^z + \beta_e E_{it}}$$

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- Inserting $C(.)$ into the revenue equation and taking logs gives

$$r_{it} = \lambda_{jt} + (1+\eta_j)(\beta_0 + \beta_k k_{it} + \sum_{z=1}^{Z} \beta_{a_z} A_{it}^z + \beta_e E_{it} - \omega_{it}) + \epsilon_{it}$$

  - λ_{jt} includes all factors constant over firms in each industry
  - ϵ_{it} is an i.i.d, zero mean error term

Appendix: Empirical Model: Stage 1 - Static Parameters

- Replace ω_{it} with productivity development process

$$
\begin{aligned}
r_{it} = \lambda_{jt} + (1 + \eta_j)(\beta_0 + \beta_k k_{it} + \sum_{z=1}^{Z} \beta_{a_z} A_{it}^{z} + \beta_e E_{it} \\
- (\alpha_1 \omega_{it\text{-}1} + \alpha_2 \omega_{it\text{-}1}^2 + \alpha_3 \omega_{it\text{-}1}^3 + \alpha_4 d_{it\text{-}1} + \alpha_5 n_{it\text{-}1} + \alpha_6 d_{it\text{-}1} \cdot n_{it\text{-}1}) + \epsilon_{it}
\end{aligned}
$$

Appendix: Empirical Model: Stage 1 - Static Parameters

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$$r_{it} = \lambda_{jt} + (1 + \eta_j)(\beta_0 + \beta_k k_{it} + \sum_{z=1}^{Z} \beta_{a_z} A_{it}^z + \beta_e E_{it}$$
$$- (\alpha_1 \omega_{it\text{-}1} + \alpha_2 \omega_{it\text{-}1}^2 + \alpha_3 \omega_{it\text{-}1}^3 + \alpha_4 d_{it\text{-}1} + \alpha_5 n_{it\text{-}1} + \alpha_6 d_{it\text{-}1} \cdot n_{it\text{-}1}) + \epsilon_{it}$$

- Problem: Productivity ω_{it} is unobserved (simultaneity bias)

Appendix: Empirical Model: Stage 1 - Static Parameters

- Control function approach á la OP 1996, LP 2003 and ACF 2015
  $\Rightarrow$ Define ω_{it} as a function of observables

Appendix: Empirical Model: Stage 1 - Static Parameters

- Control function approach á la OP 1996, LP 2003 and ACF 2015
  $\Rightarrow$ Define ω_{it} as a function of observables
- We use model structure to get material demand equation

$$m_{it} = \beta_{jt} + (1+\eta)\beta_k k_{it} + (1+\eta)\sum_{z=1}^{Z}\beta_{a_z}A_{it}^{z} + (1+\eta)\beta_e E_{it} - (1+\eta)\omega_{it}$$

$$\Leftrightarrow \omega_{it} = \left(\tfrac{1}{1+\eta_j}\right)\beta_{jt} + \beta_k k_{it} + \sum_{z=1}^{Z}\beta_{a_z}A_{it}^{z} + \beta_e E_{it} - \left(\frac{1}{1+\eta_j}\right)m_{it}$$

- Estimate revenue equation using NLLS
- Calculate productivity (ω_{it}) and profits for second stage

Appendix: Estimation: Stage 2 - Dynamic Parameters

- Dynamic Parameters
  - Estimate development cost distribution parameters $\gamma = (\gamma^d, \gamma^n)$ and long-run benefits
  - Allow costs to differ for firms with respective technology experience (continuation cost γ^{cd}, γ^{cn}) and without (startup costs γ^{sd}, γ^{sn})
  - Based on nested fixed point algorithm
  - Likelihood function Details

$$\mathcal{L}(\gamma | d_{it}, n_{it}, s_{it}) = \prod_i \prod_t P(d_{it}, n_{it} | s_{it}, \gamma)$$

  - Problem: Likelihood function is very complex $\Rightarrow$ local maxima problem when using maximum likelihood
  - Use Bayesian Markov Chain Monte Carlo estimation

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Appendix: Stage 2 - Likelihood Function

$$
\begin{aligned}
\mathcal{L}(\gamma|d_{it}, n_{it}, s_{it}) &= \prod_i \prod_t P(d_{it}|n_{it}, s_{it}, \gamma) P(n_{it}|n_{it-1}, s_{it}, \gamma) \\
&= \prod_i \prod_t P(d_{it} = 1|n_{it}, s_{it}, \gamma^d)^{d_{it}} P(d_{it} = 0|n_{it}, s_{it}, \gamma^d)^{1-d_{it}} \\
&\quad P(n_{it} = 1|n_{it-1}, s_{it}, \gamma^n)^{n_{it}} P(n_{it} = 0|n_{it-1}, s_{it}, \gamma^n)^{1-n_{it}} \\
&= \prod_i \prod_t P(d_{it} = 1|n_{it} = 1, d_{it-1} = 1, s'_{it}, \gamma^{dm})^{d_{it} n_{it} d_{it-1}} \\
&\quad P(d_{it} = 1|n_{it} = 1, d_{it-1} = 0, s'_{it}, \gamma^{ds})^{d_{it} n_{it} (1-d_{it-1})} \ldots
\end{aligned}
$$

- Firms choose to develop if exp. benefits are larger than development costs

$$
P(d_{it} = 1|(.)) = P(E[V(d_{it} = 1|(.)] - E[V(d_{it} = 0|(.)] > C^d)
$$

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Appendix: Stage 2 - Likelihood Function

- We assume development costs to be exponentially distributed

$$P(d_{it} = 1|(.)) = 1 - e^{-\frac{\delta(E[V(d_{it}=1|(.)]-E[V(d_{it}=0|(.)])}{\gamma^d}}$$

- Value functions need to be calculated while likelihood is calculated
  $\rightarrow$ Value function iteration (fixed point)
- The model gives value functions the form

$$V(d_t, (.)) = \pi + \delta E[(V(d_{t+1} = 1, (.))] - C^d(\gamma^d)(1 - e^{-\frac{\delta(E[V(d_{it}=1|(.)]-E[V(d_{it}=0|(.)])}{\gamma^d}})$$

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