PRODUCTIVITY-ENHANCING TECHNOLOGY AND LABOUR MARKET OUTCOMES

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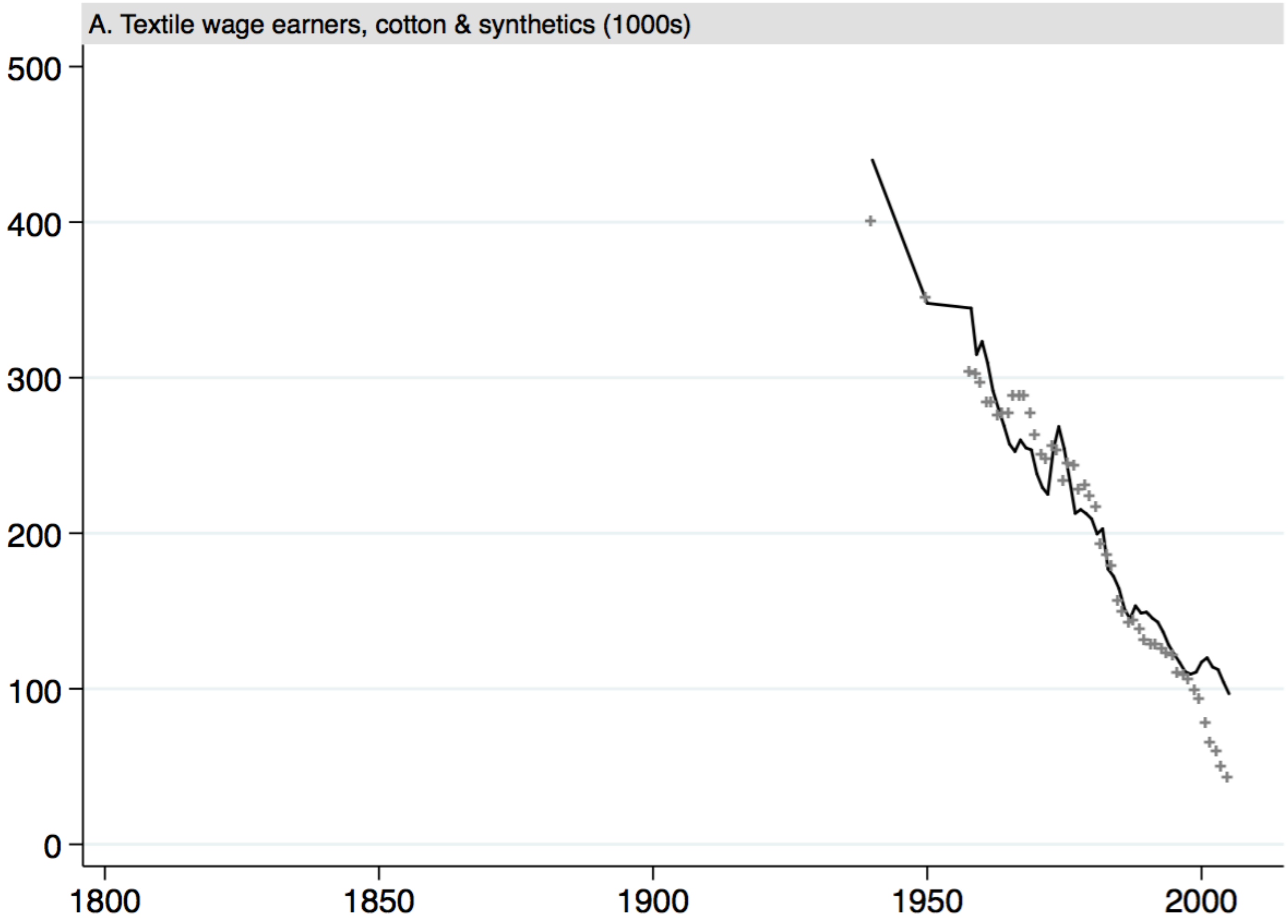
European Central Bank, July, 2019

Will AI create mass unemployment?

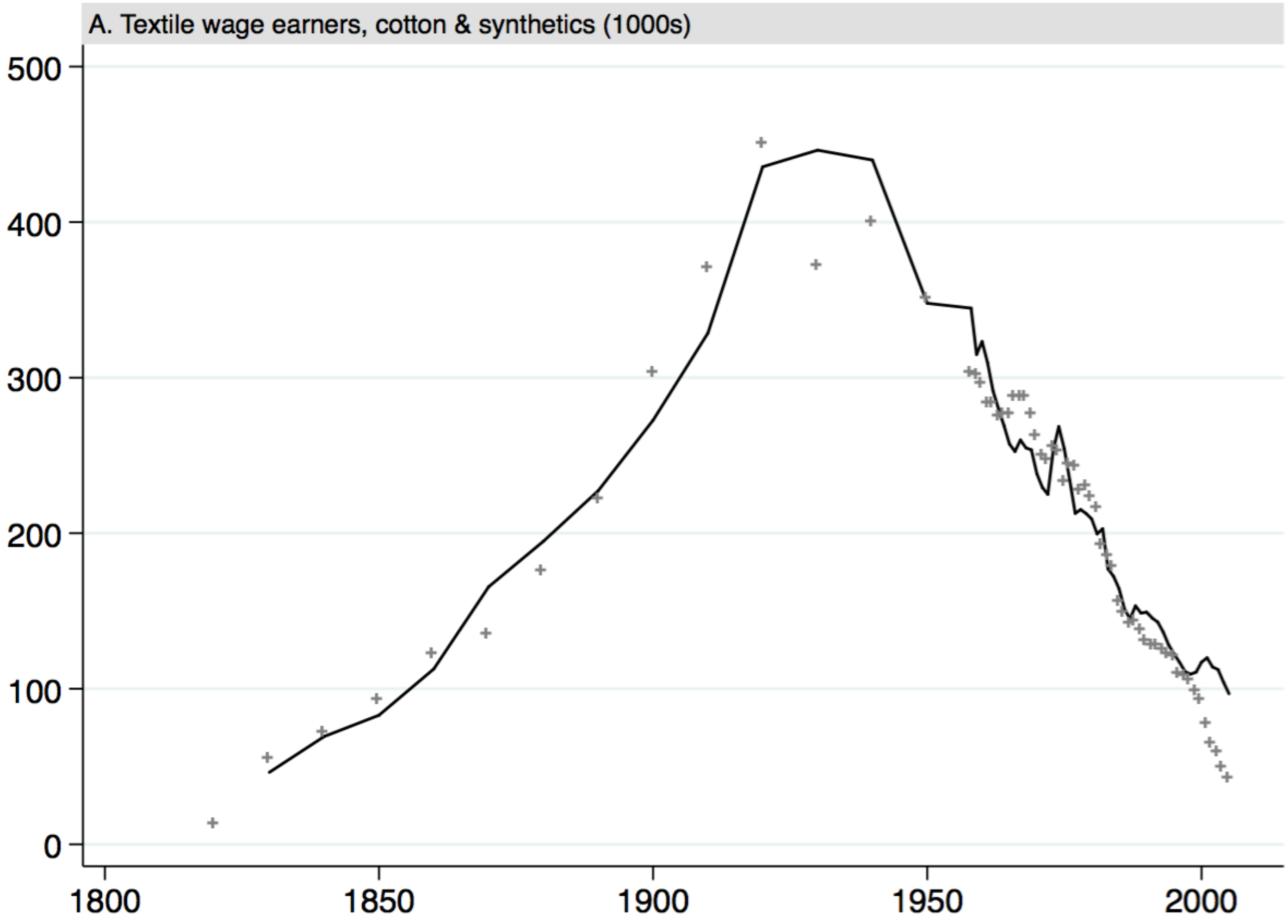
- 47% of jobs “at risk of automation” (Frey & Osborne)?

Predicted Jobs Automation Will Create and Destroy

When	Where	Jobs Destroyed	Jobs Created	Predictor
2016	worldwide		900,000 to 1,500,000	Metra Martech
2018	US jobs	13,852,530*	3,078,340*	Forrester
2020	worldwide		1,000,000-2,000,000	Metra Martech
2020	worldwide	1,800,000	2,300,000	Gartner
2020	sampling of 15 countries	7,100,000	2,000,000	World Economic Forum (WEF)
2021	worldwide		1,900,000-3,500,000	The International Federation of Robotics
2021	US jobs	9,108,900*		Forrester
2022	worldwide	1,000,000,000		Thomas Frey
2025	US jobs	24,186,240*	13,604,760*	Forrester
2025	US jobs	3,400,000		ScienceAlert
2027	US jobs	24,700,000	14,900,000	Forrester
2030	worldwide	2,000,000,000		Thomas Frey
2030	worldwide	400,000,000-800,000,000	555,000,000-890,000,000	McKinsey
2030	US jobs	58,164,320*		PWC
2035	US jobs	80,000,000		Bank of England
2035	UK jobs	15,000,000		Bank of England
No Date	US jobs	13,594,320*		OECD
No Date	UK jobs	13,700,000		IPPR



A. Textile wage earners, cotton & synthetics (1000s)
500
400
300
200
100
0
1800
1850
1900
1950
2000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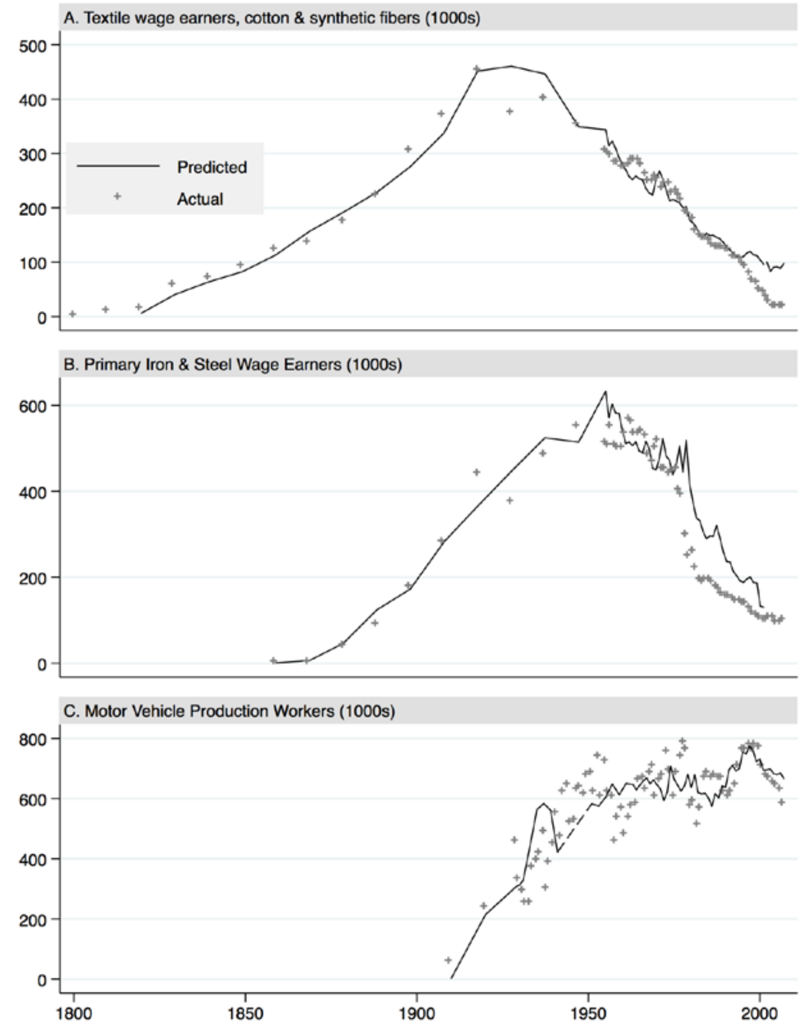

A. Textile wage earners, cotton & synthetic fibers (1000s)
Predicted
Actual
500
400
300
200
100
0
B. Primary Iron & Steel Wage Earners (1000s)
600
400
200
0
C. Motor Vehicle Production Workers (1000s)
800
600
400
200
0
1800
1850
1900
1950
2000

“Inverted U”

1. Automation/productivity can lead to job growth in affected industries

2. Disparate effects
   - Some industries grow, some shrink

3. Policy challenge: transition workers

1: “Automation and Jobs”

- *Why* employment impact of technology changed
- Why relevant today

2: “Shocking Technology” (with Cesare Righi)

- Actual impact of major IT investments
  - Disparate employment effects
  - Positive on average, but…
    - Weaker recently
    - Falling labor share / rising margins

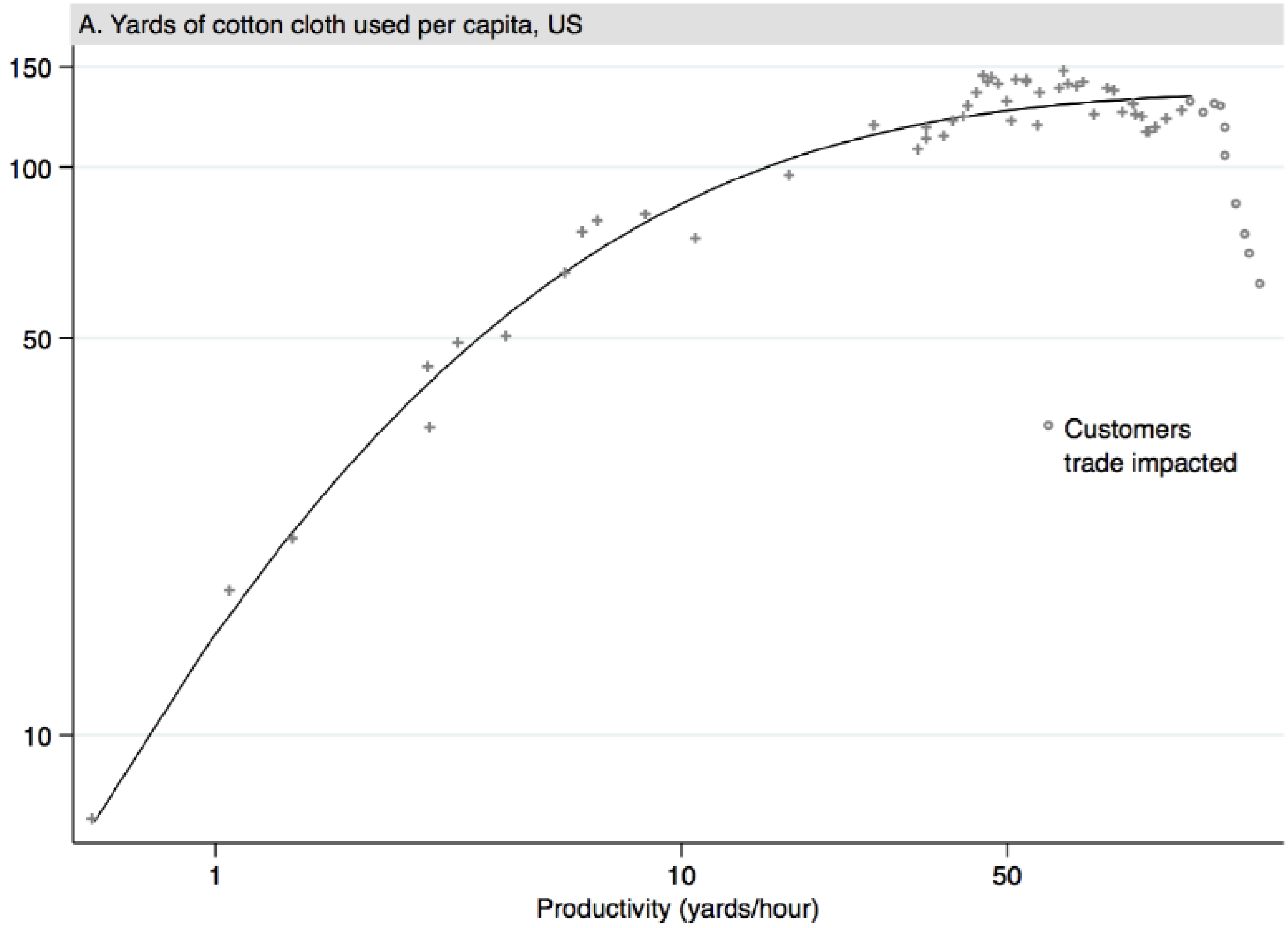
ROLE OF DEMAND

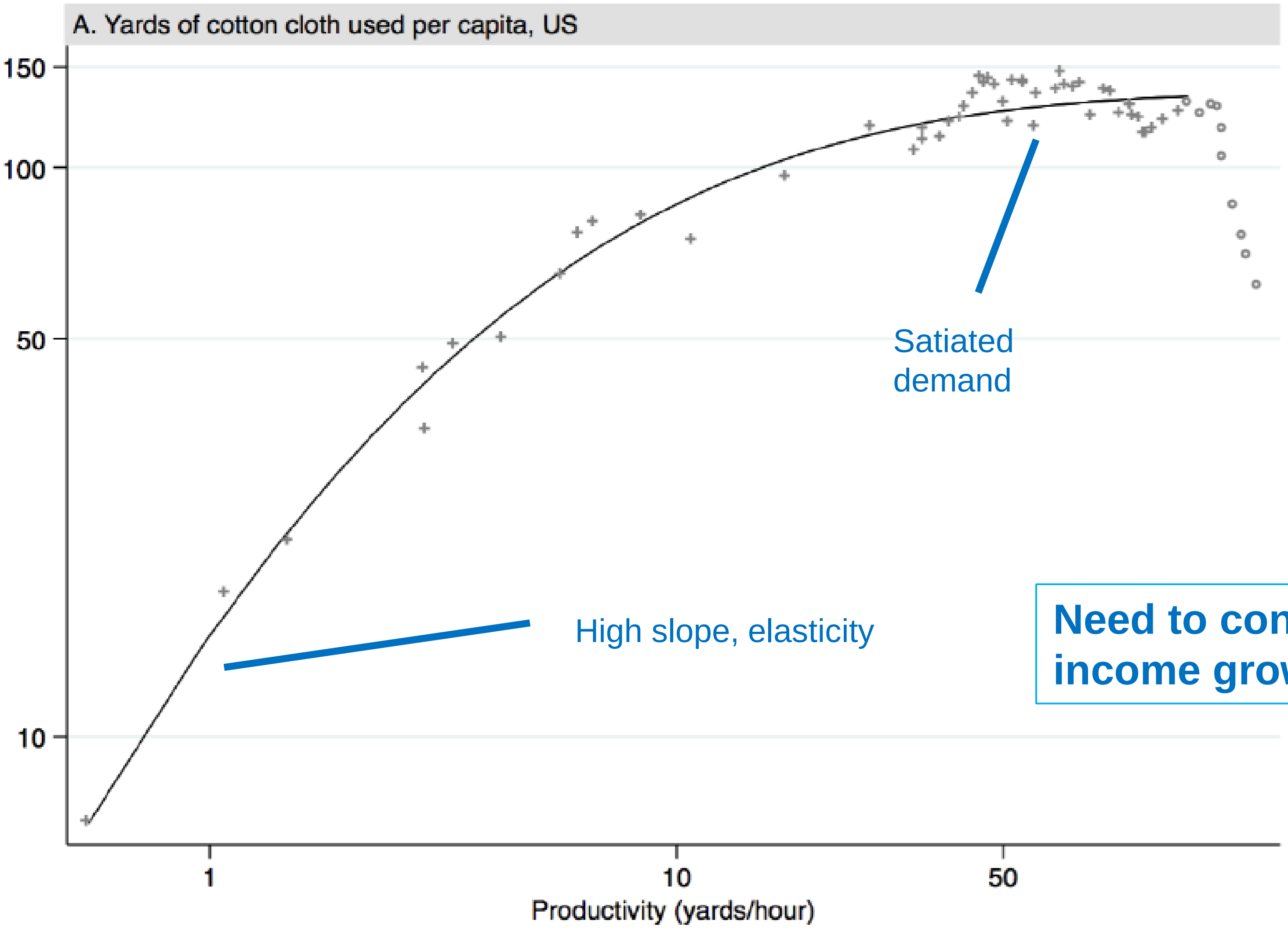
Per capita product demand

- Function of wage and price, $D = D(\frac{p}{w}, w)$
- Labor productivity $A \equiv \frac{Y}{L}$ so that $L = \frac{Y}{A}$
- At equilibrium, output equals demand
- Labor response to productivity growth

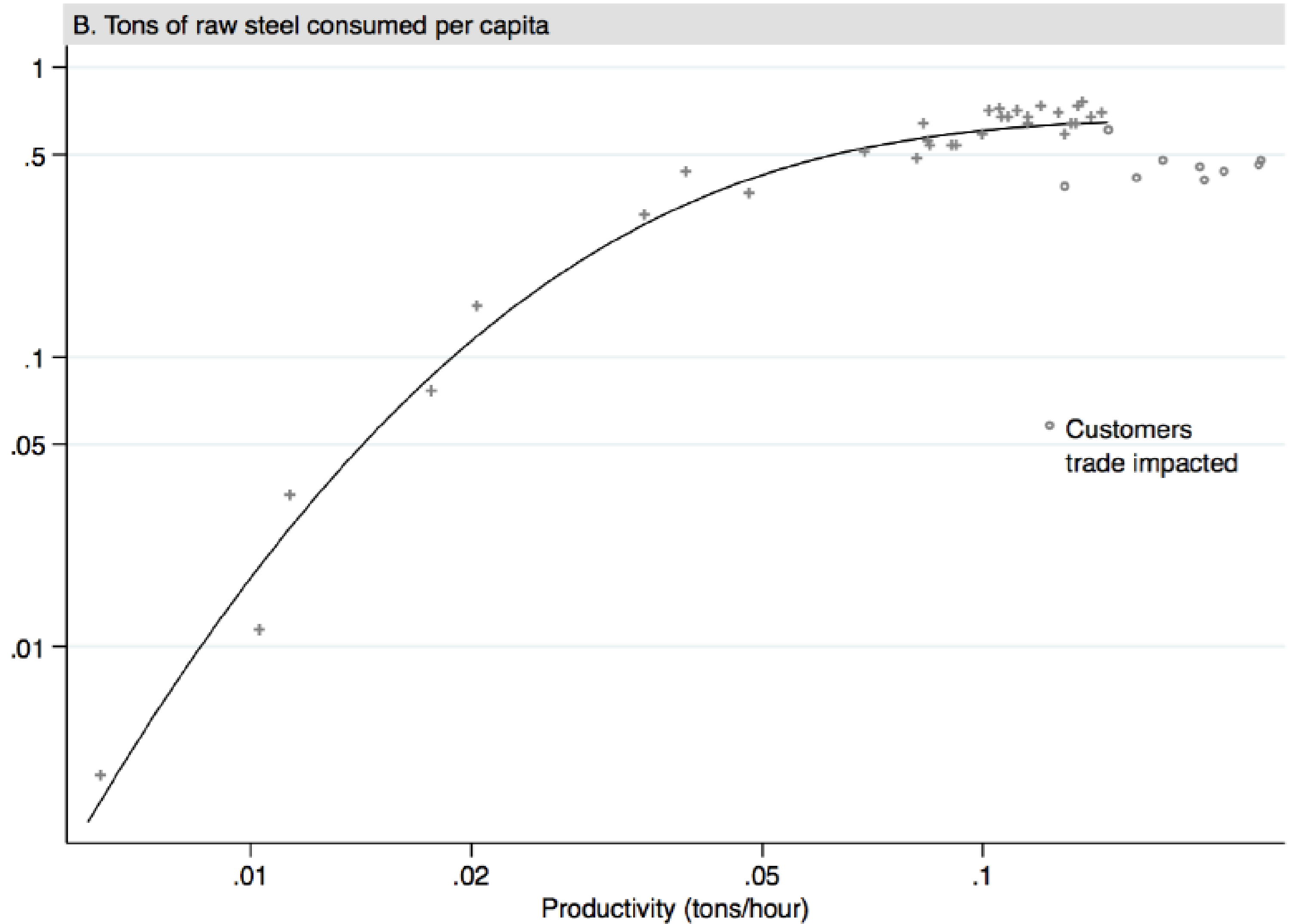
$$\frac{\partial \ln L}{\partial \ln A} = \frac{\partial \ln D}{\partial \ln A} - 1$$

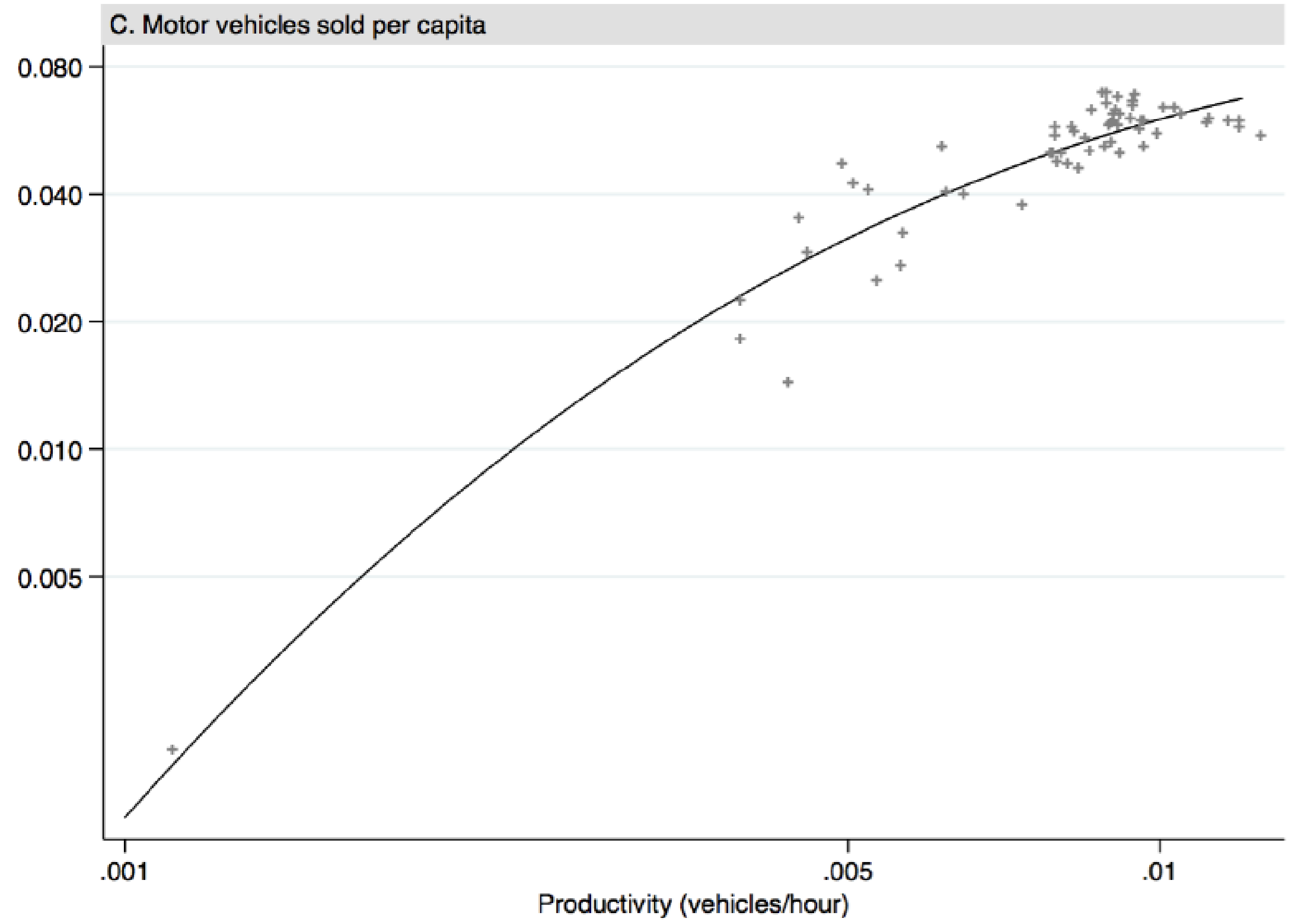
Elasticity of demand w.r.t. labor productivity


A. Yards of cotton cloth used per capita, US
150
100
50
10
1
10
50
Productivity (yards/hour)
Customers trade impacted



Need to consider income growth


B. Tons of raw steel consumed per capita
1
.5
.1
.05
.01
.01
.02
.05
.1
Productivity (tons/hour)
Customers trade impacted


C. Motor vehicles sold per capita
0.080
0.040
0.020
0.010
0.005
.001
.005
.01
Productivity (vehicles/hour)

Automation literature

- Demand / substitution elasticities constant, uniform across industries
  - Acemoglu and Restrepo 2017, 2018, Hemous and Olsen 2016, Aghion et al. 2017
- Aggregate analysis
  - Misses inter-industry reallocation
- Here:
  - Inter-industry differences in demand
    - Vs. differences in productivity
  - Industry life-cycle, dynamic changes
  - Disparate industry effects
  - Aggregate macro effects also important

NON-PARAMETRIC

Tests on $\frac{\partial \ln D}{\partial \ln A}$

1. H0: constant or increasing
2. H0: <= 1 in early years
3. H0: >= 1 in later years

Data series

- Production
  - Physical quantities, not quality adjusted
  - Household production
- Per capita demand
  - Production, adjusted for net imports, divided by population
- Employment, industry wage earners
- Labor productivity, output divided by hours worked per year
- Labor's share of revenue
  - (price & wage data)

Non-parametric regression

- Quadratic form

$$\ln D\left(\frac{p}{w}, w\right) = \alpha + \beta_1 \ln \frac{w}{p} + \beta_2 (\ln \frac{w}{p})^2 + \gamma_1 \ln w + \gamma_2 (\ln w)^2 + \varepsilon$$

Non-parametric regression

- Quadratic form

$$\ln D\left(\frac{p}{w}, w\right) = \alpha + \beta_1 \ln\frac{w}{p} + \beta_2(\ln\frac{w}{p})^2 + \gamma_1 \ln w + \gamma_2(\ln w)^2 + \varepsilon$$

- Labor's share $\quad s \equiv \frac{wL}{pY} = \frac{w}{pA}$ so that $\frac{w}{p} = As$

- $\ln D\left(\frac{p}{w}, w\right) = \alpha + \beta_1 \ln As + \beta_2(\ln As)^2 + \gamma_1 \ln w + \gamma_2(\ln w)^2 + \varepsilon$

Productivity effect

Income effect

A. Dependent Variable: ln D (log demand per capita)	1 Cotton Textiles	2 Primary Steel	3 Auto
$\ln sA$	0.71 **	-7.19 **	-12.43 **
	(0.10)	(1.50)	(1.32)
$(\ln sA)^2$	-0.13 **	-0.75 **	-0.92 **
	(0.02)	(0.15)	(0.09)
$\ln w$	-0.71	8.68 *	4.51 **
	(0.87)	(4.03)	(1.61)
$(\ln w)^2$	0.03	-0.39	-0.21 *
	(0.05)	(0.21)	(0.08)
N	52	35	61
R-squared	0.979	0.974	0.934

$$\frac{\partial \ln D}{\partial \ln A} = \frac{\partial \ln D}{\partial \ln As} \cdot \left(1 + \frac{\partial \ln s}{\partial \ln A}\right)$$

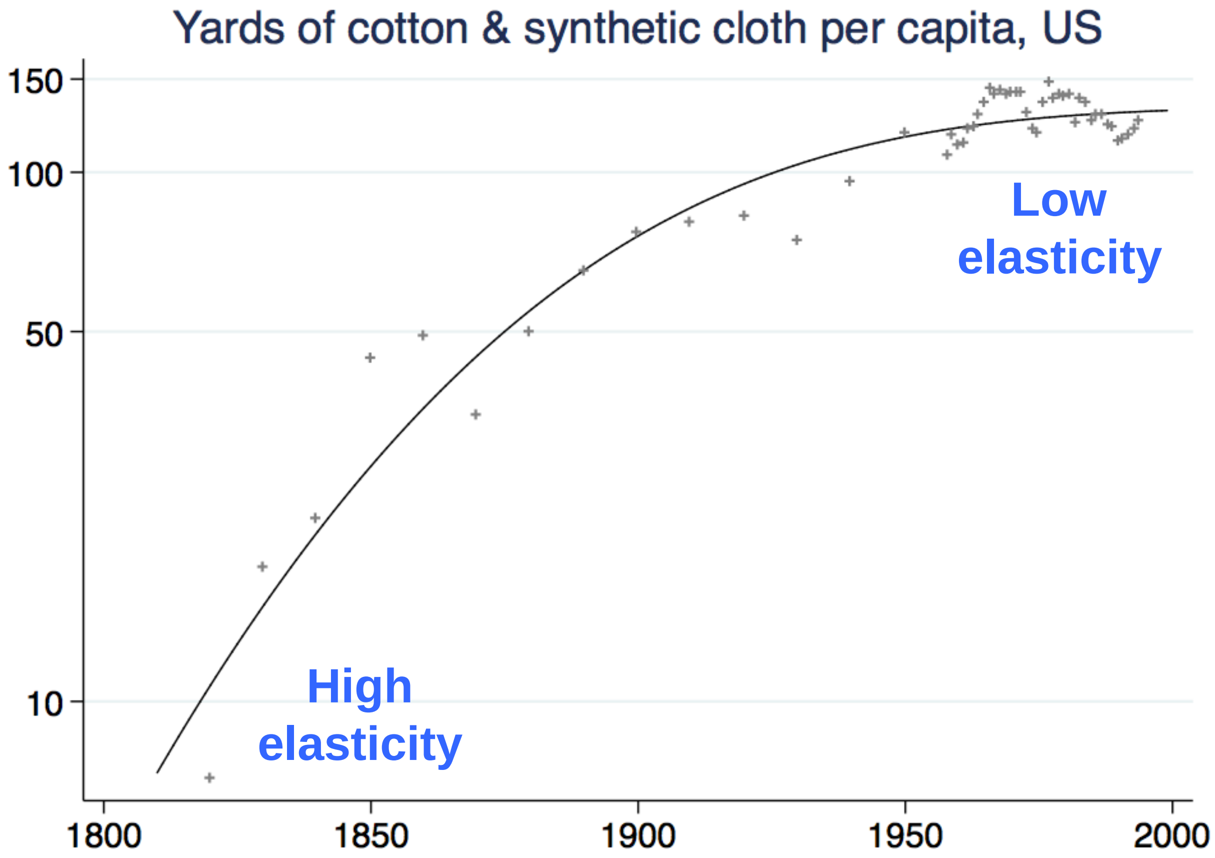
	Cotton Textiles		Primary Steel		Auto	
C. Non-parametric Estimates of Demand Elasticity, $\frac{\partial \ln D}{\partial \ln A}$						
	Year	Elasticity	Year	Elasticity	Year	Elasticity
	1820	1.3	1870	2.2	1910	2.4
H0: elasticity=1	P =	0.008	P =	0.015	P =	0.000
	1950	0.2	1950	-1.2	1951	0.4
H0: elasticity=1	P =	0.000	P =	0.000	P =	0.000
D. Model Estimates of Demand Elasticity, $\frac{\partial \ln D}{\partial \ln A}$						
	1820	1.7	1870	2.9	1910	4.4
	1950	0.2	1950	0.4	1951	1.0

Non-parametric Tests on $\dfrac{\partial \ln D}{\partial \ln A}$

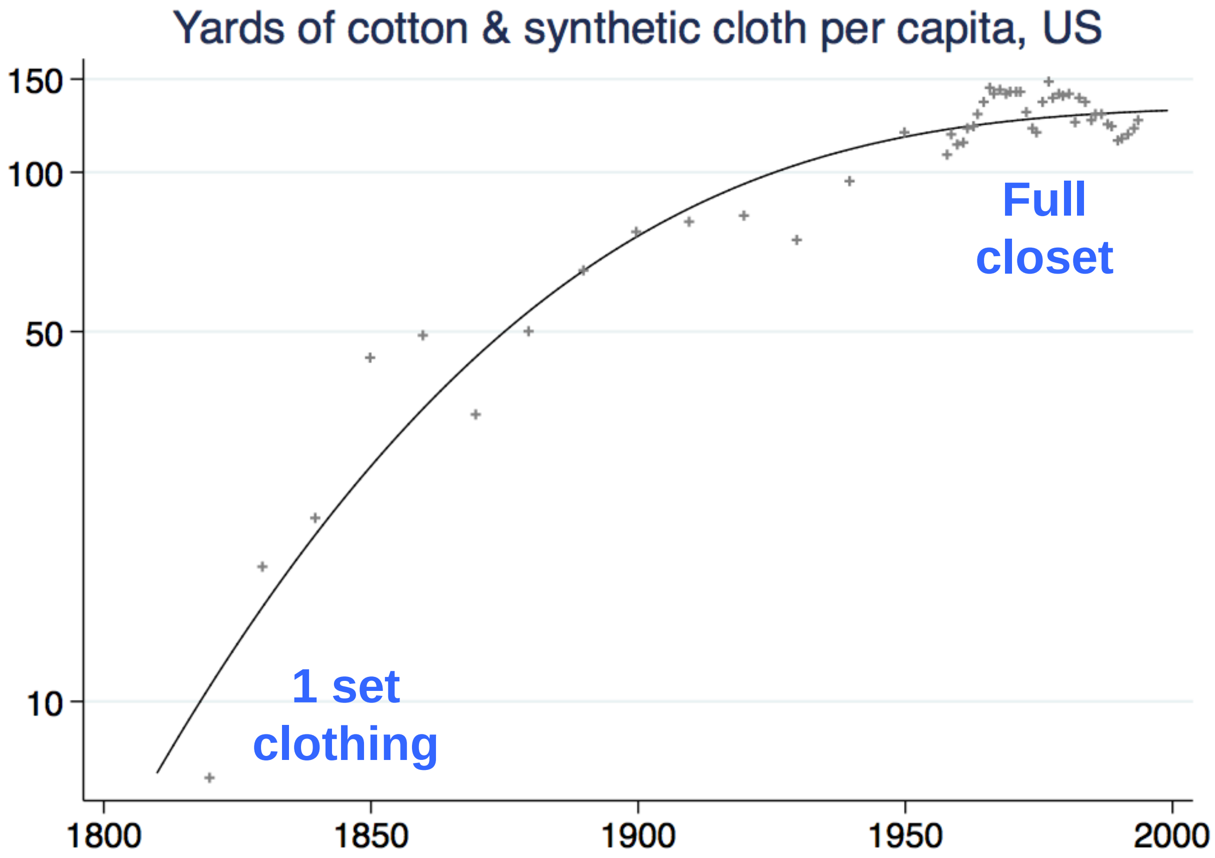
1. Decreasing over time
2. >1 in early years
3. <1 in later years

MODEL:
DEMAND SATIATION

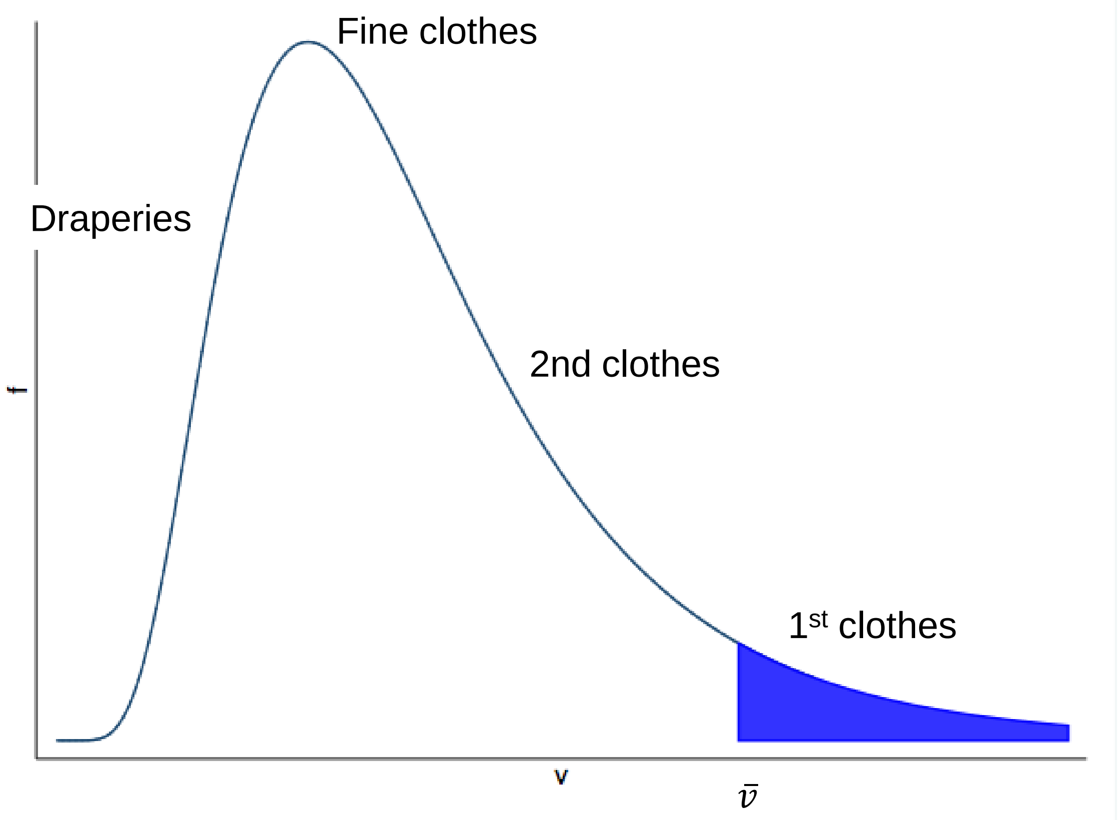
Demand per capita



Demand per capita



Consumption function



Consumer's utility

$$D(\bar{v}) = \int_{\bar{v}}^{\infty} f(z)\, dz = 1 - F(\bar{v}), \qquad F(\bar{v}) \equiv \int_{0}^{\bar{v}} f(z) dz$$

$$U(\bar{v}) = \int_{\bar{v}}^{\infty} z \cdot f(z) dz$$

- Other good, *x*,
  - additive utility $U(\bar{v}) + G(x)$

Consumers problem

- Maximize $U(\bar{v}) + G(x)$
- Subject to budget constraint $w \geq x + pD(\bar{v})$
- FOC: $\hat{v}(p,w) = p \cdot G_x(\hat{x}(p,w))$

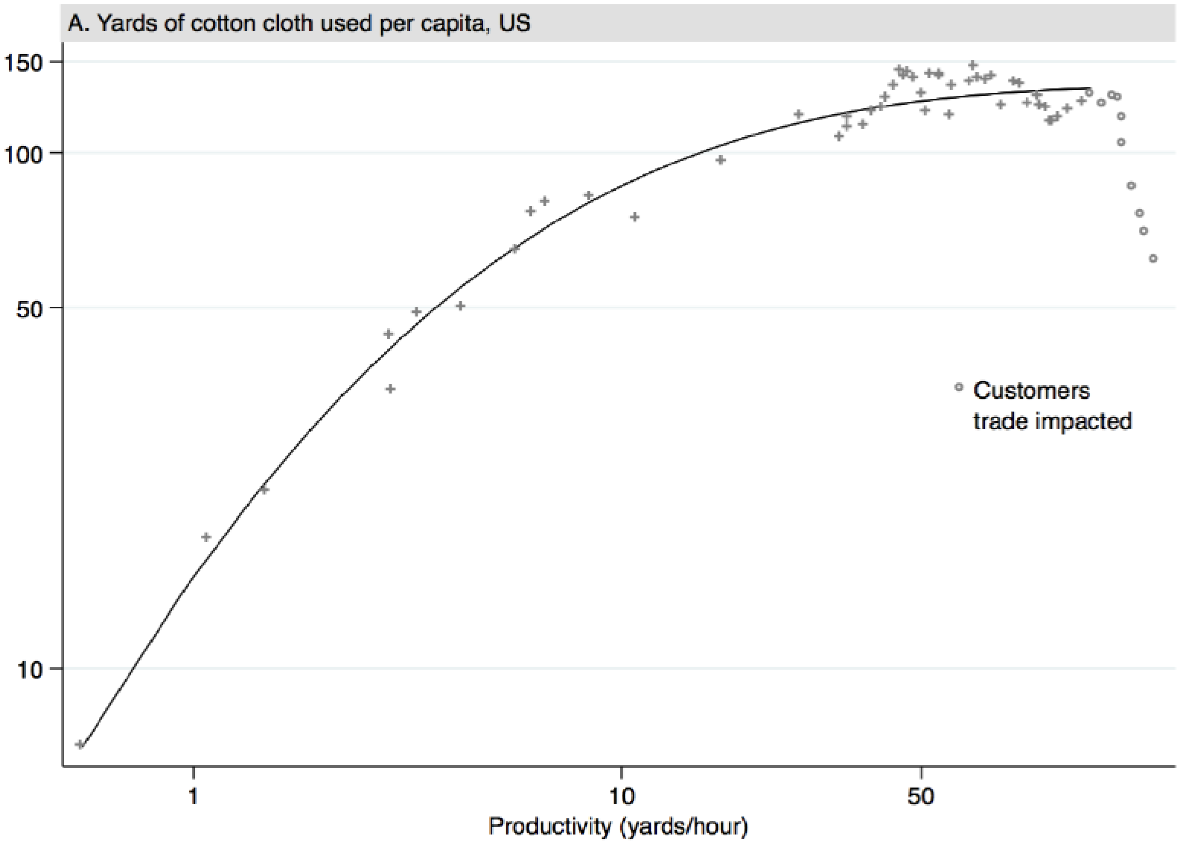
Satiation property

- For common distribution function *f*
  - Normal
  - Lognormal
  - Exponential
  - Uniform

- For *p/w* large enough, $\frac{\partial \ln D}{\partial \ln A} > 1$

- For *p/w* small enough, $\frac{\partial \ln D}{\partial \ln A} < 1$

Parametric estimation: lognormal function



Role of demand

- Demand determines sign of employment change
  - Not necessarily job losses
  - Pace of productivity growth not dispositive

- Industries differ
  - Mature
  - Industries with pent up demand, little past automation

Little evidence of large job losses

		Employment effect
IT / AI		
Akerman, Gaarder, and Mogstad (2015)	NO	+ skilled
Bessen and Righi (2019)	US	+ services, FIRE, trade; - manufacturing
Gaggl and Wright (2014)	UK	+ trade and finance
Mann and Püttmann (2017)	US	+ services, - manufacturing
Automation		
Bessen et al. (2019)	NL	Small relative to mass layoffs
Cirerra and Sabetti (2019)	53	0
Industrial Robots		
Acemoglu and Restrepo (2017)	US	-
Dauth et al. (2017)	DE	0
Graetz and Michaels (2017)	DE	0
Koch, Manuylov, Smolka (2019)	SP	+ on adopting firm, - on non-adopting

But disparate effects

- Some industries grow, some shrink

- ➔ workers make transitions
  - New industries
  - New skills
  - New occupations
  - New locations

EVIDENCE ON IT

Two Flavors of IT

- IT as routine input
  - Word processing on a PC
- IT as innovation
  - Custom software (contracted or own)
    - E.g., retail logistics system; aircraft design systems; bank credit card systems

Two Flavors of IT

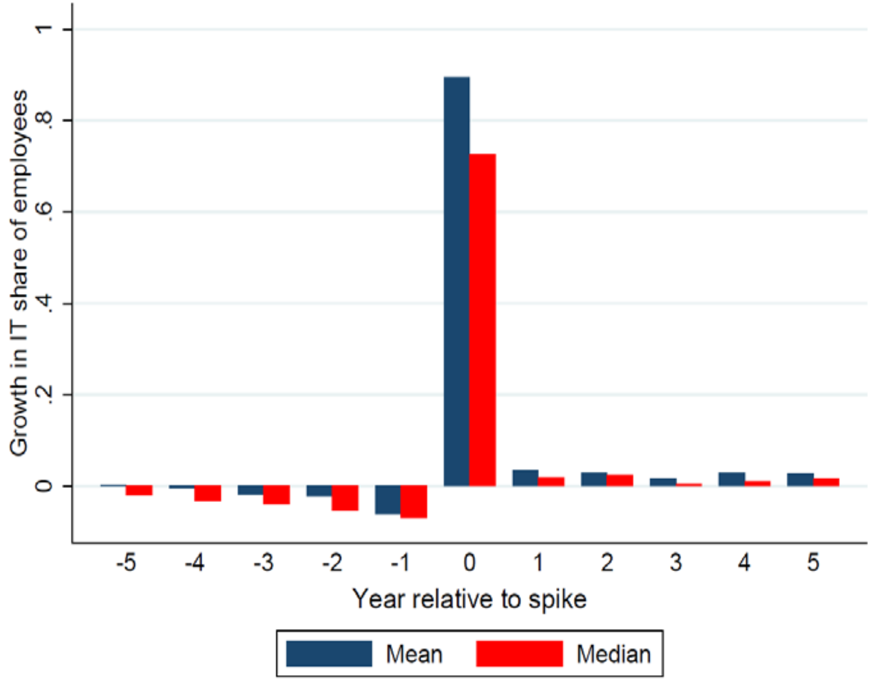
- IT as routine input
  - Word processing on a PC
- IT as innovation
  - Custom/proprietary software (contracted or own)
    - E.g., retail logistics system; aircraft design systems; bank credit card systems
- Proprietary SW
  - US: $250b = 55% of IT investment
  - Likely source of major labor effects

IT spikes

- Adapting "Automatic Reaction"
  (Bessen, Goos, Salamons, Vanden Berghe)

- Spike: $\Delta \frac{\text{SW developers}}{\text{Total employment}} > .30$

- 47% of SW hiring occurs in spikes



IT Share

- LinkedIn data: SW / systems developer/ manager titles (1,791)
  - “applications programmer analyst”
  - “information systems project manager”
  - Exclude tech support, maintenance, basic operations
- IT share: SW employees / total employees by firm-year
  - Weights by year: IT share from CPS / IT share from Linkedin
  - Link to Compustat
- AI / Big Data
  - “hadoop” “big data” “quantitative analyst” “data scientist” “machine learning”

Revenue production function

$$\ln R_{it} = a_{it} + \delta \ln L_{it} + \theta \ln K_{it} + \rho_{it},$$

Log productivity & demand shifter

Non-it labor

Revenue production function

$$\ln R_{it} = a_{it} + \delta \ln L_{it} + \theta \ln K_{it} + \rho_{it},$$

$$a_{it} = \alpha_i + \beta_t + \omega_{it} + \gamma \cdot I_{it},$$

IT

Unmeasured demand & productivity shock

Production function estimation

- Standard Cobb-Douglas

$$\ln R_{it} = \alpha_i + \beta_t + \delta \ln L_{it} + \gamma \cdot I_{it} + \theta \ln K_{it} + \epsilon_{it}, \quad \epsilon_{it} \equiv \omega_{it} + \rho_{it}$$

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Simultaneity bias

Production function estimation

- Standard Cobb-Douglas

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Simultaneity bias

- Control function (Olley-Pakes)

$$\ln R_{it} = \alpha_i + \beta_t + \delta \ln L_{it} + \gamma \cdot I_{it} + f(\ln I_{it}, \ln K_{it}) + \epsilon_{it}$$

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~~Simultaneity~~ Selection bias

- Control function (Olley-Pakes)

$$\ln R_{it} = \alpha_i + \beta_t + \delta \ln L_{it} + \gamma \cdot I_{it} + f(\ln I_{it}, \ln K_{it}) + \epsilon_{it}$$

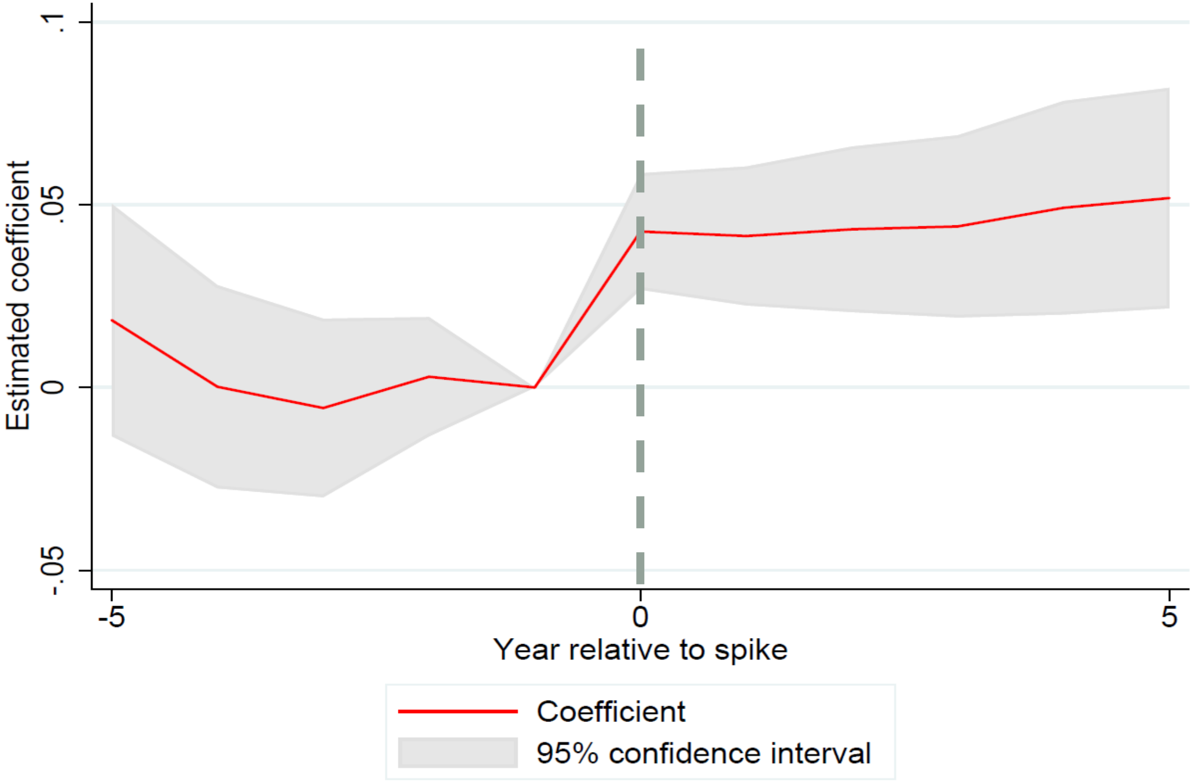
- Difference-in-differences

$$I_{it} \equiv \mathbf{1}(t \geq \tau_i)$$

Production function estimates

Dependent variable: Log Deflated Revenue			
Model	Firm FE	Olley-Pakes	Olley-Pakes 1st, FE
Post spike	0.048**	0.052**	0.046**
	(0.010)	(0.019)	(0.011)
Log(non-IT labor)	0.647**	0.627**	0.632**
	(0.027)	(0.011)	(0.027)
Log(capital)	0.204**	0.136**	
	(0.018)	(0.023)	
Year effects	✓		✓
Firm effects	✓		✓
Control function		✓	✓
Observations	47,416	45,438	44,177
R-squared	0.976	n.a.	0.975
Firms	4,056	3,872	3,800

Productivity event study



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Little selection bias

$\text{cov}[I_{it} \cdot \omega_{it}] \approx 0$

Revenue demand function

$$\ln R_{it} = \epsilon\,(a_{it} - \ln\mu \cdot c_t^0) + \rho_{it}$$

Elasticity of demand

Markup x input cost index

Revenue demand function

$$\ln R_{it} = \epsilon\,(a_{it} - \ln\mu \cdot c_t^0) + \rho_{it}$$

$$a_{it} = \alpha_i + \beta_t + \omega_{it} + \gamma \cdot I_{it},$$

Unmeasured demand & productivity shock

IT

Revenue demand function

$$\ln R_{it} = \epsilon \left(a_{it} - \ln\mu \cdot c_t^0\right) + \rho_{it}$$

$$a_{it} = \alpha_i + \beta_t + \omega_{it} + \gamma \cdot I_{it},$$

$$\ln R_{it} = \alpha'_i + \beta'_t + \epsilon \cdot \gamma \cdot I_{it} + \epsilon_{it}, \qquad \epsilon_{it} \equiv \epsilon \cdot \omega_{it} + \rho_{it}$$

Revenue & employment growth

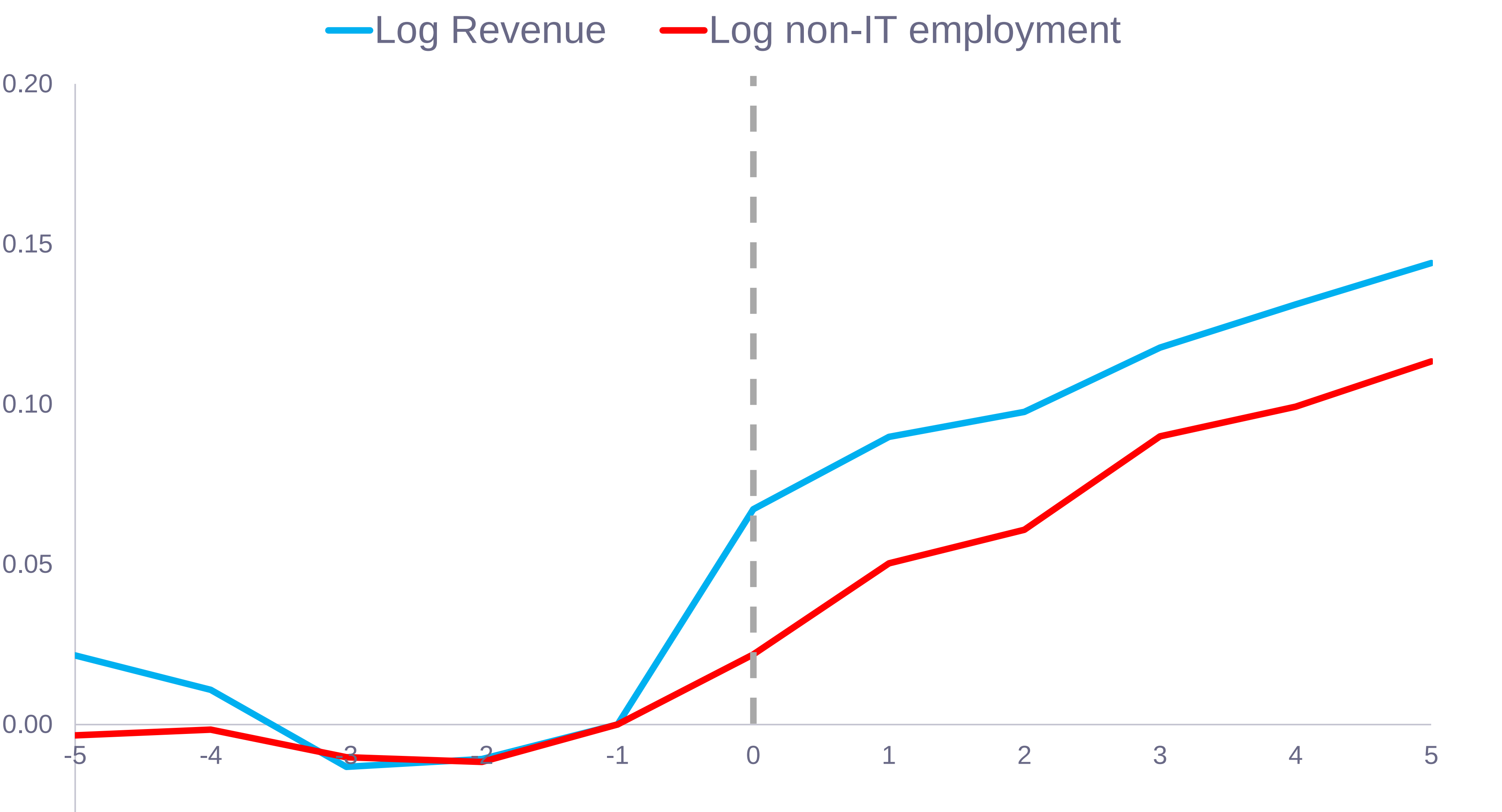
- Assuming uniform input prices
- $$\ln R_{it} = \alpha_i + \beta_t + \epsilon \cdot \gamma \cdot I_{it} + \epsilon_{it}, \qquad \epsilon_{it} \equiv \epsilon \cdot \omega_{it} + \rho_{it}$$
    - Same selection bias, $\text{cov}[I_{it} \cdot \omega_{it}] \approx 0$

Revenue & employment growth

- Assuming uniform input prices
- $$\ln R_{it} = \alpha_i + \beta_t + \gamma \cdot I_{it} + \epsilon_{it}, \qquad \epsilon_{it} \equiv \omega_{it} + \rho_{it}$$
    - Same selection bias
- $$\ln L_{it} = \alpha_i + \beta_t + \gamma \cdot I_{it} + \epsilon_{it}.$$

Growth

Dependent variable:	Log(revenue)	Log(non-IT employees)
Post spike	0.109**	0.070**
	(0.018)	(0.017)
Firm effects	✓	✓
Year effects	✓	✓
Observations	50,202	49,967
R-squared	0.939	0.942
Firms	4200	4218


Log Revenue
Log non-IT employment
0.20
0.15
0.10
0.05
0.00
-5
-4
-3
-2
-1
0
1
2
3
4
5

Firm heterogeneity

Model	Production function	Revenue	Non-IT employees
Outcome	Log(revenue)	Log(revenue)	Log(non-IT employees)
Panel A: AI/Big Data			
Post spike not AI	0.048**	0.098**	0.056**
	(0.011)	(0.018)	(0.018)
Post spike AI	0.045	0.247**	0.237**
	(0.031)	(0.068)	(0.067)
Panel D: US based			
Post spike not US	-0.011	0.055	0.055
	(0.023)	(0.041)	(0.043)
Post spike US	0.056**	0.117**	0.072**
	(0.011)	(0.019)	(0.019)
Panel E: New firms			
Post spike old firm	0.019	0.007	-0.016
	(0.011)	(0.021)	(0.022)
Post spike new firm	0.121**	0.366**	0.291**
	(0.022)	(0.032)	(0.027)

Firm, year FEs

Industry heterogeneity

Model	Production function	Revenue	Non-IT employees
Outcome	Log(revenue)	Log(revenue)	Log(non-IT employees)
Post spike nondurable mfg.	0.050 (0.031)	-0.019 (0.048)	-0.090* (0.044)
Post spike durable manufacturing	0.049** (0.015)	0.060 (0.033)	0.024 (0.032)
Post spike transport and utilities	0.135** (0.026)	0.142* (0.056)	-0.028 (0.059)
Post spike trade	0.045 (0.038)	0.175** (0.068)	0.209** (0.053)
Post spike finance	0.072** (0.025)	0.229** (0.040)	0.146** (0.051)
Post spike service	0.033 (0.026)	0.141** (0.046)	0.172** (0.043)

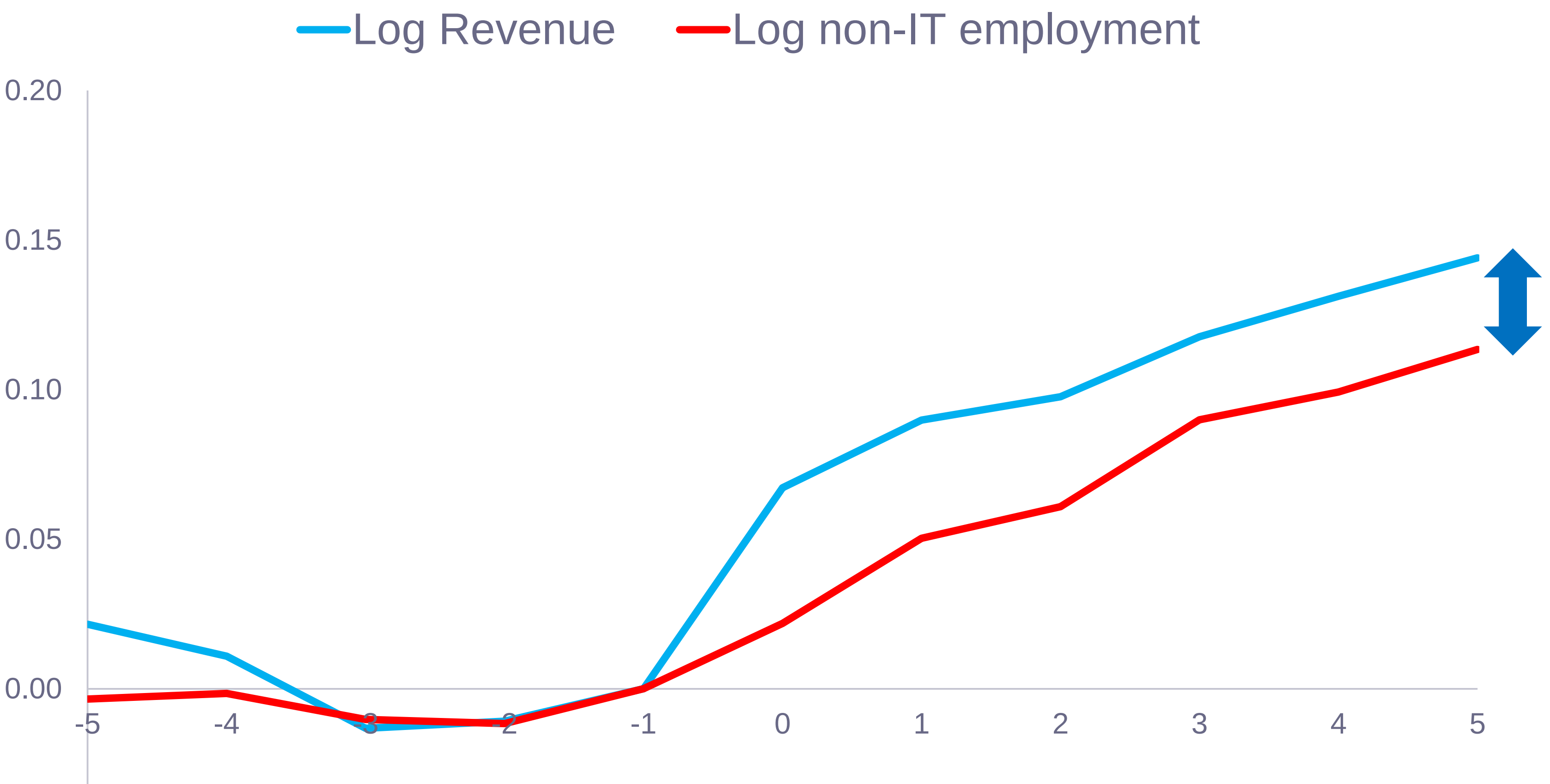
Slowing response

Model	Production function	Revenue	Non-IT employees
Outcome	Log(revenue)	Log(revenue)	Log(non-IT employees)
Panel C: Time period			
Post spike pre-2002	0.044**	0.154**	0.128**
	(0.014)	(0.027)	(0.027)
Post spike post-2002	0.052**	0.060*	0.005
	(0.016)	(0.027)	(0.025)

Firm, year FEs

Decker, Jarmin, Haltiwanger & Miranda, 2018, 2019

Declining labor share



Labor share & margins

Outcome	Labor share of revenue	Operating margin	Operating margin	Log(Capital/ non-IT employees)
Sample	All firms	All firms	No IT producers	All firms
Post spike	-0.014**	0.016**	0.012*	0.007
	(0.004)	(0.005)	(0.005)	(0.013)
Observations	49,062	49,159	37,033	48,577
R-squared	0.754	0.644	0.672	0.922
Firms	4144	4114	3035	4116

Firm, year FEs

CONCLUSION

Key challenge of Digitalization?

- Mass unemployment?

- Job transitions, skills?
  - …inequality