Digital Gains and Employment Pains?

Evidence from Indian Manufacturing

January 3, 2025

2025 ASSA Annual Meeting
San Francisco, California

Dixit Poudel
Munisamy Gopinath

Digital and Manufacturing: Global and Indian Context

MODERNDIPLOMACY
ALL VIEWS | ALL VOICES

REGIONS TOPICS BUSINESS SECURITY NEWS FINE LIVING MORE

SCIENCE & TECHNOLOGY

Digital Silk Road as part of the Chinese national strategy

BY DR.NADIA HELMY APRIL 7, 2024

Forbes

FORBES > SMALL BUSINESS

Making Digital Manufacturing A Reality In The U.S. Requires More Tha Hardware And Software

eld Forbes Councils Member
s Council
| Membership (Fee-Based)

Aug 31, 2023, 09:30am EDT

Funded by the European Union

EU

DISCOVER EU4DIGITAL THEMATI

Home / Discover EU4Digital / Projects / EU4Digital Projects / EU Digital Strate

EU Digital Strategy

Newsroom Business Employees Job Seekers Students Travelers Visas

U.S. DEPARTMENT of STATE

POLICY ISSUES COUNTRIES & AREAS BUREAUS & OFFICES ABOUT

Home > Briefings - Foreign Press Centers > Understanding Xi Jinping's Digital Strategy for China

Understanding Xi Jinping's Digital Strategy for China

FPC BRIEFING

DR. DAVE DORMAN, FORMER ADVISOR TO INDOPACOM
DR. JOHN HEMMINGS OF THE PACIFIC FORUM
WEDNESDAY, MARCH 1, 2023, 3:00 P.M. ET
WASHINGTON D.C.

MARCH 1, 2023

WORLD ECONOMIC FORUM

EMERGING TECHNOLOGIES

How can AI augment rather than dictate human action? This expert explains

Oct 18, 2024

The New York Times

OPINION

Will A.I. Take All Our Jobs? This Economist Suggests Maybe Not.

March 22, 2024

THE TIMES OF INDIA

Opinion Times View Times Evoke City India World Entertainment Sports Spirituality Business Environmen

OGS / BUSINESS / ECONOMY / The role of digitisation and analytics in manufacturing

role of digitisation and analytics in manufacturing

13, 2022, 5:12 PM IST / Dipali Goenka in Voices, Economy, India, TOI

THE ECONOMIC TIMES News

English Edition | Today's ePaper

Subscribe Sign In

New Financial Year Offer

Digital transformation high on manufacturing sector's agenda: PwC India survey

PTI • Last Updated: Jun 20, 2023, 04:50:00 PM IST

FOLLOW US SHARE FONT SIZE SAVE PRINT COMMENT

WSJ | OPINION

World Business U.S. Politics Economy Tech Markets & Finance Opinion Arts Lifestyle

OPINION COMMENTARY Follow

'Digital Twins' Could Revolutionize Planes, Cars and Hearts

A new Air Force simulator initiative has a wealth of exciting applications in the civilian world as well.

By Will Roper and Eric Schmidt
Updated June 18, 2024 11:42 am ET

THE TIMES OF INDIA

Opinion Times View Times Evoke City India World Entertainment Sports Spirituality Business Environment ...

NEWS / BLOGS / TECH / The impact of AI on digital marketing jobs in 2023

TECH

The impact of AI on digital marketing jobs in 2023

October 30, 2023, 4:24 PM IST / Rohit Mehta in Digital Mehta, Tech, TOI

BDO AUSTRALIA

Home < Insights < Manufacturing < Digital demand: Skilling Australia's manufacturing workforce

Digital demand: Skilling Australia's manufacturing workforce

Motivation (1/3)

- Macro-patterns signal the existence of digital dividends (table 1), echoing early growth theory insights on impacts of physical capital (Solow, 1956; Jorgenson and Vu, 2005; Jorgenson, 2011)

- BUT! Micro-level largely focused on **digital capital**'s productivity effects, leading to "Solow's paradox" and the "productivity miracle", mostly in the context of high-income countries

- Evolved perspective: it is an **integral input** within the production system; with rich micro-data, we can measure marginal effects of digital capital, akin to the physical capital

	1989-1995		**1995-2003**	
	GDP Growth	**Share of ICT Capital on Total GDP Growth**	**GDP Growth**	**Share of ICT Capital on Total GDP Growth**
World	2.5	10.8%	3.45	15.4%
G7 Economies	2.18	17.4%	2.56	27.0%
USA	2.43	20.2%	3.56	24.7%
Developing Asia	7.35	2.0%	5.62	7.7%
India	5.03	1.8%	6.15	4.2%

Table 1
Source: Jorgenson and Vu (2005)

Motivation (2/3): Digital Capital as Input

Digital Capital

- Direct
  - Competitive Advantages
    Bridges market information asymmetry, streamlines industrial operations
  - Eg. Digital Twin
    - Conduct safety testing and risk assessment in aerospace and automotive
    - Help refine products and reduce physical prototyping
- Indirect
  - Complements or Substitutes other inputs
  - Eg. QuickBooks
    - Replaced bound ledgers as well as simple (Excel or Google) worksheets

Motivation (3/3)

- **Why Manufacturing?**
  - High potential to capitalize on digital assets, e.g., automation
  - Its central role in R&D

- **Why India?**
  - India is representative of global context: manufacturing share of [India's GDP $\approx$ global GDP] (14.5 vs. 16.6%, WDI, 2021)
  - **Supply chain diversification:** India is the key destination in the China+1 strategy → ongoing shift in operations to India
  - Large informal sector - 86.8% of total employment is in informal (2017/18)
  - Recently experienced significant employment losses in manufacturing (Kujur & Goswami, 2021)

Related Literature

- **Globally:**
  - Ceccobelli et al. (2012) for OECD countries, Stiroh (2002) and Jorgenson (2011) for the U.S., Li and Wu (2023) for China, Niebel (2018) for 55 developing/developed nations: **formal manufacturing and macro consequences** of digital capital

- **India-focused:**
  - Tariff liberalization (Sivadasan, 2009; Topalova and Khandelwal, 2011), input shortages (Allcott et al., 2016), public investment liberalization (Nataraj, 2011; Chatterjee et al., 2021)

- **Digital capital on Indian manufacturing** (aggregate or micro level):
  - Erumban and Das (2020), Gupta and Kumar (2018), Sharma and Singh (2013), Commander et al. (2011) and Jorgenson and Vu (2005): ICT capital contributed to India's economic growth, aggregated or qualitatively
  - Notable exception: Khanna and Sharma (2022), direct impact of IT capital on large and formal manufacturing firms

- **Employment literature in India:**
  - De-reservation on employment (Martin et al., 2017), public infrastructure on labor skill premium (Chatterjee et al., 2024), employment policies (Martin et al., 2017), trade liberalization on labor share (Ahsan and Mitra, 2014)
  - Kumar and Kumar (2022): from 2000-10, ICT intensity increased employment in a few industries

- **Policy Background:**
  - Several government policies backed by digitalization efforts, but mixed outcomes

Contributions & Results Preview

- Quantified **digital dividends (assuming it as different input)** by estimating **firm-/plant-level** technologies, using **nested-CES** specification allowing for physical and digital capital substitutability

- Studies both **formal and informal manufacturing**: 2010-2021 for 11 major industries and all states
  - Prowess (formal firms, panel),
  - Annual Survey of Industries, ASI (formal plants, repeated cross-section), and
  - National Sample Survey on Unorganized Manufacturing, NSSO (informal firms, repeated cross-section)

- **Simultaneity** in inputs and productivity shock is addressed using the control function approach of Levinsohn and Petrin (2003) and Ackerberg et al. (2015). And, the alternative strategy from Sivadasan (2009) and Chatterjee et al. (2021) for repeated cross-sectional estimation

- **Heterogeneity** of employment between high- and low-digital intensity entities for both sectors

- Yes, statistically and economically significant digital dividend is identified: ranges from 0.02 to 0.17 for industries in the formal sector, and 0.02 to 0.05 for industries in the informal sector

- Contrary to common beliefs, greater digital capital intensity is associated with higher labor and skilled-labor intensity in formal industries

Theoretical Model and Empirical Strategy

- Consider a manufacturing entity (i), can be a firm/plant in formal/informal sector, in industry j located in state s at time t. Employs its labor (L_{it}), physical capital (K_{it}) and digital capital (D_{it}) using a value-added function:

$$Y_{it} = f(L_{it}, K_{it}, D_{it} | \delta_j, \delta_s, \delta_t) \quad (1)$$

  - where,
  - $Y_{it} \in \mathbb{R}_N{}^{+}$ is the value-added (gross output net of intermediate inputs), and
  - δ_j, δ_s and δ_t are the industry-, state- and time-fixed effects.

- Let $f(.)$ be represented by a non-constant return to scale nested-CES function where an entity is allowed to substitute between K and D with parameter θ:

$$lnY_{it} = \beta_0 + \beta_1 lnL_{it} + \frac{\beta_2}{\theta} ln[\gamma_1 K_{it}^{\theta} + (1-\gamma_1)D_{it}^{\theta}] + \delta_j + \delta_s + \delta_t + \eta_{it} \quad (2)$$

- Marginal productivity of each input or elasticity (ε) is deduced using FOC. For digital capital:

$$\varepsilon_D = \overline{D}_{it} \frac{\partial \, lnY_{it}}{\partial \, D_{it}} = \overline{D}_{it} \frac{\widehat{\beta_2}}{\hat{\theta}} \left[\frac{\hat{\theta}(1-\widehat{\gamma_1})\overline{D}_{it}^{\hat{\theta}-1}}{\widehat{\gamma_1}\overline{K}_{it}^{\hat{\theta}} + (1-\widehat{\gamma_1})\overline{D}_{it}^{\hat{\theta}}} \right] \quad (3)$$

Mechanism

Digital Capital

Direct

Competitive Advantages
Bridges market information asymmetry, streamlines industrial operations

$$\varepsilon_D > 0$$

Eg. Digital Twin

For safety testing and risk assessment in aerospace and automotive

Help refine products and reduce physical prototyping

Indirect

Complements or Substitutes other inputs

θ allows K and D substitution

if is θ higher, industries capitalize on declining prices of digital tools, substitutes away from traditional K

Nested structure assumes L and capital mix are essential inputs

Direct estimation of subs. or comp. between L and D requires price data, so we rely on reduced form estimation along Martin et al. (2017) lines

Identification: Semi-Parametric Control Function (1/3)

- **Simultaneity** (inputs are a function of unobserved productivity shocks):
  - $\eta_{it} = \omega_{it} + \eta^*_{it}$, is additively separable; Hicks-neutral productivity shock (ω_{it}) and white noise (η^*_{it})
  - ω_{it} is state variable influencing entity's production decision
  - ω_{it} is known to the producer, but not to econometrician, leading $E[\eta_{it}|X_{it}] \neq 0$

- **Control Function:**
  - Levinsohn and Petrin, LP, (2003) for baseline and Ackerberg et al., ACF, (2015) for robustness
  - Three common assumptions:
    (i) ω_{it} is the only scalar unobservable present in the chosen proxy's demand equation,
    (ii) monotonicity in proxy's demand function,
    (iii) ω_{it} follows a first-order Markov process

- **Alternative Strategy: Repeated cross-section case**
  - Sivadasan (2009), Chatterjee et al. (2021): with a broader assumption that instead of using the ω_{it-1} for each firm (not observable in repeated cross-sections) to predict ω_{it}, one can use average productivity in lagged period for a matched industry-state-size combination, i.e., $\bar{\omega}_{i,t-1} = \frac{1}{n_{cell_i}} \sum_{cell=1}^{n_{cell_i}} \omega_{cell,t-1}$. Here, $cell_i$ denotes each industry-state-size cell

Data

- **Three largest Indian databases:**
  (a) Prowess$_{\text{DX}}$ (2009-2021) – panel firm-level (mostly large firms, formal)
  (b) Annual Survey of Industries (ASI) (2009-2020) – repeated cross-section plant-level (all plants, formal)
  (c) Unincorporated Non-Agricultural Enterprises National Sample Survey (NSSO) (three latest surveys, 2006, 2011 and 2016) – repeated cross-section plant-level (all plants, informal)

- **Variables:**
  - Information on output, sales, intermediate expenses, and fixed and variable inputs
  - Firm characteristics allowing an investigation of industry performance and dynamics
  - Annual national average of the Wholesale Price Index and Consumer Price Index are used for deflation

- **Real digital capital stock construction:**
  - Weighted sum of gross computer and IT, communication, and software investments
  - Three different approaches to the **perpetual inventory method** following Srivastava (1996), Topalova and Khandelwal (2011), Harrison (1994), Sivadasan (2009), and adjusting quality using state-level telecommunication usage data from Telecom Regulatory Authority of India
  - High correlation between these alternative D (0.79 to 0.97)

Some Descriptives

Table 2: Industry-Wise Samples

Classified Industry	Prowess Samples	ASI Samples	NSSO Samples
1. Food	10,050	40,845	21,597
2: Textiles and Apparels	9,351	33,877	31,616
3: Wood, Paper and Printings	3,552	15,273	14,732
4: Chemical and Rubber	15,875	33,225	2,137
5: Fuels and Minerals	3,745	17,603	8,270
6: Metals	13,874	31,683	9,994
7: Machinery	7,096	17,841	913
8: Electricals and Electronics	8,193	20,465	1,046
9: Transport Vehicles and Equipments	6,942	18,635	645
10: Pharmaceuticals	5,114	11,627	125
11: Others	1,868	5,887	5,153

Table 3: Summary Stat for Pooled Samples

	Prow (annual)	ASI (annual)	NSSO (month)
Gross Output (GO)	5,012.04	1,331.74	0.091
	(689.20)	(239.63)	(0.021)
Value Added (Y)	2,396.51	613.25	0.046
	(311.98)	(109.50)	(0.014)
Labor (L)	179.73	152.26	4.284
	(30.66)	(49.02)	(2.000)
Materials (M)	2,425.38	681.87	0.039
	(310.72)	(114.99)	(0.005)
Energy (E)	190.14	36.62	0.006
	(19.39)	(1.12)	(0.001)
Physical Capital (K)	2,536.96	846.48	0.356
	(283.02)	(105.79)	(0.050)
Digital Capital (D_1)	22.00		
	(2.06)		
Alternative: D_2	27.67	9.56	0.001
	(2.25)	(0.75)	(0.000)
N	80,972	232,258	78,522

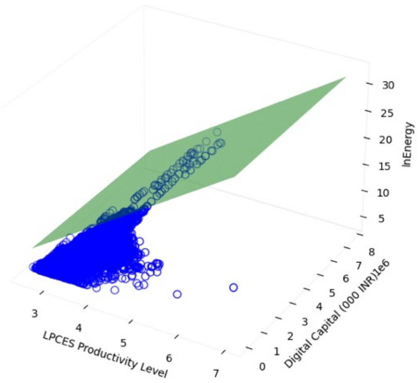
Values in parentheses are medians. All real values are in INR million except labor (L)
Labor represented as annual real compensation INR million (Prowess), total annual man-days worked '000 (ASI), total labor worked in the plant for last 30 days (NSSO)

A) Concavity of production function

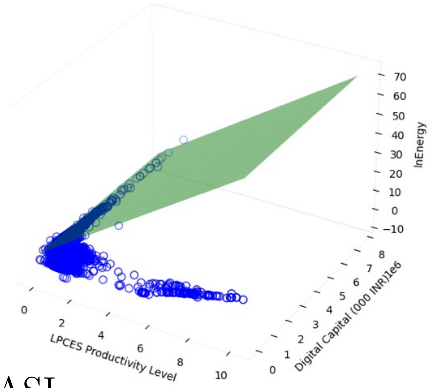
- Assessed through a semi-definite Hessian Matrix

B) Monotonicity of proxy's demand

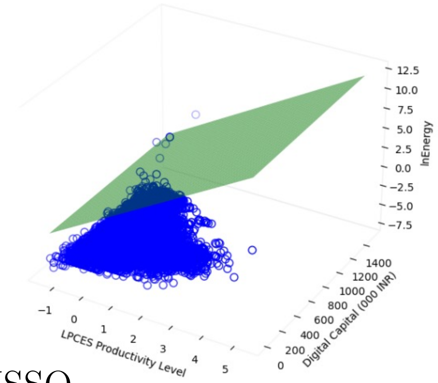
- Assumotion is valid



Prowess



ASI



NSSO

Figure 4.A: Testing Monotonicity (energy as proxy)

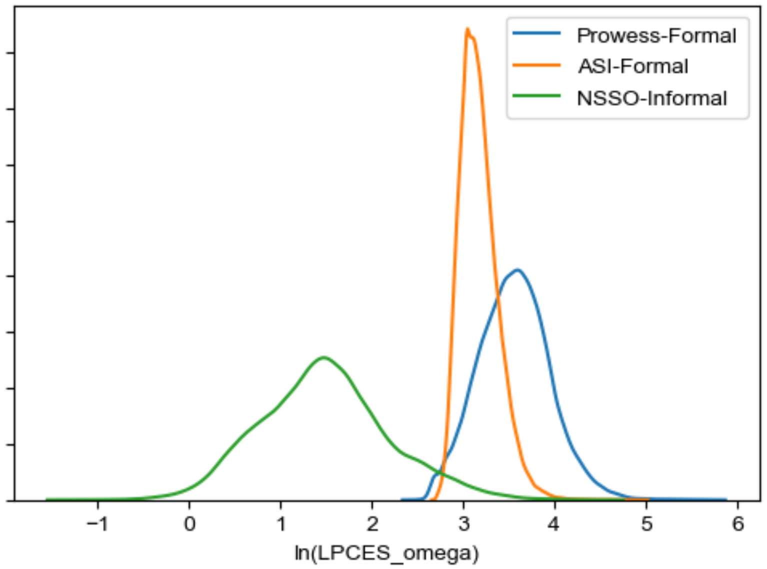


Figure 4.B: Distribution of Productivity Level

Results (1/4)

Table 4: Industry-wise Effects of Digital Capital: Prowess

Outcome: lnY	Pooled	Industry 1 Food	Industry 2 Tex. & Apparel (TA)	Industry 3 Wood & Paper (WP)	Industry 4 Chem. & Rub. (CR)	Industry 5 Fuel & Miner. (FM)	Industry 6 Metals	Industry 7 Machinery	Industry 8 Electr -ic & -onic (EE)	Industry 9 Trans. & Equip. (TE)	Industry 10 Pharma.	Industry 11 Other Manuf. (OM)
lnL	0.637***	0.541***	0.556***	0.674***	0.643***	0.660***	0.549***	0.783***	0.706***	0.717***	0.749***	0.761***
	(0.0219)	(0.057)	(0.059)	(0.043)	(0.031)	(0.032)	(0.0352)	(0.0466)	(0.0356)	(0.0143)	(0.0000)	(0.1199)
ε_K	0.155***	0.110***	0.154***	0.039***	0.207***	0.318***	0.188***	0.116***	0.138***	0.165***	0.073***	0.028***
	(0.0011)	(0.0024)	(0.0016)	(0.0035)	(0.0017)	(0.0014)	(0.0028)	(0.0026)	(0.0045)	(0.0033)	(0.0033)	(0.0032)
ε_D	0.050***	0.107***	0.123***	0.014***	0.074***	0.079***	0.027***	0.059***	0.025***	0.057***	0.060***	0.058***
	(0.0005)	(0.0018)	(0.0012)	(0.0005)	(0.0012)	(0.0011)	(0.0004)	(0.0018)	(0.0009)	(0.0019)	(0.0015)	(0.0035)
θ	0.182***	0.297***	0.353***	0.058***	0.256***	0.503***	0.115***	0.331***	0.143***	0.332***	0.179***	0.250***
	(0.0022)	(0.005)	(0.005)	(0.008)	(0.0051)	(0.0105)	(0.0018)	(0.0119)	(0.0138)	(0.0114)	(0.0065)	(0.0036)
$\sigma = \frac{1}{1-\theta}$	1.222	1.422	1.546	1.062	1.344	2.012	1.130	1.495	1.167	1.497	1.218	1.333
RTS	0.842	0.758	0.833	0.727	0.924	1.057	0.764	0.958	0.869	0.939	0.882	0.847
N	80,972	9,462	8,748	3,316	15,003	3,517	13,068	6,793	7,814	6,648	4,821	1,782

Results (2/4)

Table 5: Industry-wise Effects of Digital Capital: ASI

Outcome: lnY	Pooled	Industry 1 Food	Industry 2 Tex. & Apparel (TA)	Industry 3 Wood & Paper (WP)	Industry 4 Chem. & Rub. (CR)	Industry 5 Fuel & Miner. (FM)	Industry 6 Metals	Industry 7 Machinery	Industry 8 Electr -ic & -onic (EE)	Industry 9 Trans. & Equip. (TE)	Industry 10 Pharma.	Industry 11 Other Manuf. (OM)
lnL	0.635***	0.630***	0.543***	0.647***	0.642***	0.631***	0.589***	0.716***	0.779***	0.719***	0.675***	0.650***
	(0.0125)	(0.0245)	(0.0223)	(0.0228)	(0.0166)	(0.0239)	(0.0254)	(0.0251)	(0.0284)	(0.0115)	(0.0000)	(0.0104)
ε_K	0.357***	0.296***	0.272***	0.347***	0.388***	0.378***	0.405***	0.249***	0.277***	0.273***	0.330***	0.210***
	(0.0025)	(0.0007)	(0.0005)	(0.0019)	(0.0006)	(0.0009)	(0.0000)	(0.0014)	(0.0015)	(0.0011)	(0.0009)	(0.0014)
ε_D	0.030***	0.036***	0.092***	0.0056***	0.032***	0.061***	0.0040***	0.107***	0.023***	0.095***	0.064***	0.176***
	(0.0002)	(0.0005)	(0.0004)	(0.0004)	(0.0003)	(0.0006)	(0.0000)	(0.0009)	(0.0007)	(0.0010)	(0.0008)	(0.0013)
θ	0.728***	0.4302***	0.672***	0.798***	0.764***	0.748***	0.800***	0.797***	0.733***	0.703***	0.483***	0.662***
	(0.0058)	(0.0005)	(0.0022)	(0.0011)	(0.0062)	(0.0057)	(0.0000)	(0.0013)	(0.0168)	(0.0089)	(0.0124)	(0.0068)
$\sigma = \frac{1}{1-\theta}$	3.676	1.755	3.049	4.950	4.237	3.968	5.000	4.926	3.745	3.367	1.934	2.959
RTS	1.022	0.962	0.907	1.000	1.062	1.070	0.998	1.072	1.079	1.087	1.069	1.036
N	232,258	38,594	31,697	14,352	31,239	16,609	29,554	16,815	19,264	17,640	10,938	5,556

Table 6: Industry-wise Effects of Digital Capital: NSSO

Outcome: lnY	Pooled	Industry 1 Food	Industry 2 Tex. & Apparel (TA)	Industry 3 Wood & Paper (WP)	Industry 4 Chem. & Rub. (CR)	Industry 5 Fuel & Miner. (FM)	Industry 6 Metals	Industry 11 Other Manuf. (OM)
lnL	0.716***	0.705***	0.638***	0.729***	0.636***	0.538***	0.726***	0.550***
	(0.0256)	(0.0459)	(0.0372)	(0.0283)	(0.1042)	(0.1326)	(0.0527)	(0.0529)
ε_K	0.284***	0.051***	0.111***	0.309***	0.346***	0.239***	0.184***	0.230***
	(0.0135)	(0.0046)	(0.0074)	(0.0159)	(0.0123)	(0.0042)	(0.0051)	(0.0071)
ε_D	0.034***	0.027***	0.049***	0.031***	0.043***	0.024***	0.053***	0.034***
	(0.0029)	(0.0019)	(0.0033)	(0.0022)	(0.0036)	(0.0023)	(0.0033)	(0.0027)
θ	0.485***	0.167***	0.282***	0.508***	0.517***	0.489***	0.368***	0.490***
	(0.0221)	(0.0159)	(0.0190)	(0.0222)	(0.0214)	(0.0184)	(0.0187)	(0.0205)
$\sigma = \frac{1}{1-\theta}$	1.942	1.200	1.393	2.033	2.070	1.957	1.582	1.961
RTS	1.034	0.783	0.798	1.069	1.025	0.801	0.963	0.814
N	78,522	16,678	30,003	11,936	1,421	5,006	7,886	4,026

Results (4/4): Digitalization-Employment Nexus

Modified from Martin et al. (2017): $$ln\left(\frac{L}{Y}\right)_{it} = \delta_0 + \delta_1(Top\ Digital\ Quantile = 1)_{it} + \tau_j + \tau_s + \tau_t + \varepsilon_{it} \quad (4)$$

- where, $ln(\frac{L}{Y})$ represents the log of labor intensity, Top Digital Quantile=1 if i falls in top 25th percentile of digital intensity $(\frac{D}{Y})$

Table 7: Effect of Digital Capital Intensity on Employment

Industry	(1) Prowess	(2) ASI	(3) NSSO
Pooled	0.768*** (0.043)	0.707*** (0.029)	0.086 (0.062)
Food	0.727*** (0.157)	0.731*** (0.102)	-0.111 (0.127)
Tex. & Apparel	0.631*** (0.061)	0.679*** (0.087)	0.049 (0.036)
Wood & Paper	0.597*** (0.044)	0.648*** (0.034)	0.286** (0.121)
Chem. & Rub.	0.716*** (0.041)	0.692*** (0.032)	0.060 (0.225)
Fuel & Miner.	0.753*** (0.092)	0.607*** (0.091)	-0.130 (0.159)
Metals	0.989*** (0.131)	0.741*** (0.099)	0.171 (0.119)
Machinery	0.720*** (0.042)	0.672*** (0.047)	
Electr -ic & -onic	0.884*** (0.084)	0.778*** (0.055)	
Trans. & Equip.	0.603*** (0.076)	0.554*** (0.048)	
Pharma.	0.757*** (0.031)	0.894*** (0.038)	
Other Manuf.	1.026*** (0.172)	0.865*** (0.205)	0.698*** (0.166)

Robustness

- **Variations:**
  - Other identification method (ACF), Cobb-Douglas value added function, alternative measures of digital capital
  - Choice of proxies for correcting simultaneity: energy vs. intermediates
  - Changes the depreciation rate of digital capital from 10 to 25%
  - Data winsorization

- Across the board, **results remain robust**, but with some deviations for the informal sector
  - Example: Depreciation rate change: results are consistent, except for NSSO, where the digital dividend increased by 1% when D_3 is used

- **Sectoral results:**
  - Informal firms have, in general, higher labor elasticity and lower capital elasticity
  - Observed returns to scale, and labor and physical capital elasticities are mostly consistent

- **Across broad literature:**
  - Consistent with literature on India and other regions

Takeaways

- **Digital dividends are real:**
  - Across industries, formal firms reap higher benefits (0.02-0.17), compared to informal ones (0.02 to 0.05)
- **Substitution between K and D:**
  - Lower for informal industries (than formal). Subs. of digital for physical capital points to opportunities for digitalization
- **Digitalization-Employment Nexus:**
  - Digitally-intensive entities in the formal sector tend to also have a high labor- and skilled-labor intensities, unlike informal
  - Entities with high-digital capital account for a larger share of employment in every industry in the formal sector
- **So what?**
  - Digitalization and formalization of informal firms are essential for enhancing value addition and employment
  - Invest in digital skills and accessibility to expand formal sector capacity and integrate informal into larger markets
  - Heterogenous implications across industries, but better idea on where investment's benefit can be maximized
  - Innovations in big data, cloud computing, AI: improved digital capital will shape the digital future of India and beyond

Thank you!

DikshitPoudel@uga.edu OR M.Gopinath@uga.edu