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The impact of artificial intelligence on output and inflation

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Views are those of the authors and not necessarily those of the Bank for International Settlements.

The rise of artificial intelligence

- AI has the potential to be "the most important general-purpose technology of our era" (Brynjolfsson et al (2023))

- Recent inroads of generative AI in everyday applications have triggered hopes of widespread efficiency gains
  - Productivity gains for workers (Brynjolfsson et al (2023); Noy and Zhang (2023); Peng et al (2023))
  - Improvements in sales & employment growth, productivity & innovation for firms (Yang (2022); Czarnitzki et al (2023), Babina et al (2024))

- By transforming occupational tasks, altering corporate strategies, and affecting production efficiency, AI may have significant consequences for labour markets, firms, and whole industries
  - Broad agreement: positive for productivity (1-1.5% range), GPT

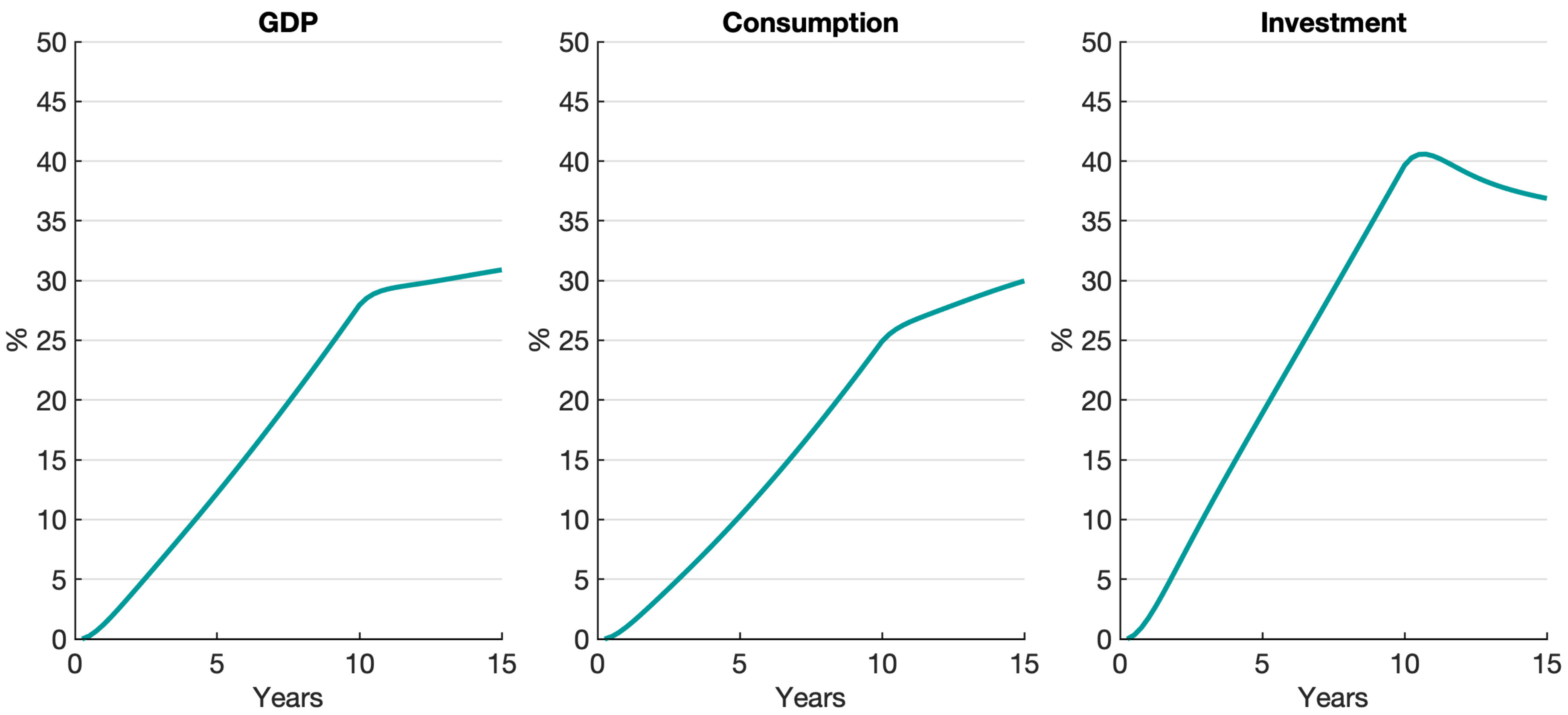
Research question and methodological approach

- What are the effects of AI on aggregate output and inflation, as well as on output in different sectors?

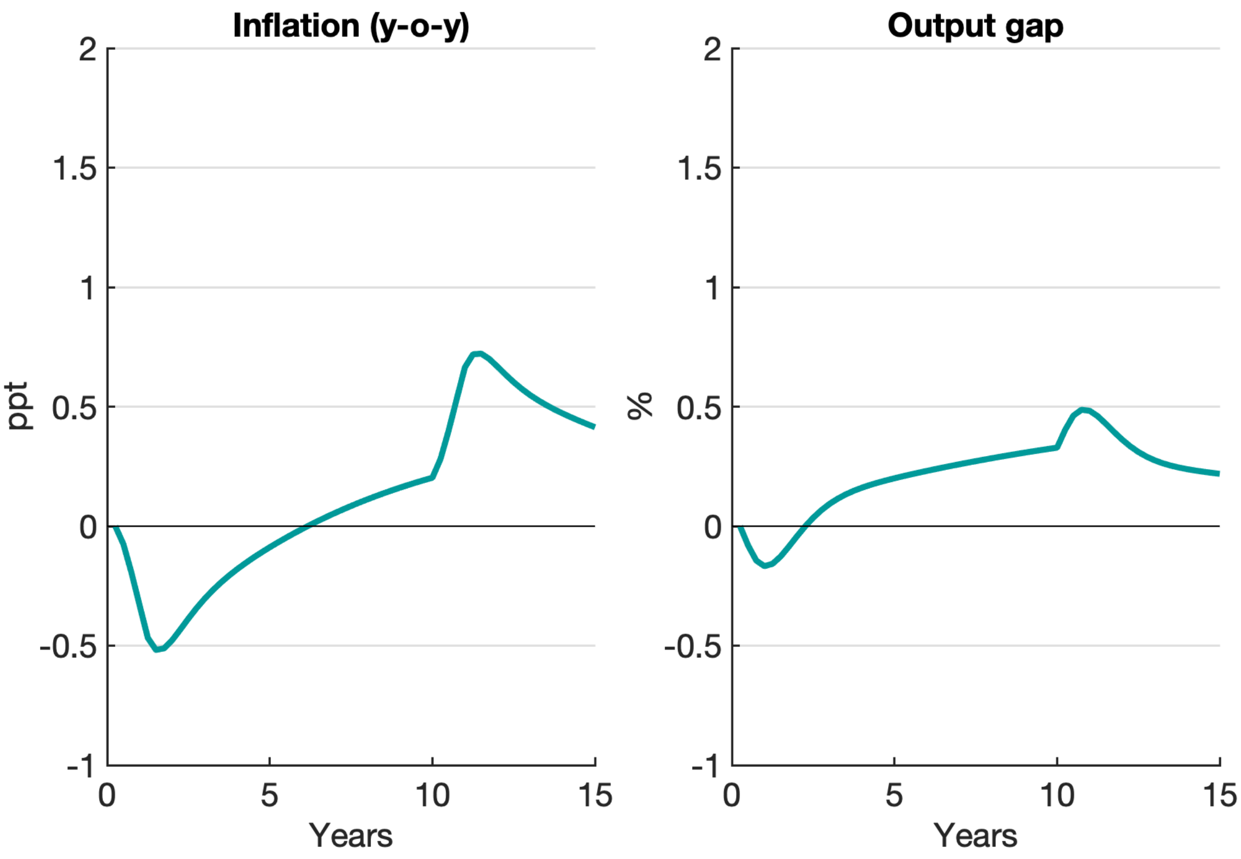
Outline

- Construct industry-level measure of exposure to AI (AIIE) at the 2-digit NAICS level, building on Felten et al (2021)
- Calibrate multi-sector macroeconomic model in which AI is a positive productivity shock with a differential impact across sectors
  - Allocate the shock across sectors using the AIIE measure
- Investigate effects on macro-aggregates & sectors; use model for counterfactual analyses
  - Effects of AI could "unanticipated" or "anticipated" by agents

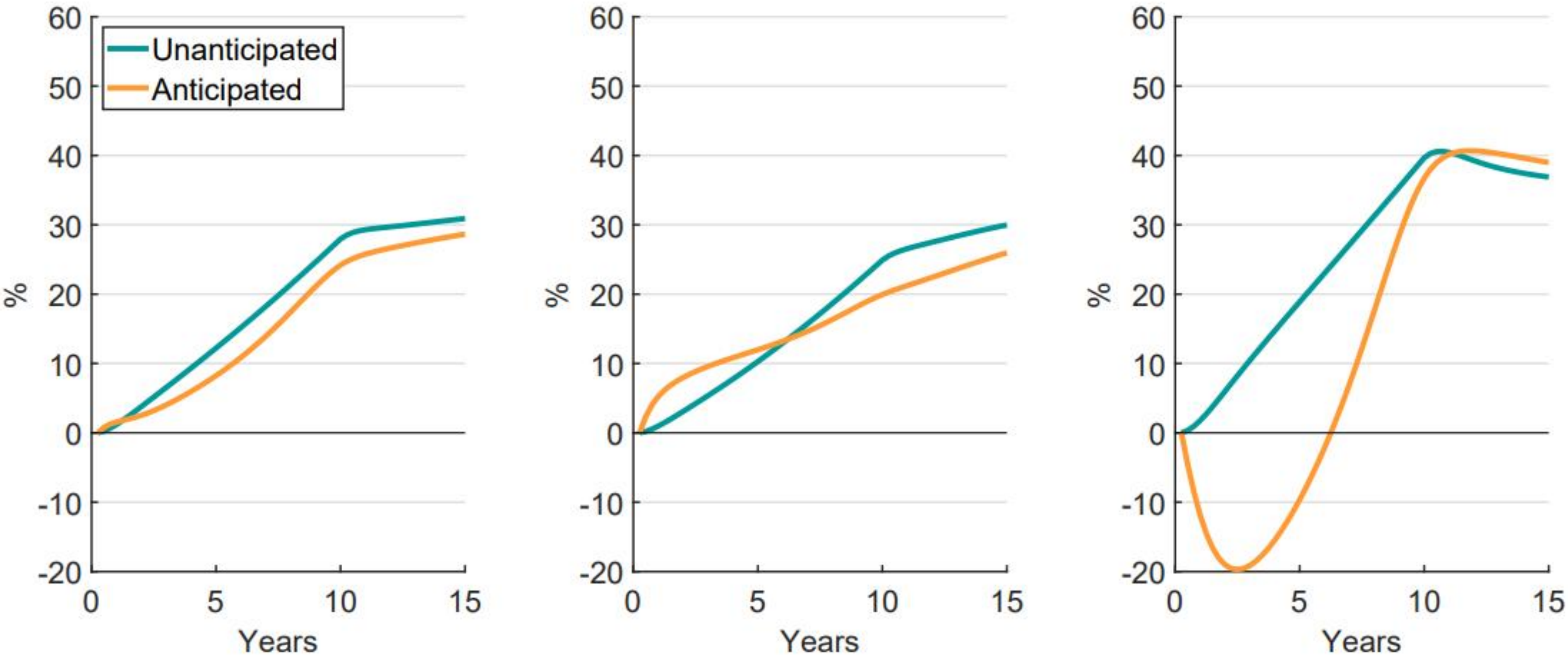
AI increases GDP, consumption and investment (unanticipated)



Initially disinflationary, AI over time leads to inflation

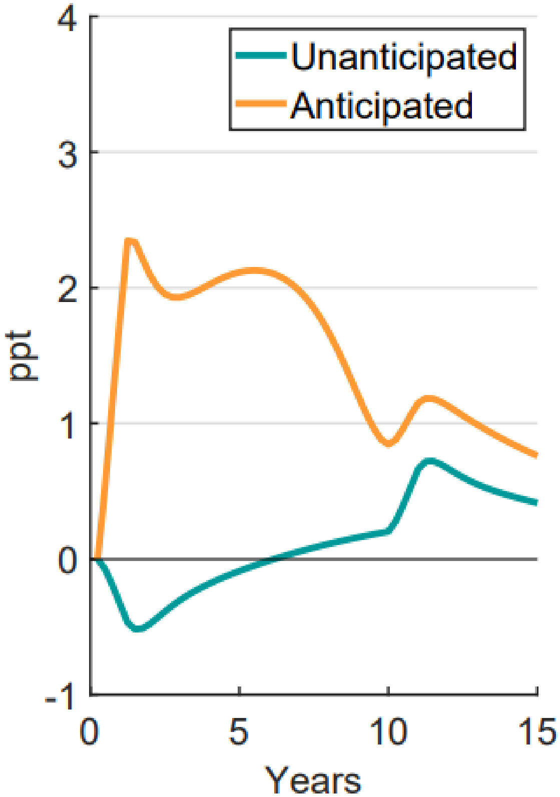


When anticipated, investment takes time to pick up…

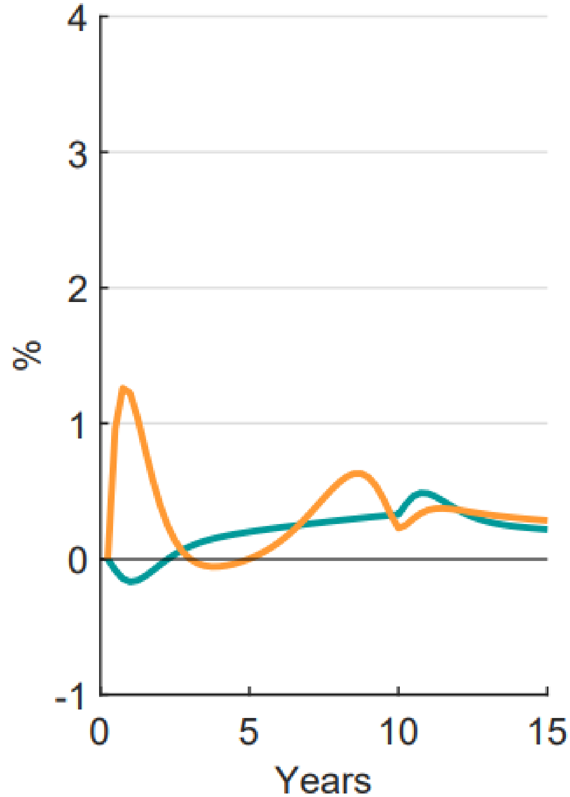


(a) GDP (b) Consumption (c) Investment

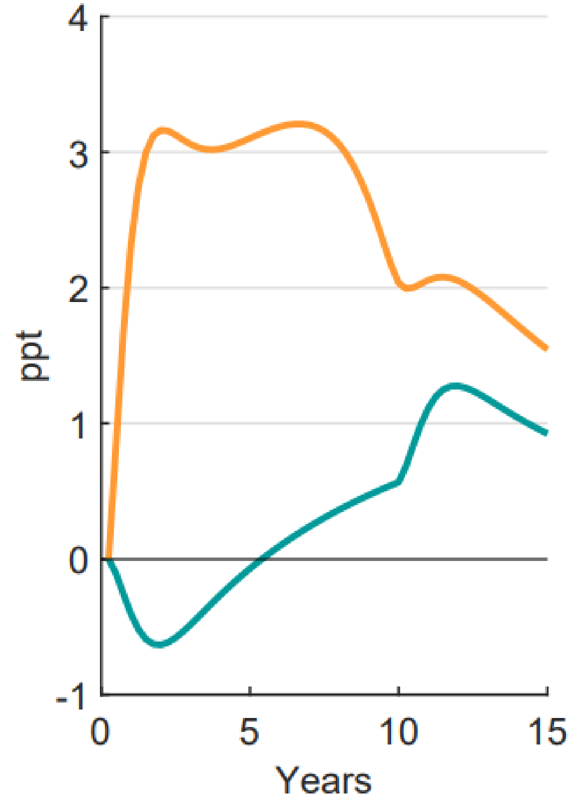
… and the dynamics of inflation, output gap and rates differ



(a) Inflation



(b) Output gap



(c) Policy rate

The impact of AI across industries

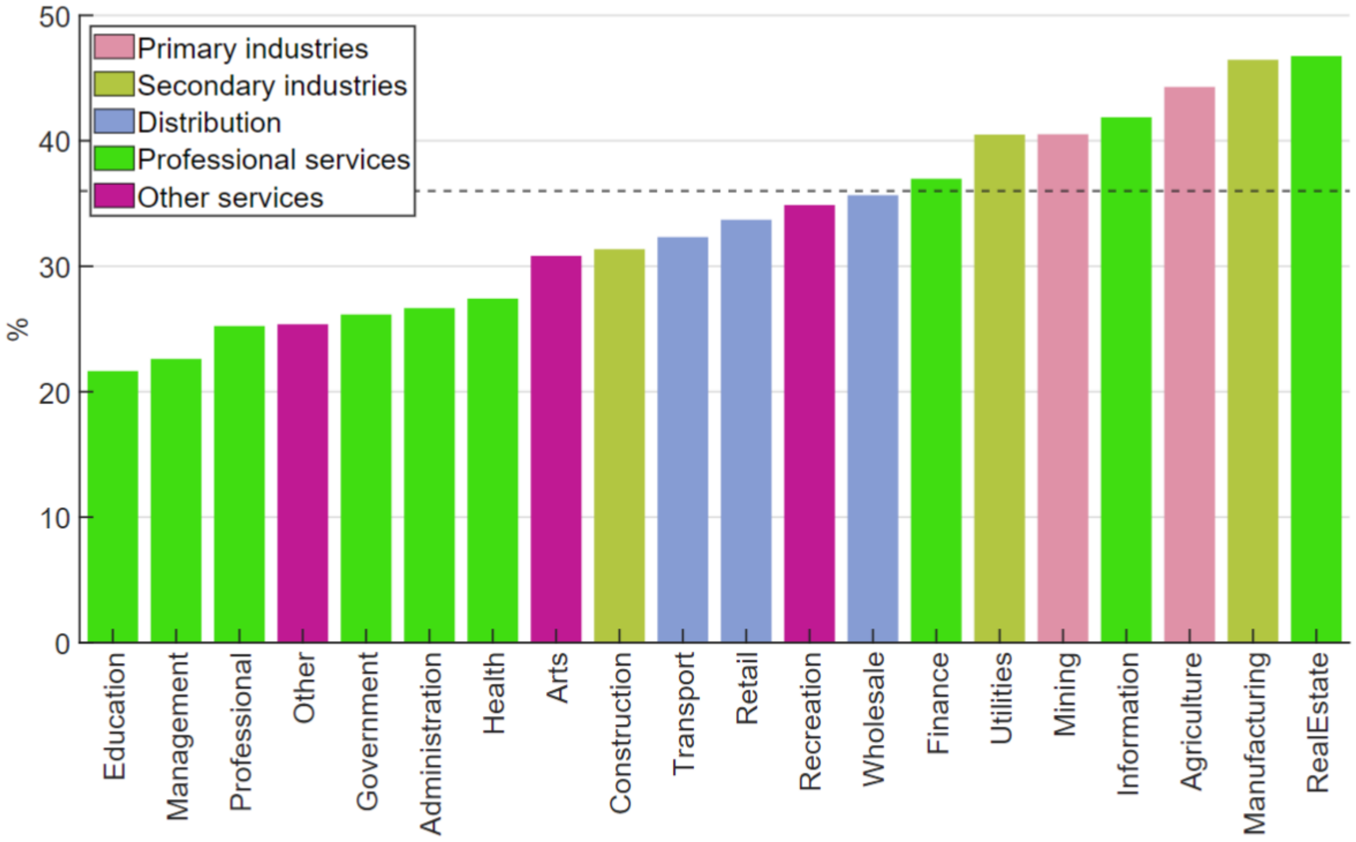
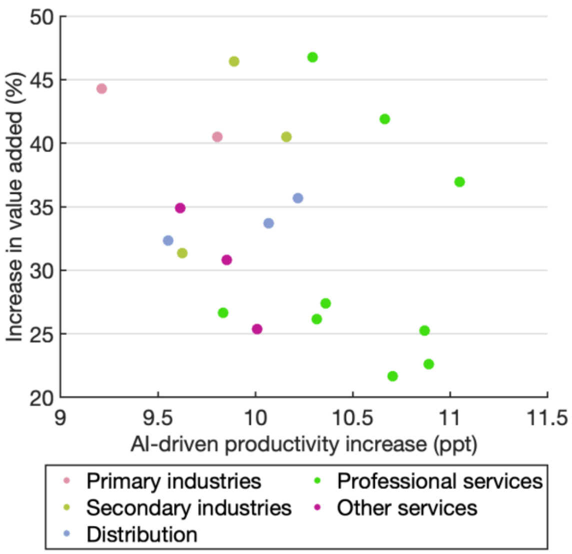


Figure 9: **Long-run increase in industry value added**

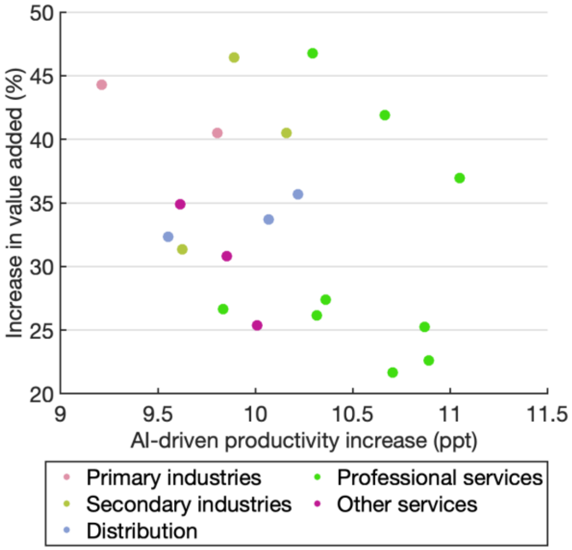
1. Output rises in all sectors: general purpose tech
2. Variation across industries
3. Some industry groups clearly benefit more than others

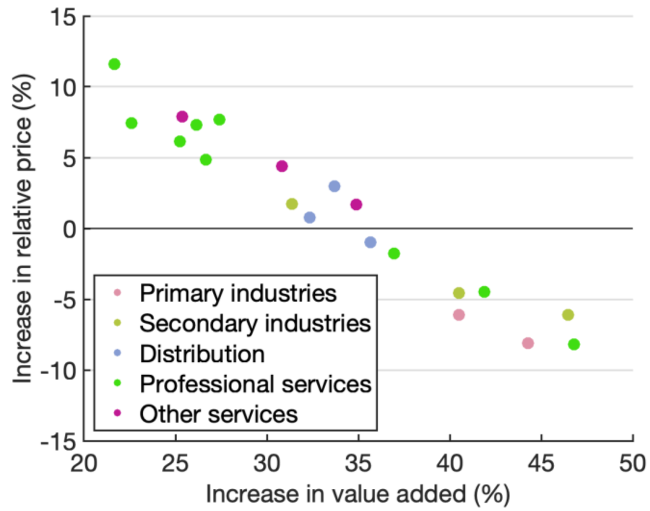
Important to account for general equilibrium effects



- No direct mapping between initial industry exposure to AI & long run increase in value added

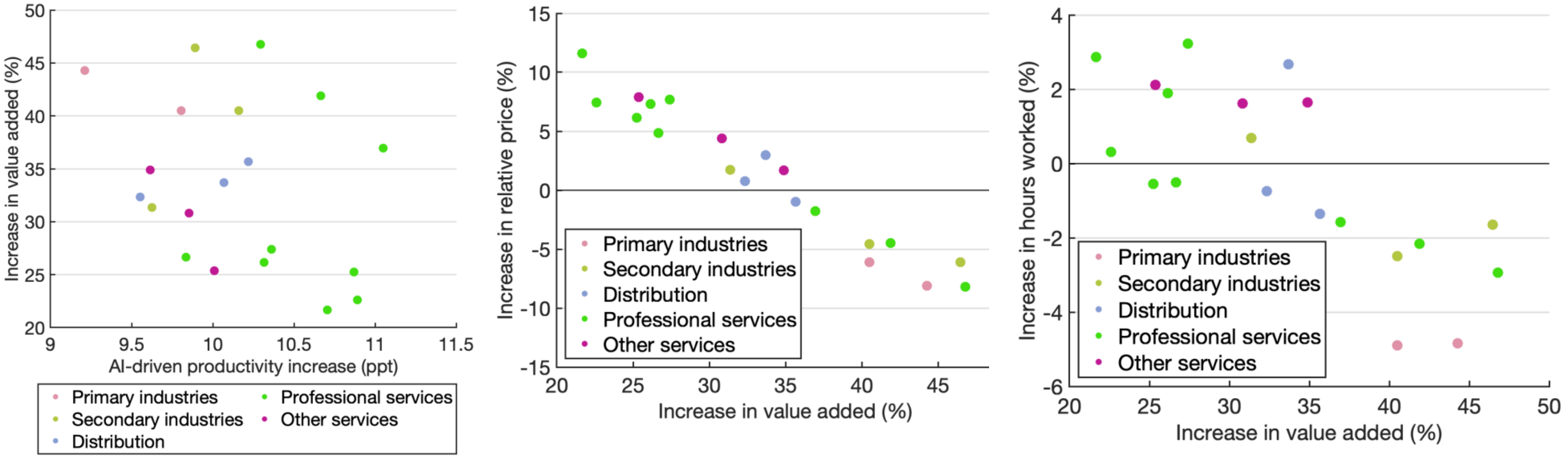
Important to account for general equilibrium effects





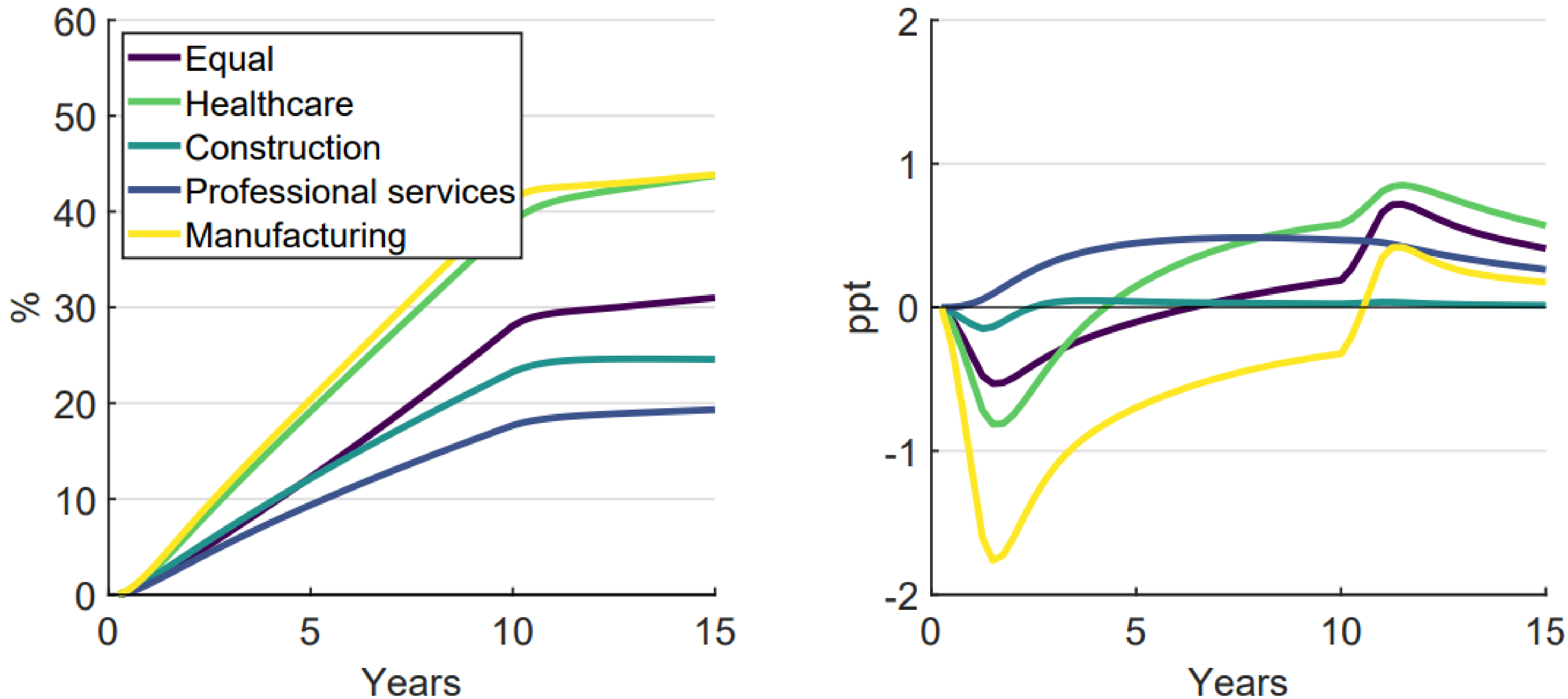
- No direct mapping between initial industry exposure to AI & long run increase in value added
- Sectors with largest increase in output see largest declines in prices …

Important to account for general equilibrium effects



- No direct mapping between initial industry exposure to AI & long run increase in value added
- Sectors with largest increase in output see largest declines in prices …
- … and in hours worked

Counterfactual #1: Exploring industry variation on the effect of AI

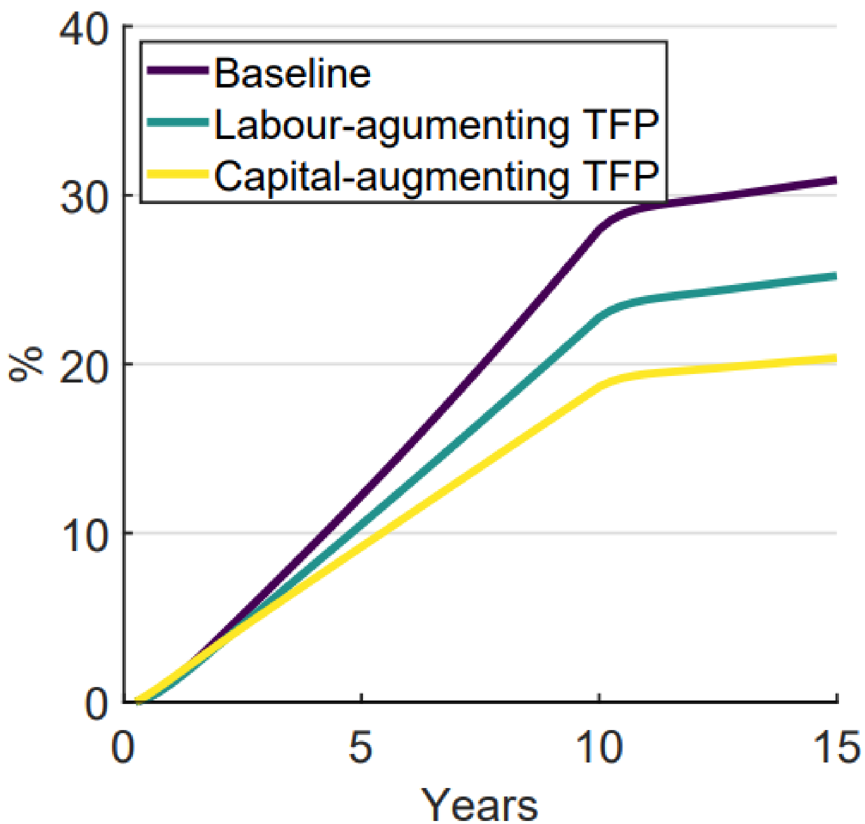


(a) Gross Domestic Product

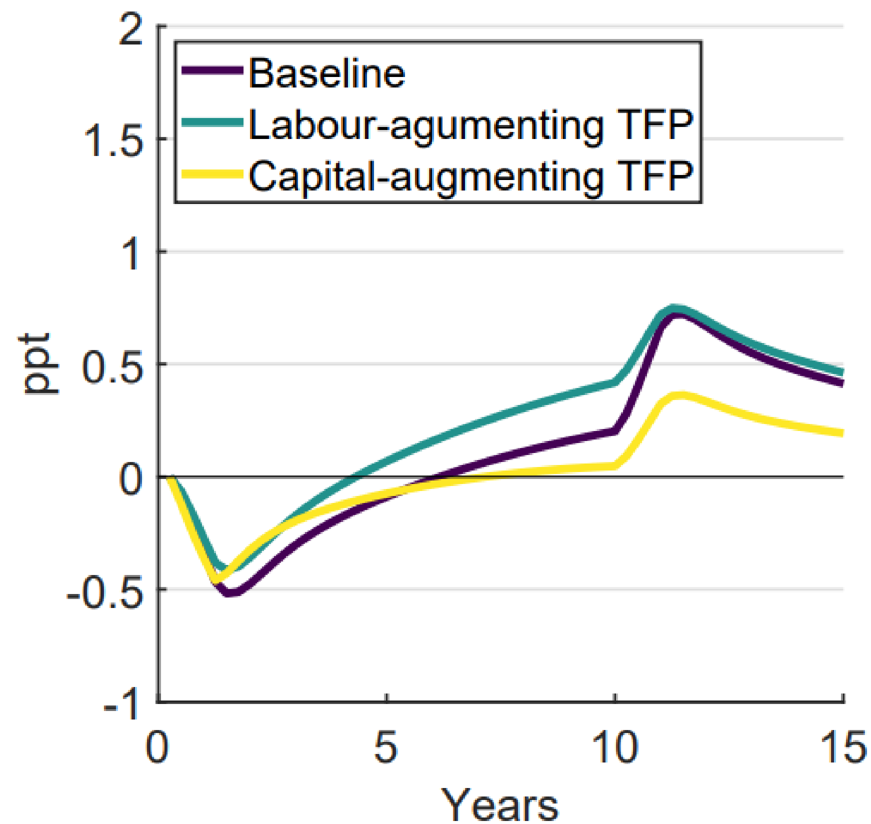
(b) Inflation (year-on-year)

- Recall: little variation across sectors from AIIE baseline calibration
  - Counterfactual: AI raises productivity in only one sector
- Where AI shock is concentrated matters, especially for inflation
  - Role for production linkages

Counterfactual #2: general purpose vs factor-specific technology



(a) Gross Domestic Product



(b) Inflation (year-on-year)

- Instead of GPT, have AI be either L- or K-augmenting
- Not much difference w.r.t. baseline, quantitatively & qualitatively

Conclusion

- First multisector macro model that studies impact of AI on macro outcomes & the effects across industries
  - Grounded on granular measure of impact of AI across occupations & industry aggregation based on production structure

- From counterfactuals: focus more on use of industry output (proximity to final demand & linkages) rather than industry factor-intensity
  - Where AI shock concentrates matters, especially for path of inflation

  → More research needed here!

- Lots of caveats!
  - But a useful tool to ground our thinking while remaining open

Thank you for your time & attention!

Further reading

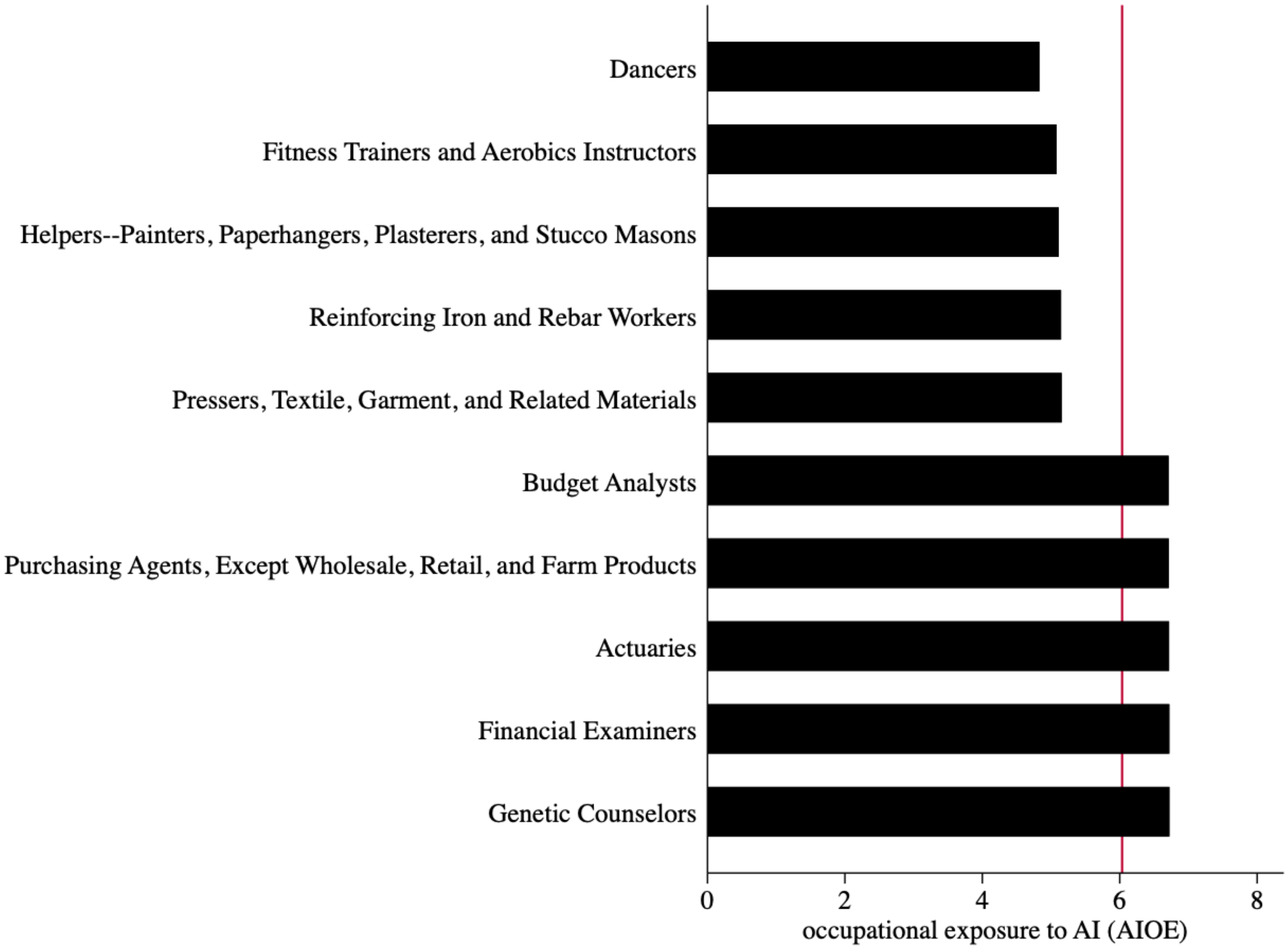
- BIS Annual Economic Report Chapter III (2024): "Artificial intelligence and the economy: implications for central banks"
- Aldasoro, I, O Armantier, S Doerr, L Gambacorta and T Oliviero (2024a): "Survey evidence on gen AI and households: job prospects amid trust concerns", *BIS Bulletin*, no 86, April.
- ——— (2024b): "The gen AI gender gap", *Economics Letters*, forthcoming.
- Aldasoro, I, S Doerr, L Gambacorta, G Gelos and D Rees (2024): "Artificial intelligence, labour markets and inflation", mimeo.
- Aldasoro, I, S Doerr, L Gambacorta, S Notra, T Oliviero and D Whyte (2024): "Generative artificial intelligence and cybersecurity in central banking", *BIS Papers*, no 145, May.
- Aldasoro, I, L Gambacorta, A Korinek, V Shreeti and M Stein (2024): "Intelligent financial system: how AI is transforming finance", *BIS Working Papers*, no 1193.
- Aquilina, M, D Araujo, G Gelos, T Park and F Perez-Cruz (2024): "Harnessing artificial intelligence for monitoring financial markets", *BIS Working Papers*, forthcoming.
- Araujo, D, S Doerr, L Gambacorta and B Tissot (2024): "Artificial intelligence in central banking", *BIS Bulletin*, no 84, January.
- Cornelli, G, J Frost and S Mishra (2023): "Artificial intelligence, services globalisation and income inequality", *BIS Working Papers*, no 1135, October.
- Gambacorta, L, B Kwon, T Park, P Patelli and S Zhu (2024): "CB-LMs: language models for central banking", *BIS Working Papers*, forthcoming.
- Gambacorta, L, H Qiu, D Rees and S Shian (2024): "Generative AI and labour productivity: a field experiment on code programming", mimeo.
- Park T, H S Shin and H Williams (2024): "Mapping the space of economic ideas with LLMs", *BIS Working Papers*, forthcoming.
- Perez-Cruz, F and H S Shin (2024): "Testing the cognitive limits of large language models", *BIS Bulletin*, no 83, January

ANNEX

Index of impact of AI by industry (AIIE, Felten et al (2021))

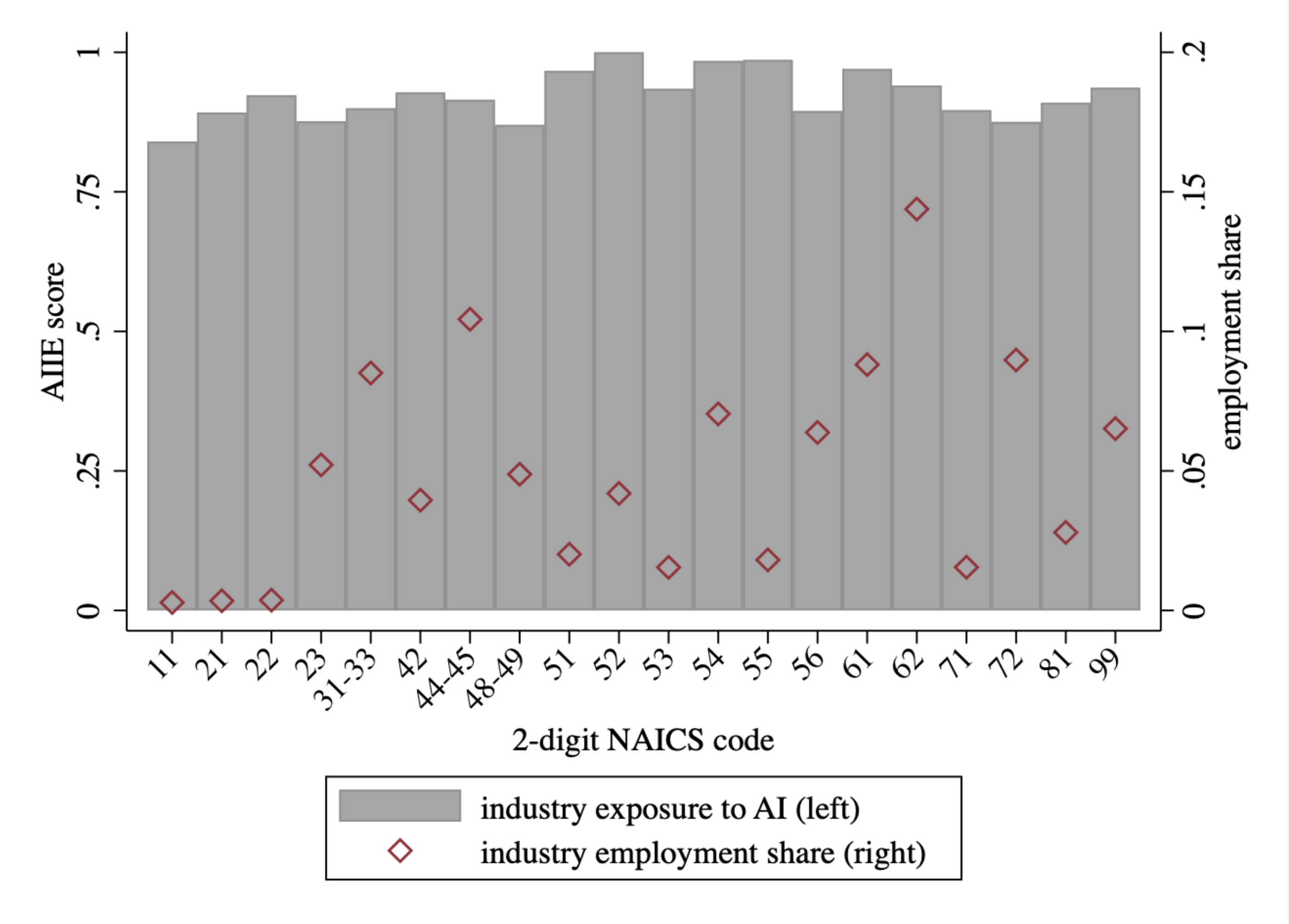
1. Survey: 10 AI applications covering AI's most likely use cases are linked to a list of 52 workplace abilities
   - For each ability, survey respondents indicate whether they think the respective AI application can be used
   - Results in relatedness measure for each occupation-ability combination ranging from 0 (no relation) to 1 (high relation)
2. Each ability's exposure = sum of the relatedness value across all AI applications, ranges from 0 (no exp) to 10 (high exp)
3. Each occupation's exposure to AI (AIOE) = average across 52 abilities' exposures to AI, weighted by abilities' prevalence in each occupation
4. Aggregate to industry level (AIIE) based on occupations' employment shares within each two-digit industry

Artificial Intelligence occupation exposure (AIOE)



- Lowest-scoring mostly high-degree of physical effort
- Highest exposure mostly white collar requiring advanced degrees

Artificial intelligence industry exposure (AIIE)



- Highest: finance & insurance, management companies
- Lowest: agriculture, forestry & fishing, transportation & warehousing

The model

- Quantitative multi-industry macroeconomic model (Rees (2020))
  - *Households (HH):* CES consumption/labour bundles
  - *Industries* w/ many firms producing differentiated goods under monopolistic competition; 2-stage production w/ intermediate inputs; Ind-specific TFP
    - Capital/labour intensive; consumption/investment/intermediate goods
  - *Government*: purchases goods & services from firms & transfers resources between HH
  - *Central bank*: adjusts policy rate based on Taylor-type rule

- Calibrate using US input-output tables & values from literature

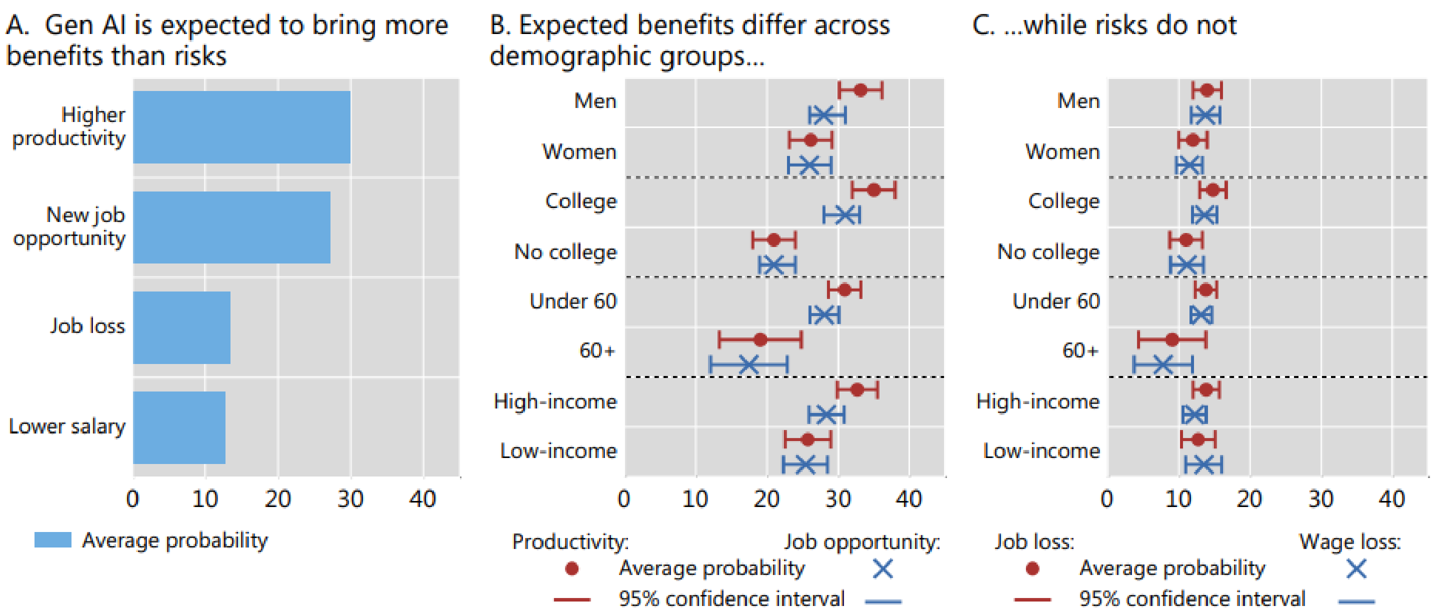
- Use AIIE to allocate +TFP across industries, under aggregation constraint, assuming AI boosts TFP growth for 10 years

- Effects of AI could "unanticipated" or "anticipated" by agents

What do we know about HH expectations regarding AI?

Highway to automation or stairway to job security? Gen AI and job prospects

In per cent Graph 2

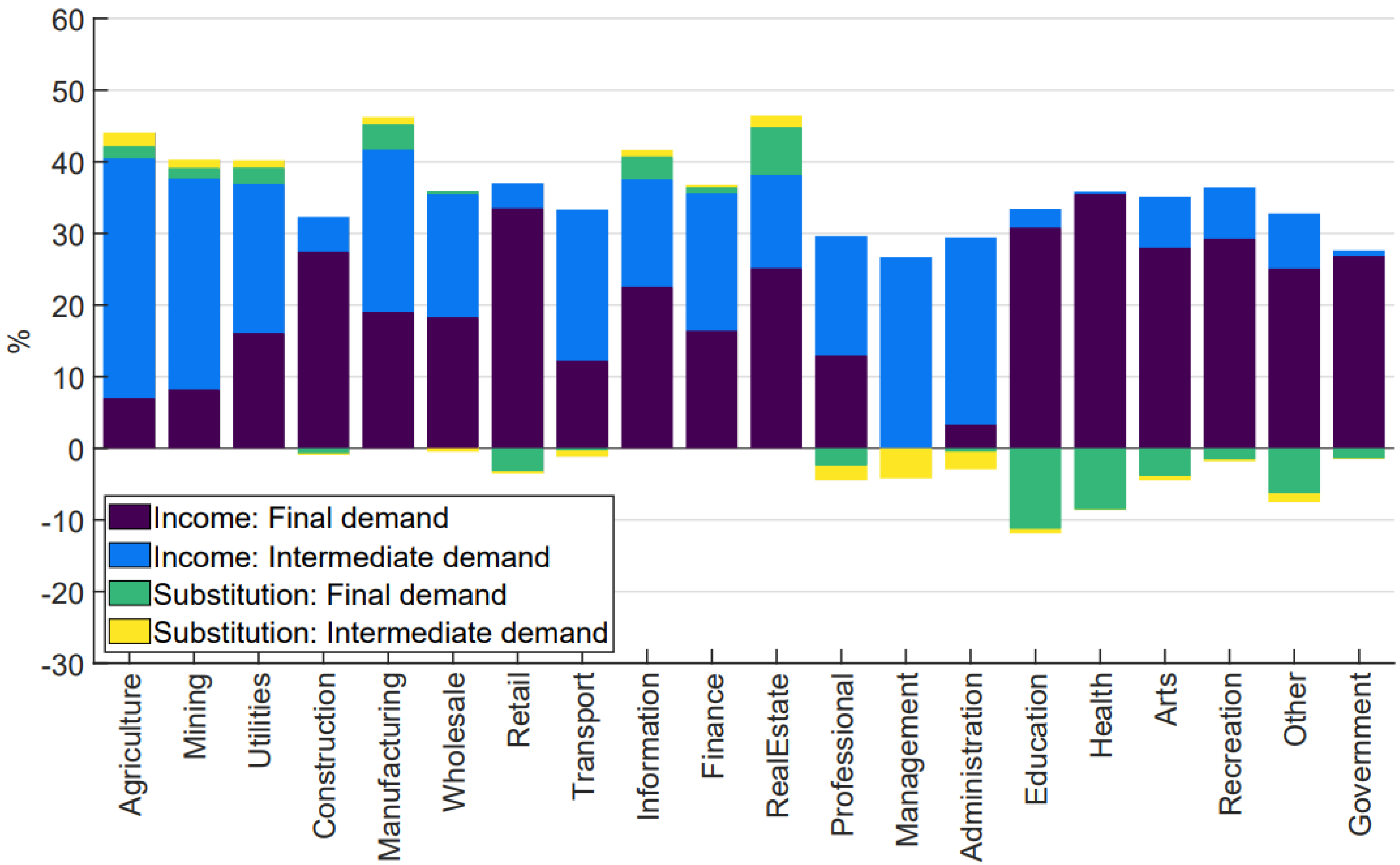


Panel A reports the average responses to the following questions: 1 "What do you think are the chances that artificial intelligence will increase your productivity at work?", 2 "What do you think are the chances that artificial intelligence will help you find new job opportunities?", 3 "What do you think are the chances that you will lose your current job because of artificial intelligence tools?" and 4 "What do you think are the chances that your salary in your current job will decrease because of artificial intelligence tools?" Respondents could indicate their assessment on a scale of 0 to 100%. Panel B reports average probabilities and 95% confidence intervals by household groups to questions 1 (red dot) and 2 (blue cross). Panel C reports average probabilities and 95% confidence intervals by household groups to questions 3 (red dot) and 4 (blue cross).

Source: Federal Reserve Bank of New York, *Survey of Consumers Expectations*; authors' calculations.

Aldasoro et al (2024a): "Survey evidence on gen AI and households: job prospects amid trust concerns", BIS Bulletin #86.
Aldasoro et al (2024b): "The gen AI gender gap", Economics Letters, forthcoming.

Decomposition of value added across industries



Scaled-down model 1

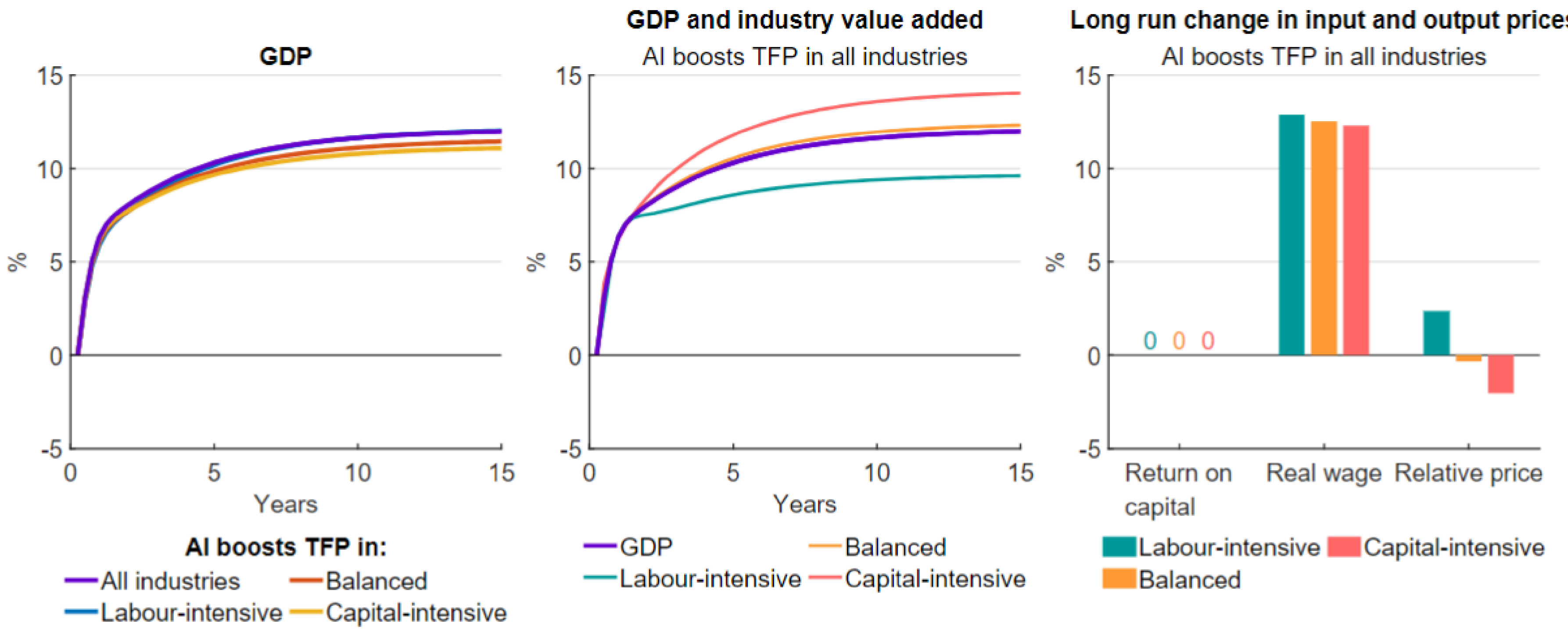


Figure 3: Simple model 1 – Cross-industry differences in production technologies

Scaled-down model 1

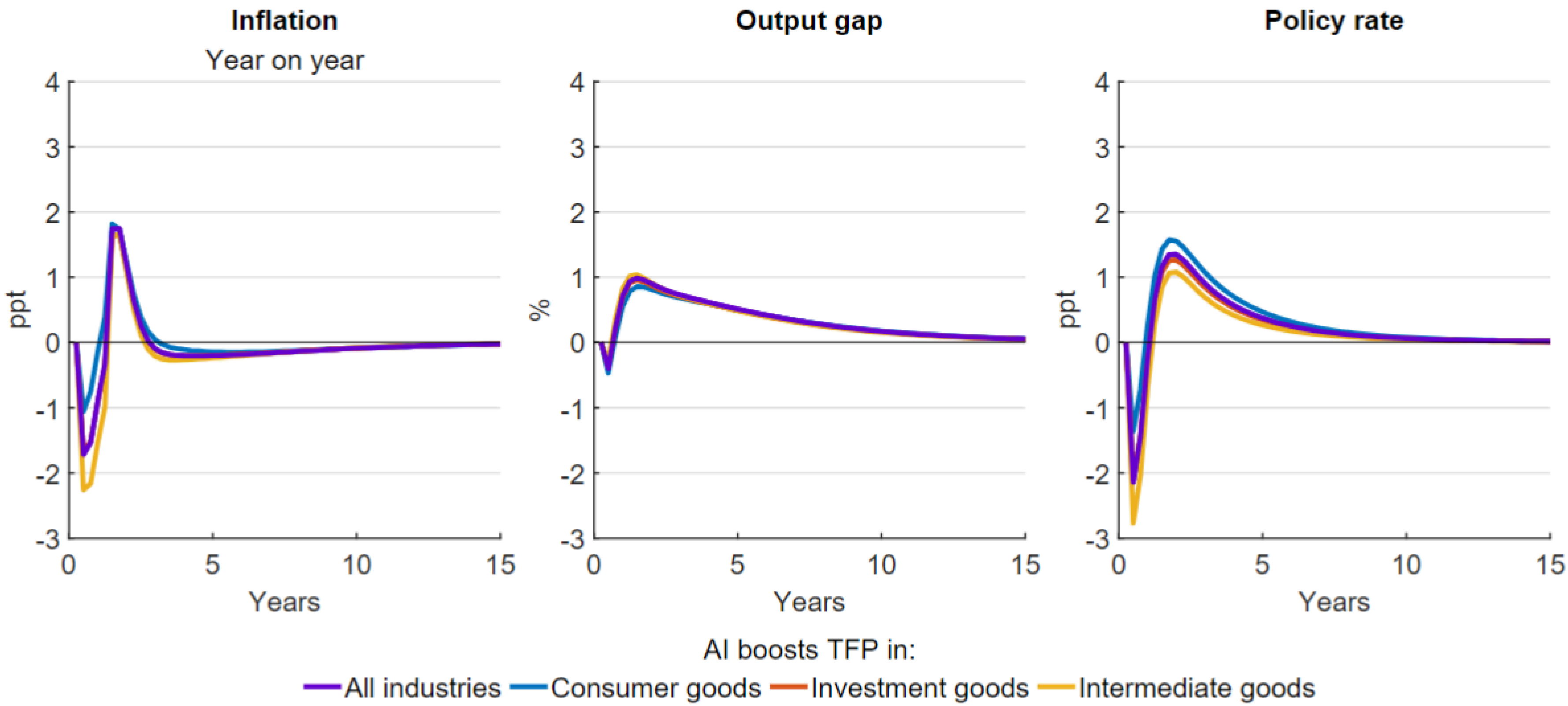


Figure 5: Simple model 1

Scaled-down model 2

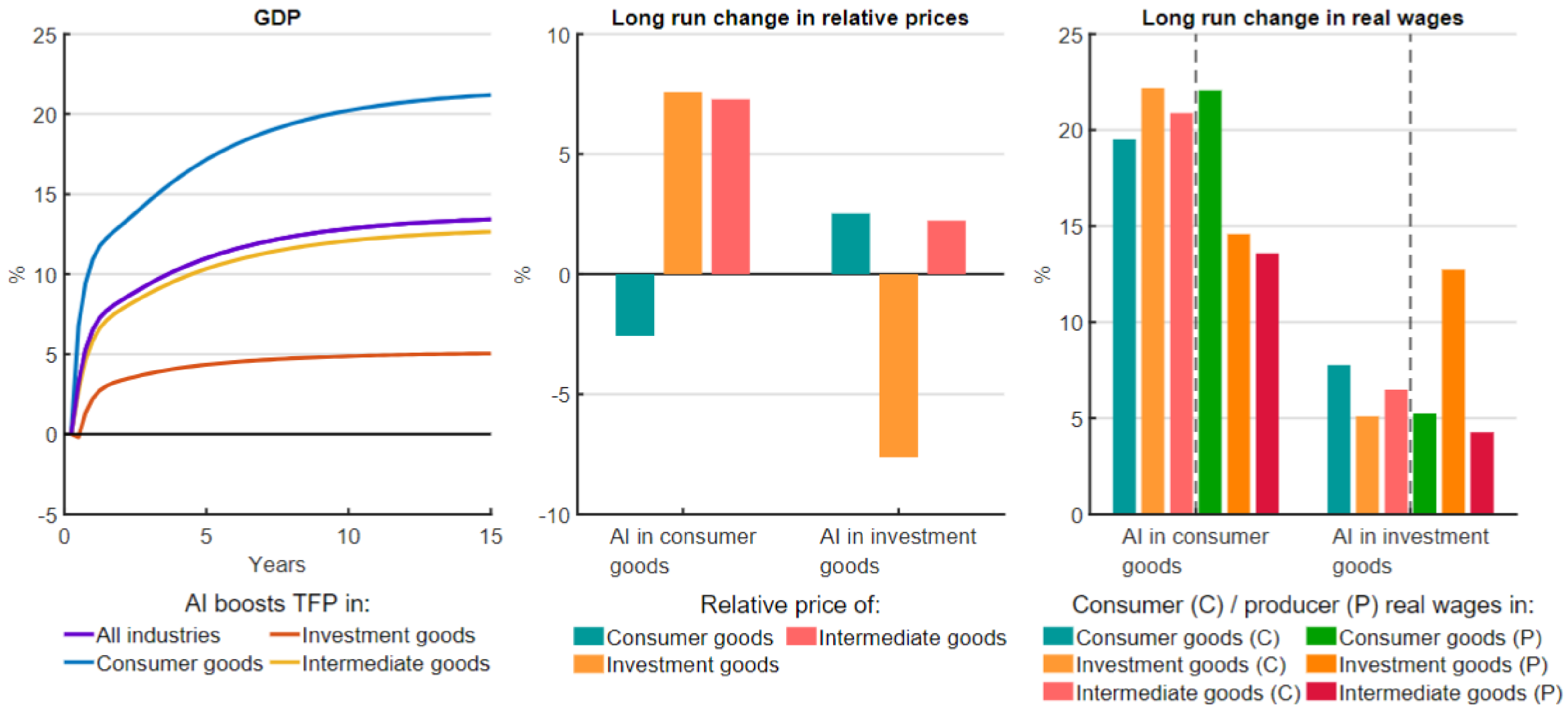


Figure 4: Simple model 2 – Differences in the use of industry output

Scaled-down model 2

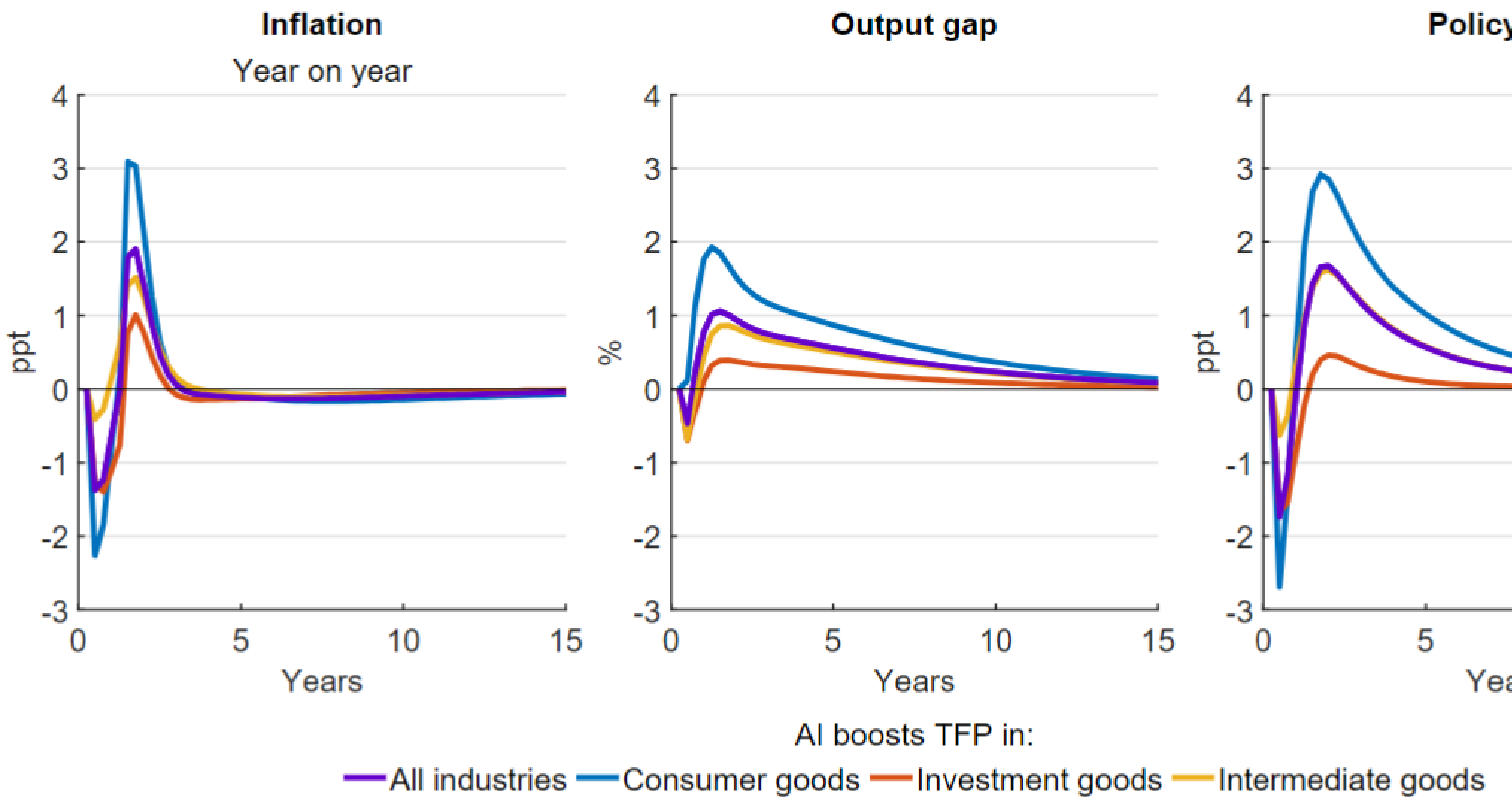
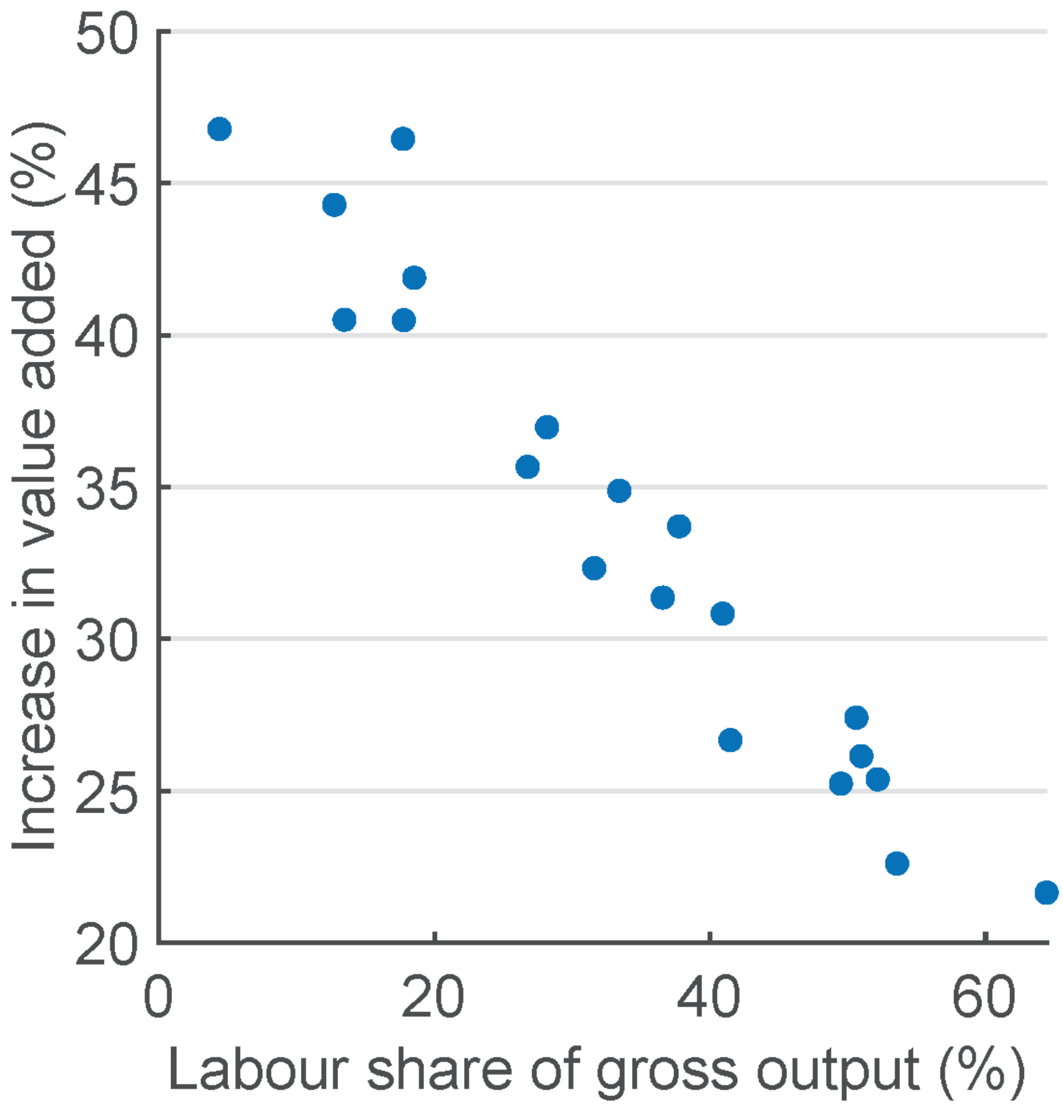


Figure 6: Simple model 2

Value-added increases less in labour-intensive industries



Calibration

Table 1: Calibration of key parameters

Parameter	Description	Value
β	Discount rate	0.99
h	Habits	0.70
Spp	Investment adjustment cost	3.00
η	Elasticity of substitution in demand CES	0.90
ζ	Elasticity of substitution between capital and labour	0.95
φ	Elasticity of substitution between intermediates and capital / labour	0.60
ψ	Elasticity of substitution between intermediates	0.40
ν	Frisch labour supply elasticity	2.00
ε_w	Labour supply elasticity across industries	5.00
δ	Depreciation rate	0.02
ρ_r	Taylor rule - autoregressive parameter	0.80
ϕ_π	Taylor rule - response to inflation	1.50
ϕ_{gap}	Taylor rule - response to output gap	0.25
θ_{sticky}	Calvo - sticky price sectors	0.80
$\theta_{semi-flex}$	Calvo - semi-flexible price sectors	0.50
θ_{flex}	Calvo - flexible price sectors	0.25
χ_p	Price indexation	0.20
θ_w	Calvo - wages	0.75

Note: Sticky price sectors are Agriculture and Mining; Semi-flexible price sectors are Utilities, Manufacturing, Retail trade, Wholesale trade and Transport.

Function forms of production functions

- Gross output:

$$\underbrace{Y_{j,t}}_{\text{Gross output}} = \underbrace{A_{j,t}}_{\text{TFP}} \left[\omega_{y,j}^{\frac{1}{\varphi}} \underbrace{f_{j,t}^{\frac{\varphi-1}{\varphi}}}_{\substack{\text{Labour +} \\ \text{capital bundle}}} + (1-\omega_{j,y})^{\frac{1}{\varphi}} \underbrace{x_{j,t}^{\frac{\varphi-1}{\varphi}}}_{\substack{\text{Intermediate} \\ \text{inputs}}} \right]^{\frac{\varphi}{\varphi-1}}$$

  - Labour + capital bundle

$$\underbrace{f_{j,t}}_{\substack{\text{Labour +} \\ \text{capital bundle}}} = \left[\omega_{n,j}^{\frac{1}{\zeta}} \underbrace{n_{j,t}^{\frac{\zeta-1}{\zeta}}}_{\text{Labour}} + (1-\omega_{n,j})^{\frac{1}{\zeta}} \underbrace{k_{j,t}^{\frac{\zeta-1}{\zeta}}}_{\substack{\text{Capital} \\ \text{services}}} \right]^{\frac{\zeta}{\zeta-1}}$$