The macroeconomic effects of AI innovation

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The Impact of Artificial Intelligence on the Macroeconomy and Monetary Policy

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Disclaimer: *The views expressed in this paper are those of the authors and do not represent those of the Bank of Italy or the European System of Central Banks.*

Introduction

- **Artificial intelligence (AI)** = "the science and engineering of making intelligent machines"
  - Turing (1950), McCarthy et al. (2007)
- Release of AI-based chatbots like Chat GPT $\Rightarrow$ lively debate on the **economic effects of AI**
  - Focus on labor market implications: complementarity vs substitutability
- What are the **aggregate implications**?
  - AI $\Rightarrow$ **game changer**
    - AI is a General-Purpose Technology (Bresnahan & Trajtenberg 1995, Brynjolfsson et al. 2023, etc)
    - Goldman Sachs $\Rightarrow$ +7% GDP, +1.5% prod growth in US (p.a. over next 10 years)
  - AI $\Rightarrow$ **incremental**
    - Gains are modest (Acemoglu, 2024; *"What happened to the AI revolution?"*, The Economist, 2024)

This paper

- Studies **empirically** the **aggregate** economic implications of **AI innovation** ($\mathcal{AI}int_t$)
  - Our sample predates the development of LLM such as ChatGPT..
  - ..but covers the rise of the digital economy and its major companies
  - In line with other empirical papers on the topic (Bonfiglioli et al., 2023)

- Identify **shocks** to $\mathcal{AI}int_t$ by exploiting US **patent** data

- Employ **local projections** (LPs) $\Rightarrow$ ideal to study dynamic effects at long horizons

Preview of results

- $\mathcal{AI}int_t$ shocks are **expansionary** and affects the economy as a **technology shock**
- Evidence of sizable **general equilibrium effects** (neglected in micro-estimates)
- Downside is an increase in **wealth inequality**

Literature

- Economic implications of automation and AI
  - Acemoglu and Restrepo (2020) Prettner and Strulik (2020) Moll et al. (2022), Grennan and Michaely (2020), Hui et al. (2023), Brynjolfsson et al. (2023), Bonfiglioli et al. (2023), Pizzinelli et al. (2023), Acemoglu (2024), Babina et al. (2024)

  $\Rightarrow$ First empirical evidence on aggregate effects of AI

- Patents in empirical macro
  - Cascaldi-Garcia and Vukotić (2022), Miranda-Agrippino et al. (2020), Ferriani et al. (2023)

  $\Rightarrow$ Exploit novel dataset to measure AI intensity of innovation

- Missing intercept
  - Wolf (2023), …

  $\Rightarrow$ Sizable general equilibrium effects of AI innovation

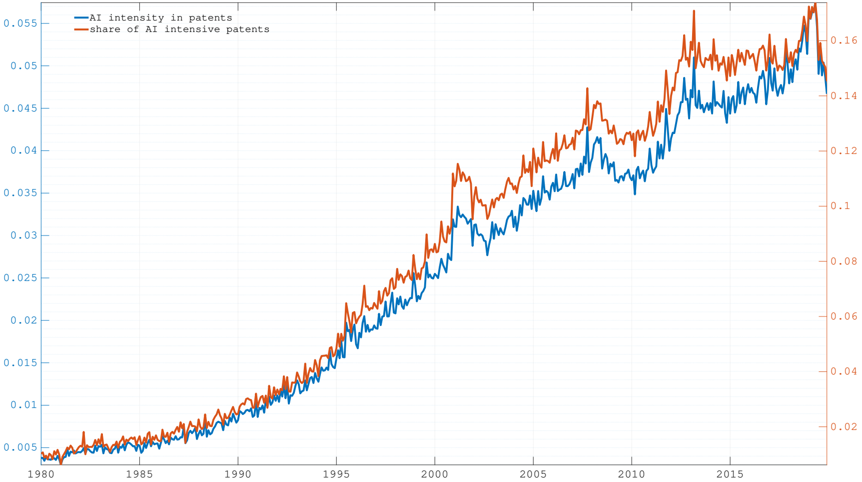
AIPD Data

- AI advances are often open-source
- But patents informative on the AI *content* of new technology (e.g. Webb, 2019)
- Exploit **Artificial Intelligence Patent Dataset** (AIPD)
  - from the United States Patent and Trademark Office (USPTO) $\Rightarrow$ Giczy et al. (2022)
  - **Patent-level score of the AI content of the tech** for all patents (1980-2019)
  - Based on 8 AI domains detected through machine learning and experts validation
- We construct an aggregate index of **AI intensity in US innovation**

$$\mathcal{AI}int_t = \sum_{i=1}^{N_t} \mathcal{AI}int_{i,t} \tag{1}$$

$N = \#$ of patents filed in each month (t month of filing)

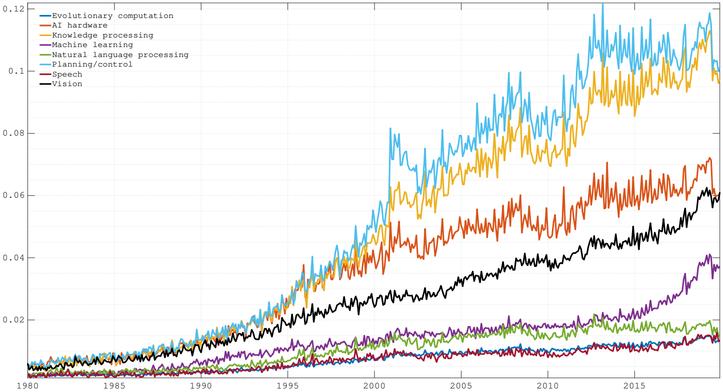
AI intensity over time



Note. The figure displays $\mathcal{AI}int_t$ *and* $\mathcal{AI}share_t$ *at the monthly frequency between 1980 and 2019.*

$$\mathcal{AI}share_t = \frac{\sum_{i=1}^{N_t} \mathcal{I}(\mathcal{AI}int_{i,t} > 0.5)}{N_t}$$ *discretized version*

AI classification



- **Knowledge processing**: representing and deriving facts about the world and using this information in automated systems.
- **Speech recognition**: includes techniques to understand a sequence of words given an acoustic signal.
  Apple's **Siri**, Amazon's **Alexa**, or Microsoft's **Cortana**
- **Machine learning**: contains a broad class of computational models that learn from data.

- **AI hardware**: AI hardware includes physical computer components designed to meet AI computing power through increased processing efficiency and/or speed.
  Google's **Tensor Processing Unit** for neural networks
- **Evolutionary computation**: a set of computational routines using aspects of nature and, specifically, evolution as *genetic algotithms*.
  Chevron's evolutionary approach to predicting available petroleum reserves.
- **Natural language processing**: Understanding and using data encoded in written language.
  Large language models
- **Computer Vision**: extracts and understands information from images and videos.
  The Mayo Foundation for Medical Education and Research and Arizona State University patented a software to detect abnormalities in images taken during colonoscopies.
- **Planning and control**: contains processes to identify, create, and execute activities to achieve specified goals.
  Stochastic optimal control for dynamic optimization under uncertainty

Pre-estimation step

- Patenting potentially **endogenous** to expected economic conditions
  - Miranda-Agrippino et al. (2022)
- We test orthogonality of $\mathcal{AI}int_t$ wrt
  1. economic forecasts
  2. TFP
  3. total number of patents per month
  4. structural shocks
- Similar to what is done in Ferriani, Gazzani & Natoli (2023) on green patents

  $\Rightarrow$ No correlation with other structural shocks

  $\Rightarrow$ correlation with TFP and patenting activity

Orthogonality test

Panel (a): Macroeconomic aggregates

	W-stat	P-value	Obs.	Diff R^2
Long-term Consensus Forecast	0.77	0.38	318	
McCracken and Ng (2016) FRED-MD factors	0.84	0.36	468	
TFP	3.45	0.04	156	<0.001
# patents ($\mathcal{AI}int$)	5.18	0.02	468	<0.001
# patents ($\mathcal{AI}share$)	1.86	0.17	468	<0.001

Panel (b): Monthly structural shocks

Shocks	ρ	P-value	Obs.
Baumeister and Hamilton (2019) oil supply	-0.03	0.46	480
Känzig (2021) oil supply news	0.001	0.97	480
Gertler and Karadi (2015) monetary	-0.03	0.60	324
Romer and Romer (2004) monetary	0.05	0.48	204
Baker et al. (2016) EPU	-0.04	0.38	390
Bloom (2009) uncertainty	0.002	0.95	456
Gilchrist and Zakrajšek (2012) EBP	-0.08	0.07	480
Känzig (2022) carbon policy shocks	-0.001	0.99	246

Panel (c): Quarterly structural shocks

Shocks	ρ	P-value	Obs.
Basu et al. (2006) TFP	-0.03	0.76	128
Smets and Wouters (2007) TFP	-0.08	0.44	100
Beaudry and Portier (2014) news	0.02	0.79	131
Barsky and Sims (2011) news	-0.21	0.03	111
Kurmann and Otrok (2013) news	-0.06	0.55	102
Romer and Romer (2010) fiscal	-0.05	0.57	112
Ramey (2011) fiscal	0.006	0.94	124
Fisher and Peters (2010) fiscal	-0.04	0.71	116
Mertens and Ravn (2013) private tax	-0.06	0.51	108
Mertens and Ravn (2013) corporate tax	-0.06	0.56	108

Notes. Panel (a): $\mathcal{AI}int$ is regressed on a constant, its own 12 lags, and the explanatory variables of interest. The Wald test statistics correspond to the joint significance tests of the coefficient associated with the explanatory variables. In the case of FRED-MD factors, 7 factors are extracted from the FRED-MD database. Panel (b)-(c) report the correlation between the $\mathcal{AI}int$ residual extracted from an AR(12) process and various structural shocks from the literature.

Empirical analysis

- **Identifying assumption**: $\mathcal{AI}int_t$ employed as **internal instrument** in **local projections (LP)**
  - contemporaneously exogenous wrt the other variables in the system
  - requires weaker assumptions compared to identification via external instruments
    - Plagborg-Møller and Wolf (2021)
  - LP more reliable to study medium/long run effects than VARs

- **LP specification** throughout the analysis for each endogenous variable of interest y:

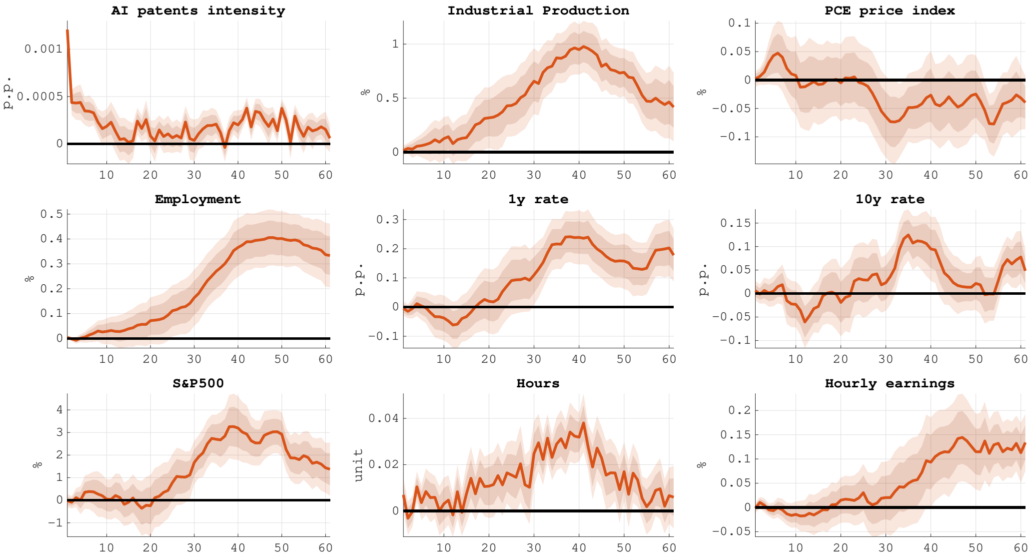
$$y_{t+h} = \alpha_h + \beta_h \mathcal{AI}int_t + \delta_h X_{t-1} + \varepsilon_{t+h} \qquad h = 0, .., 60 \tag{2}$$

where $h =$ horizon of the response, $\alpha =$ constant, β captures IRFs; $X =$ set of controls that include 12 lags of y, $\mathcal{AI}int_t$, and other variables that are specific to each econometric exercise; $\varepsilon_{t+h} =$ residual with moving average structure across $h \Rightarrow$ the inference is based on Newey and West (1994) standard errors.

Roadmap

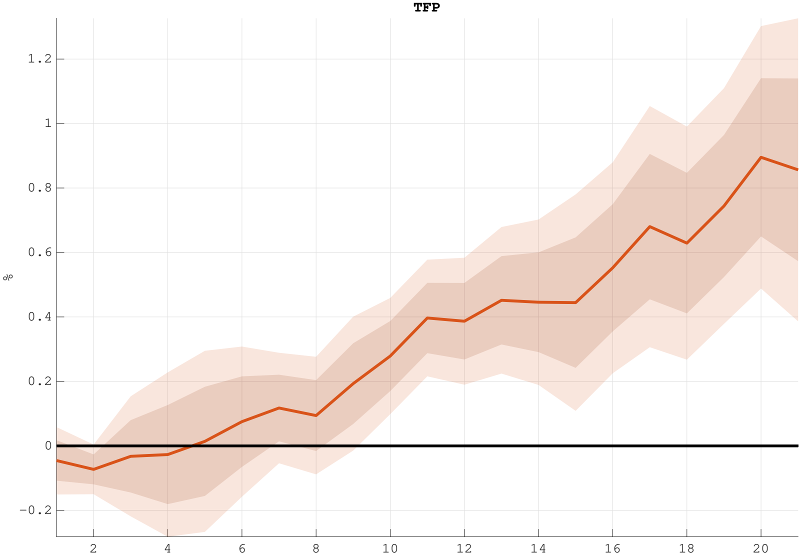
1. **Macroeconomic effects**
   - Baseline IRFs
   - TFP
   - Disaggregated consumer prices
2. Labor market
   - Flows
   - Sectoral heterogeneity
   - Education heterogeneity
3. Inequality
   - Income
   - Wealth

Baseline



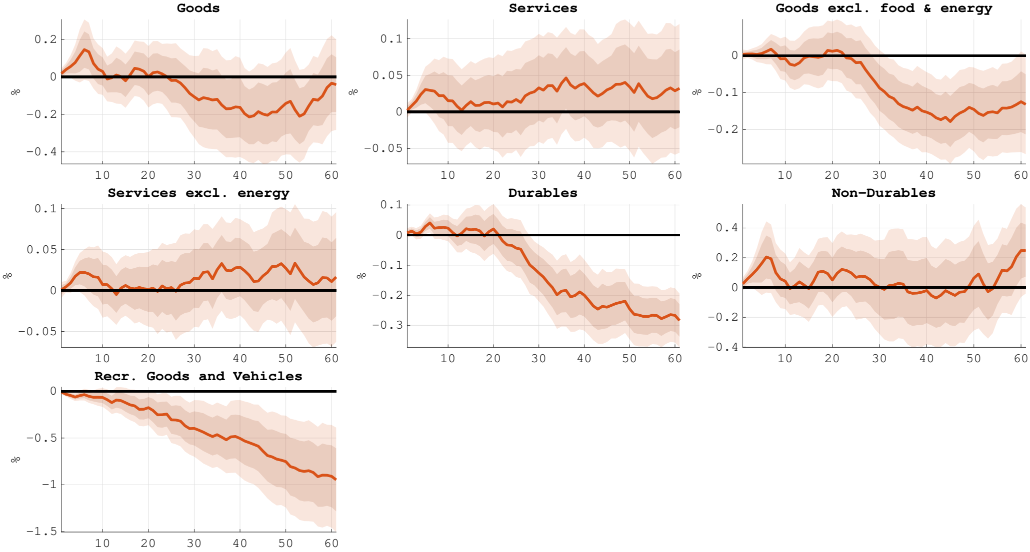
Note. The figure displays the IRFs to a $\mathcal{AI}int$ shock. Sample 1980-2019. The estimates are based on local projections with 12 lags and Newey-West standard errors. Point estimate and 68%-90% confidence bands.

TFP



Note. The figure displays the IRFs to a $\mathcal{AI}$int shock. Sample 1980-2019. The estimates are based on local projections with 4 lags and Newey-West standard errors. Point estimate and 68%-90% confidence bands.

Heterogeneity in consumer prices response



Note. The figure displays the IRFs to a $\mathcal{AI}int_t$ shock. Sample 1980-2019. The estimates are based on local projections with Newey-West standard errors. Point estimate and 68%-90% confidence bands.

Variance decomposition

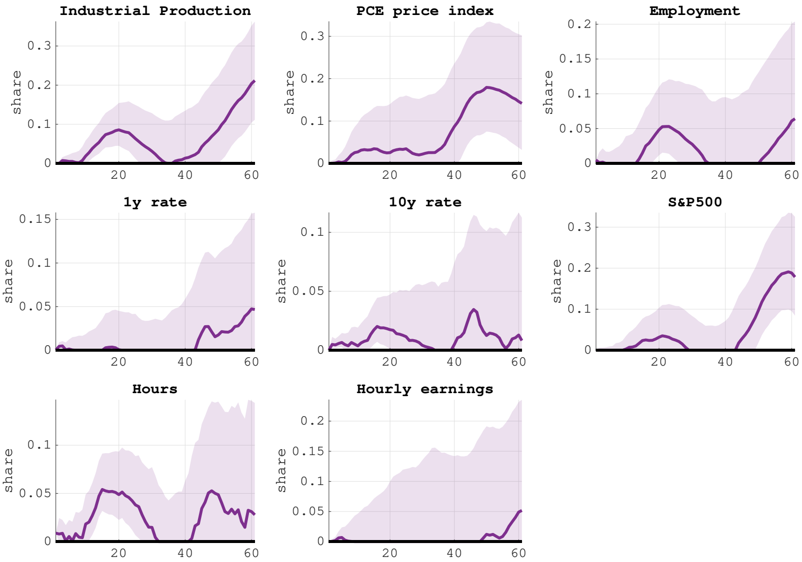
- Quantitative contribution of $\mathcal{AI}int_t$ shock $\Rightarrow$ forecast error variance decomposition
- Follow Gorodnicenko and Lee (2020, JBES) $\Rightarrow$ R^2 approach

$$y_{t+h} = \alpha_h + \beta_h \mathcal{AI}int_t + \delta_h X_{t-1} + \varepsilon_{t+h} \qquad h = 0, .., 60 \tag{3}$$

$$\widehat{\varepsilon}_{j,t+h|t-1} = \omega_{z,0}\widehat{\varepsilon}_{AI,t+h} + \cdots + \omega_{z,h}\widehat{\varepsilon}_{AI,t} + \tilde{v}_{t+h|t-1} \qquad \forall j = \text{endog. vars} \tag{4}$$

- R^2 from regression in Equation (4) yields variance contribution of $\mathcal{AI}int_t$ to y
- Inference based on bootstrap

Variance decomposition (2)



Note. The figure displays the variance contribution of $\mathcal{AI}$int shock. Sample 1980-2019. The estimates are based on local projections with 12 lags. Point estimate and 90% confidence bands from bootstrap.

Summary of macro outcomes

- $\mathcal{AI}int_t$ behave like **expansionary technology shocks**
  - output $\uparrow\uparrow$, prices $\downarrow$
  - **monetary policy** responds to the boost in **economic activity** (quantitatively small implications)

- Expansionary effects on the **labor market**

Interpretation - "The missing intercept problem" (Wolf, 2022 AER)

Results suggestive of large **general equilibrium effects** (complementary AI - labor)

- Fall in aggregate CPI masks glaring heterogeneity
  - Drop in aggregate prices driven by **core prices**
  - Driven by **durables**
  - Driven in particular by **high-tech products**

- Quantitatively, AI development has not been a major driver of the US economy

Robustness and additional results

- Use $\mathcal{AI}share_t$ instead of $\mathcal{AI}int_t$ Share
- Include alternative price indexes PCE core CPI CPI core
- Alternative stock prices Nasdaq High tech vs industrials
- Stationary $\mathcal{AI}int_t$ Linear detrending Qudratic detrending Trend in LP
- Estimates based on iid shocks iid shocks
- Controlling for # patents # patents
- No overlap with robotics patents Table # rob patents % rob patents
- Controlling for financial/uncertainty conditions EBP VXO EPU

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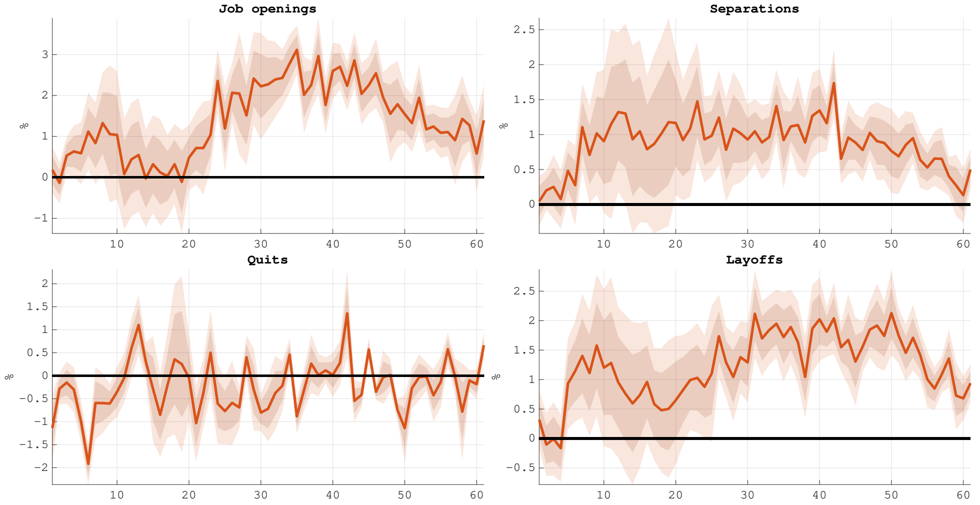
   - Education heterogeneity

3. Inequality
   - Income
   - Wealth

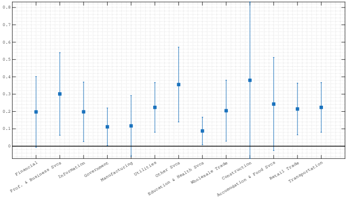
Labor market flows



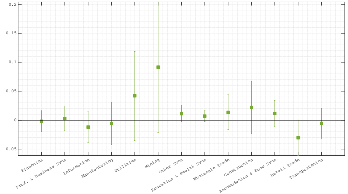
Note. The figure displays the IRFs to a $\mathcal{AI}int_t$ shock. Sample 2006-2019. The estimates are based on local projections with Newey-West standard errors. Point estimate and 68%-90% confidence bands.

Labor market overview

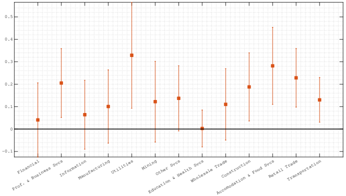
(a) Employment



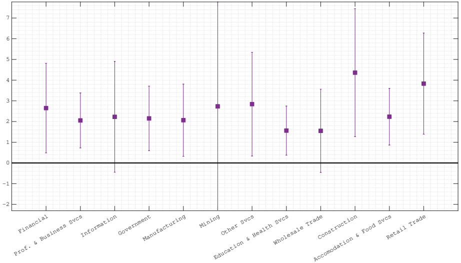
(b) Hours



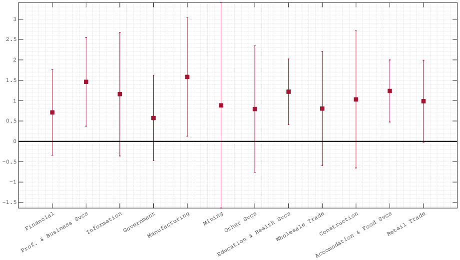
(c) Real wage



(d) Openings

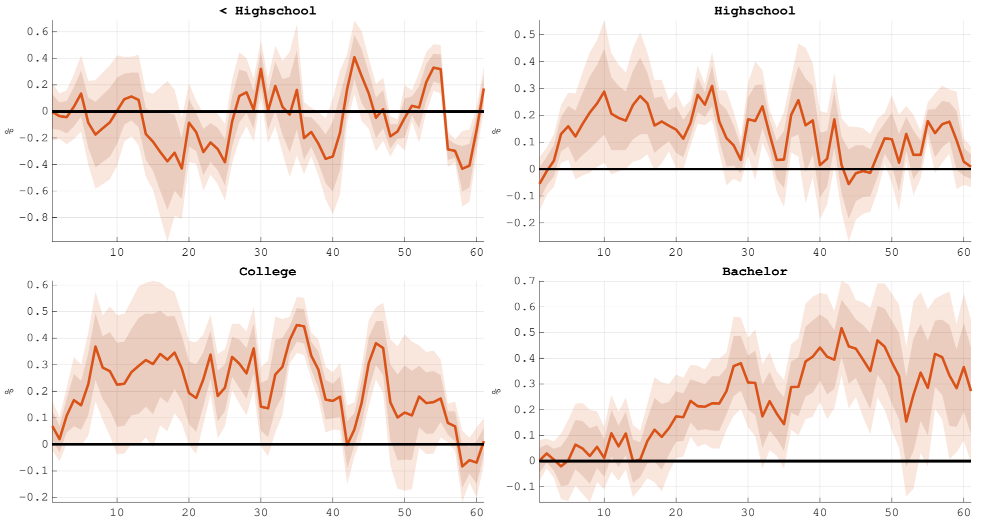


(e) Separations



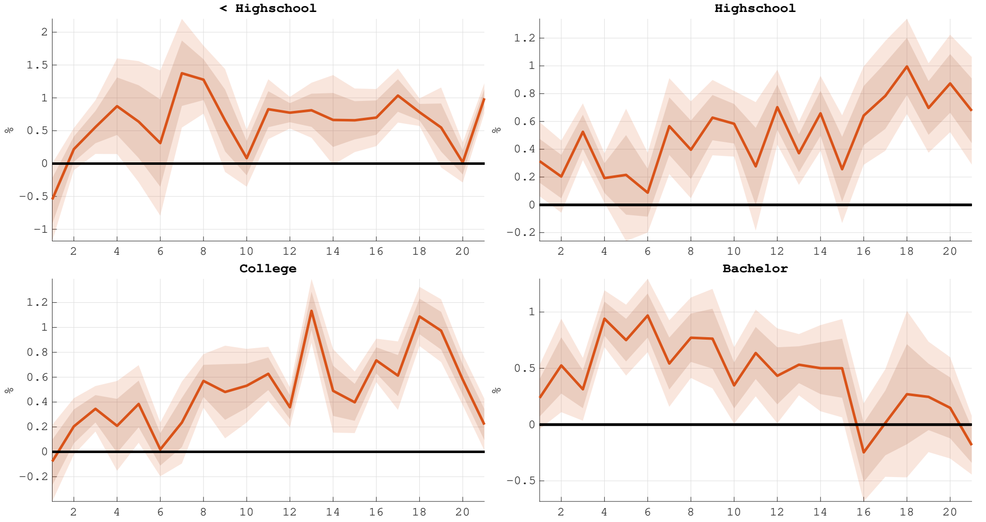
Note. The figure displays the cumulated IRFs over 60 months to a AIint shock. Sample 2006-2019. The estimates are based on local projections with Newey-West standard errors. Point estimate and 90% confidence bands.

Employment by education



Note. The figure displays the IRFs to a Alint shock. Sample 2000-2019. The estimates are based on local projections with Newey-West standard errors. Point estimate and 68%-90% confidence bands.

Earnings by education



Note. The figure displays the IRFs to a Alint *shock. Sample 2000-2019. The estimates are based on local projections with Newey-West standard errors. Point estimate and 68%-90% confidence bands.*

Summary of labor market outcomes

- **Widespread improvement** in labor market conditions
  - Suggestive of GE effects and/or complementarity
  - Consistent with findings in Albanesi et al. (2023)

- **Transformation** of demand **tasks**
  - Openings & layoffs $\uparrow$ ..
  - .. but the net effect is positive

- Heterogeneity by **education**
  - All groups benefit in terms of earnings
  - Employment gains proportional to education

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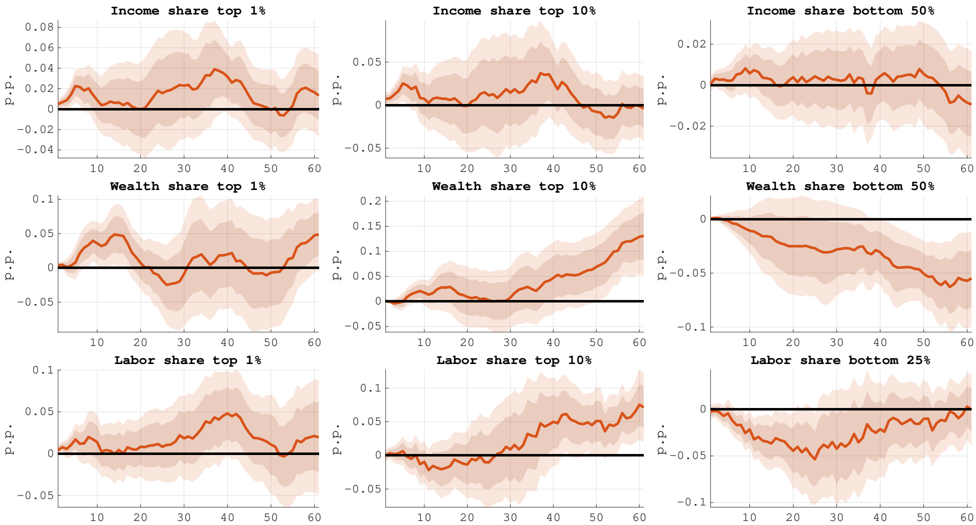
   - Income
   - Wealth

Inequality

- We employ Blanchet et al. (2022) "Real-time inequality" database

Inequality



Note. The figure displays the IRFs to a Alint shock. Sample 1980-2019. The estimates are based on local projections with Newey-West standard errors. Point estimate and 68%-90% confidence bands.

Inequality

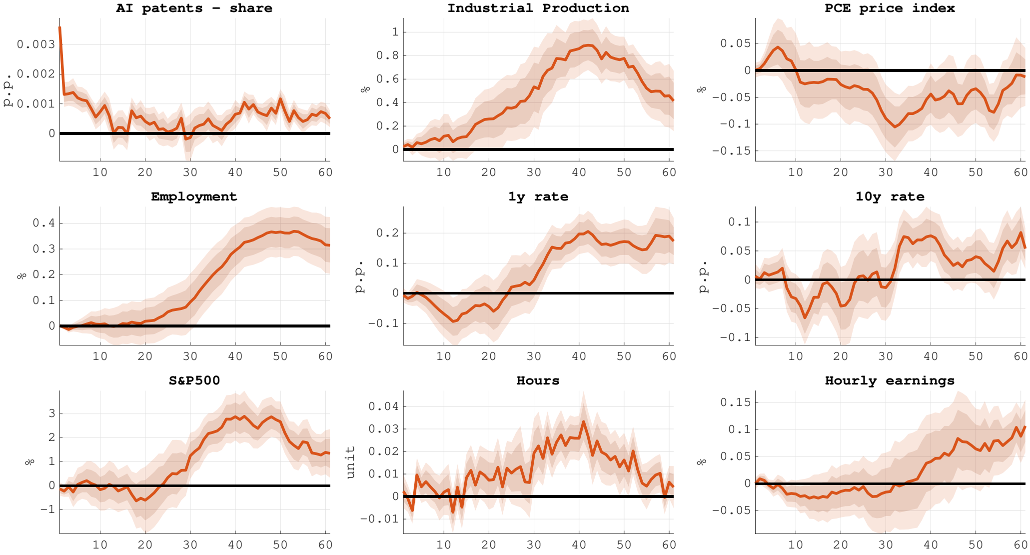
- We employ Blanchet et al. (2022) "Real-time inequality" database
- Our results echo those in Moll et al. (2022, Econometrica)
  - automation $\Rightarrow$ **asset returns** $\Rightarrow$ wealth inequality
- Effects on labor income inequality are more transitory
- Considering variable in absolute terms Absolute
  - All groups benefit in terms of income
  - But not in terms of wealth

Conclusions

- Economic implications of AI very uncertain
- Issue very challenging to measure and study
- We have exploited historical data on **patents** to overcome these challenges
- Highlight **general equilibrium effect of AI innovation**
  - Neglected in micro-based estimates
  - The **missing intercept problem**
- AI affects relatively more economic activity than consumer prices
- Small monetary policy implications

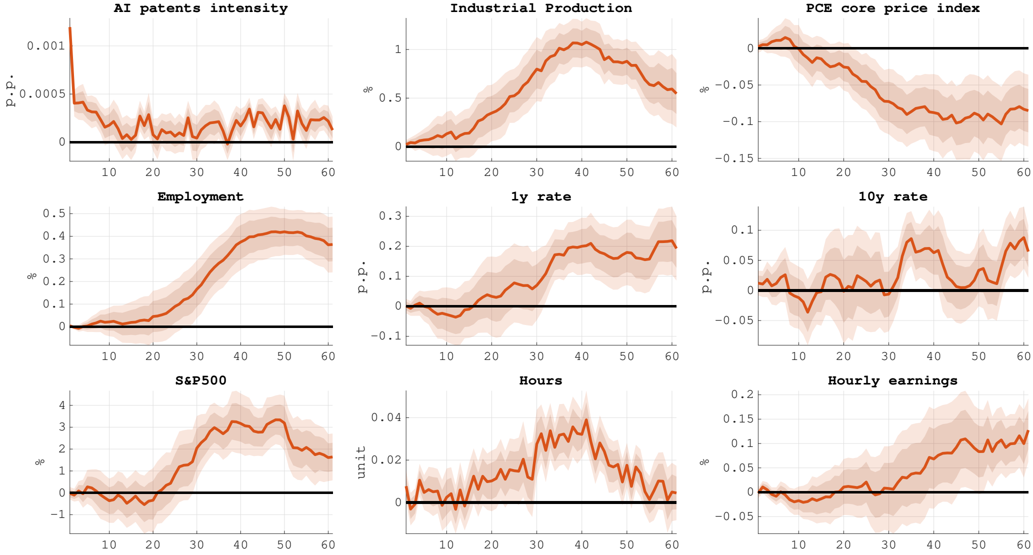
Background

AI share



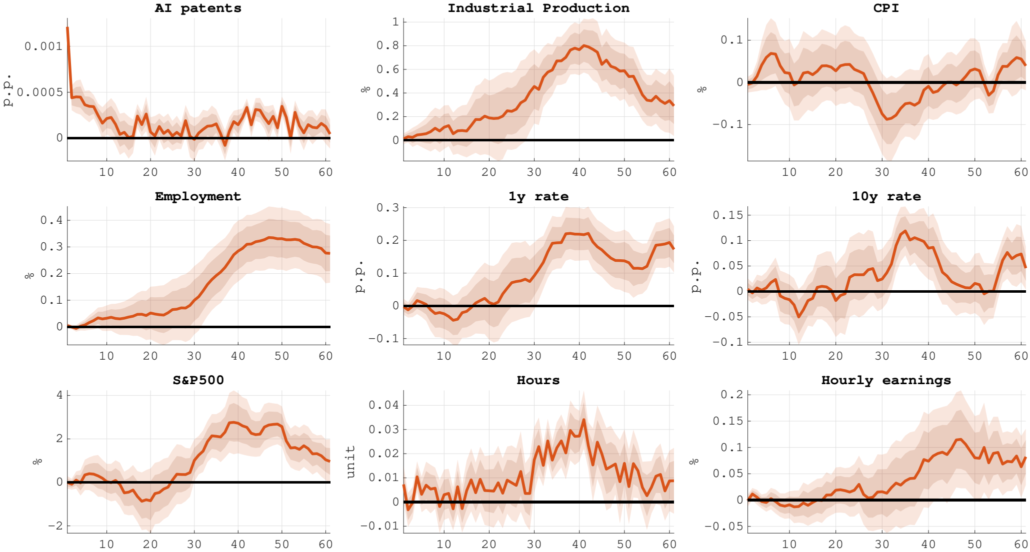
Note. The figure displays the IRFs to a shock to a AIshare. Sample 1980-2019. The estimates are based on local projections with Newey-West standard errors. Point estimate and 68%-90% confidence bands. Back

Core PCE



Note. The figure displays the IRFs to a shock to a AIint. Sample 1980-2019. The estimates are based on local projections with Newey-West standard errors. Point estimate and 68%-90% confidence bands. Back

CPI



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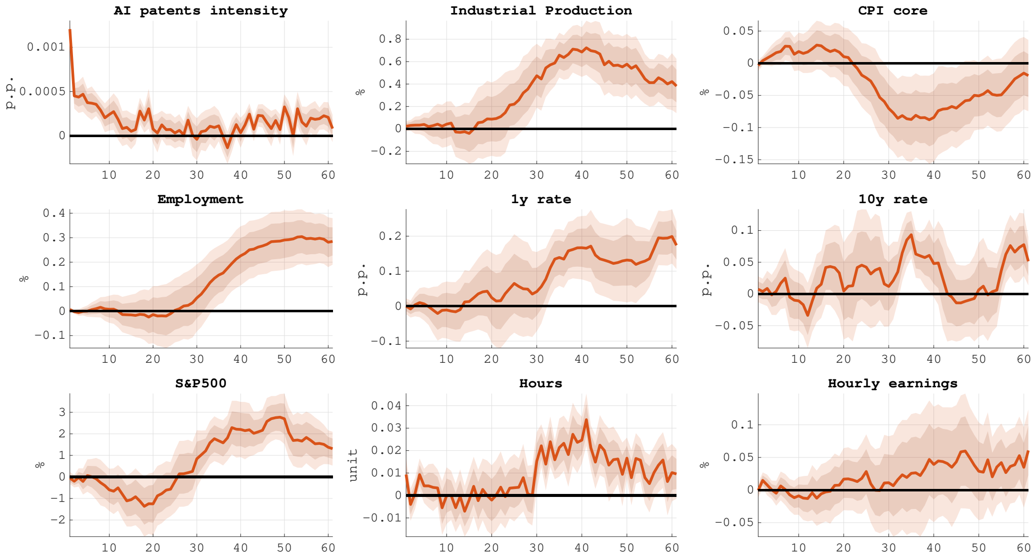
Core CPI



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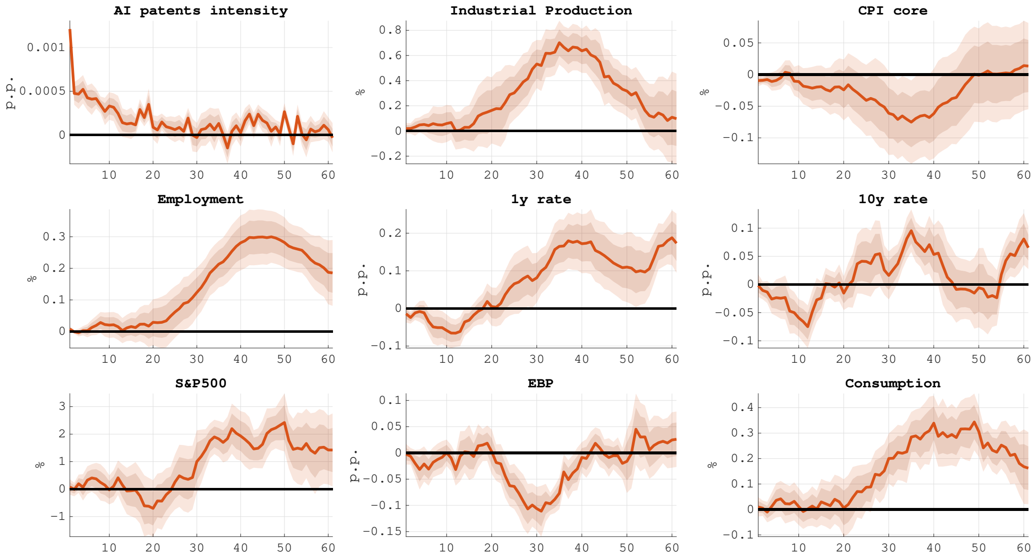
EBP and consumption



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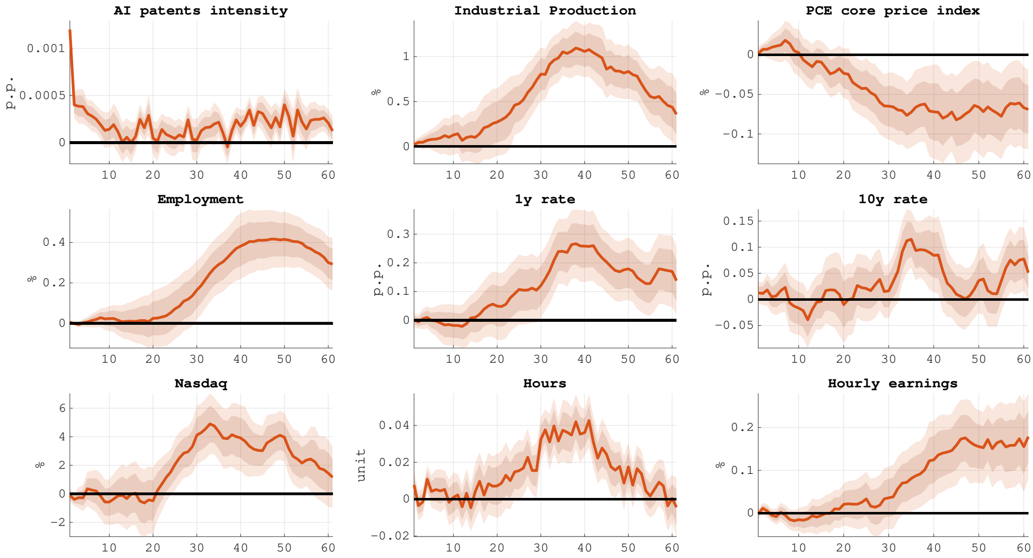
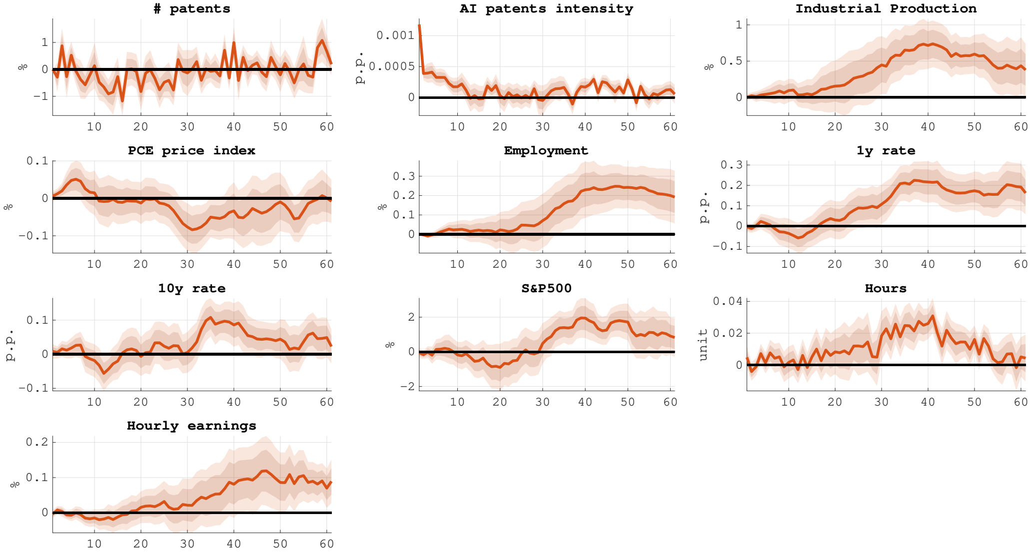
Nasdaq



Note. The figure displays the IRFs to a shock to a AIint. Sample 1980-2019. The estimates are based on local projections with Newey-West standard errors. Point estimate and 68%-90% confidence bands. Back

Controlling for patents



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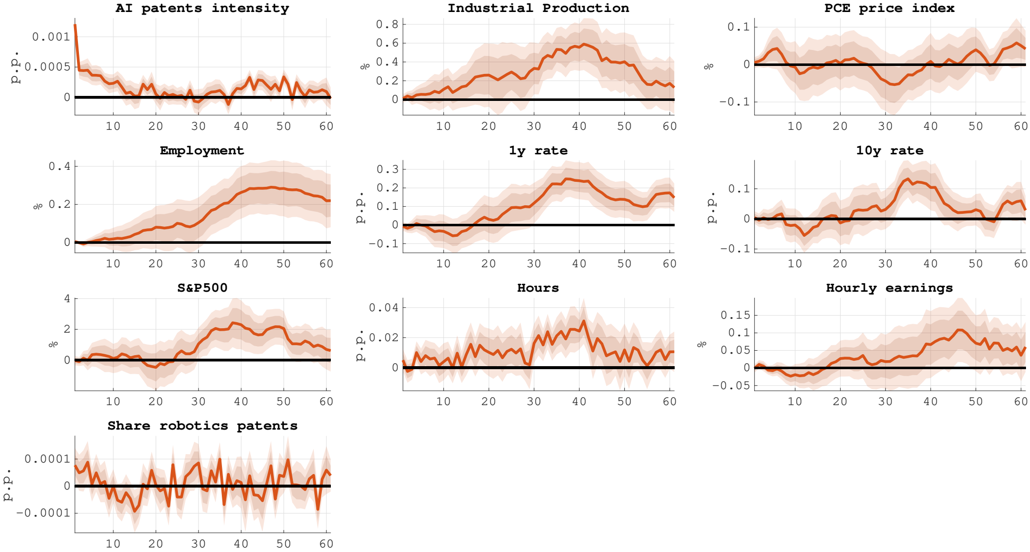
Back

AI intensity in robotic patents

	Robotic patent?	
	0 (no)	1 (yes)
# observations	13,675,265 (99.8%)	30,129 (0.2%)
AI score	0.034 (0.099)	0.035 (0.104)
AI intensive patent	0.115 (0.319)	0.134 (0.341)
AI prediction score from machine learning model	0.018 (0.114)	0.028 (0.147)
AI prediction score from evolutionary computation model	0.009 (0.053)	0.010 (0.053)
AI prediction score from natural lang. processing model	0.014 (0.094)	0.007 (0.058)
AI prediction score from speech model	0.009 (0.077)	0.007 (0.063)
AI prediction score from vision model	0.036 (0.151)	0.069 (0.210)
AI prediction score from knowledge processing model	0.068 (0.229)	0.085 (0.256)
AI prediction score from planning/control model	0.075 (0.233)	0.076 (0.228)
AI prediction score from AI hardware model	0.048 (0.161)	0.050 (0.171)

Back

Controlling for % of robotics patents



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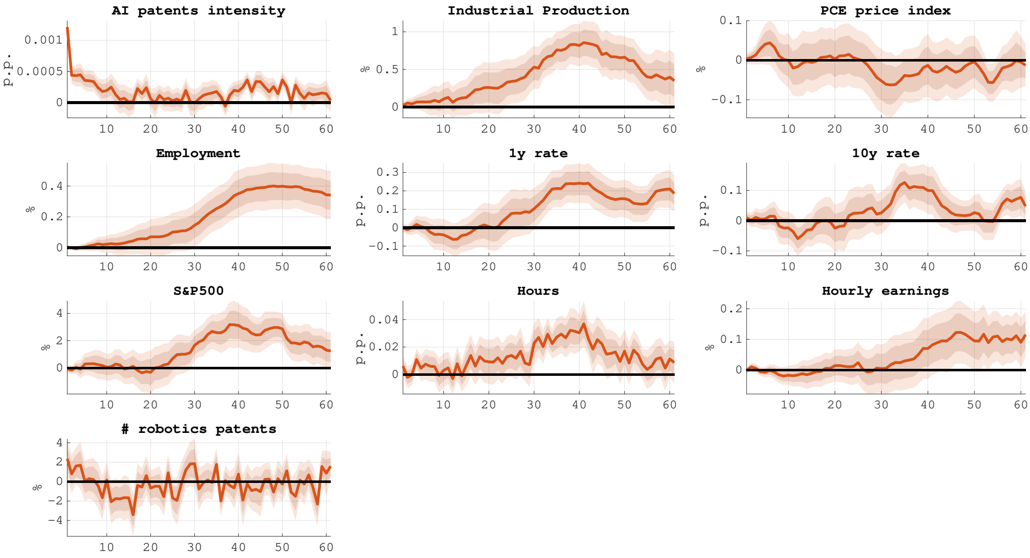
Controlling for # of robotics patents



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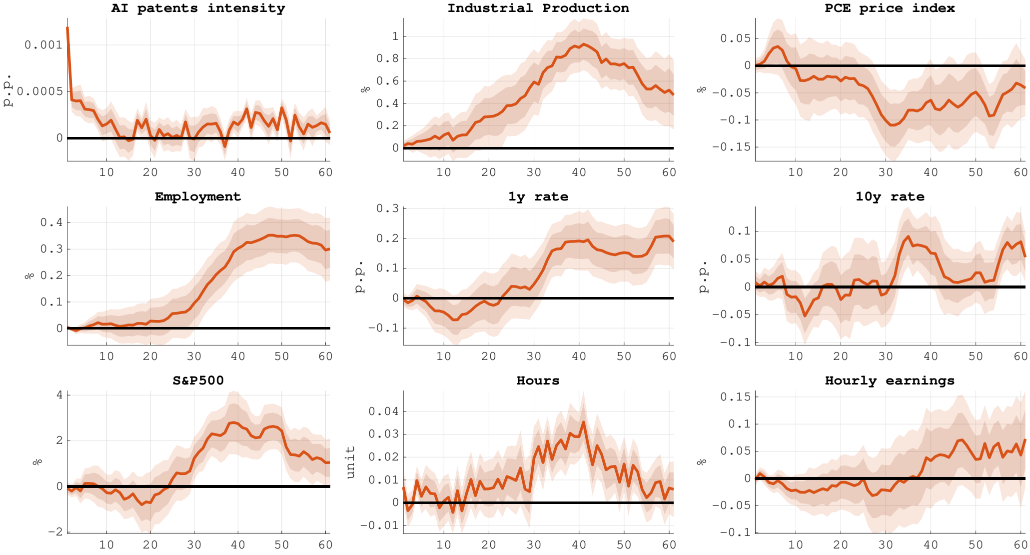
Detrended *AIint*



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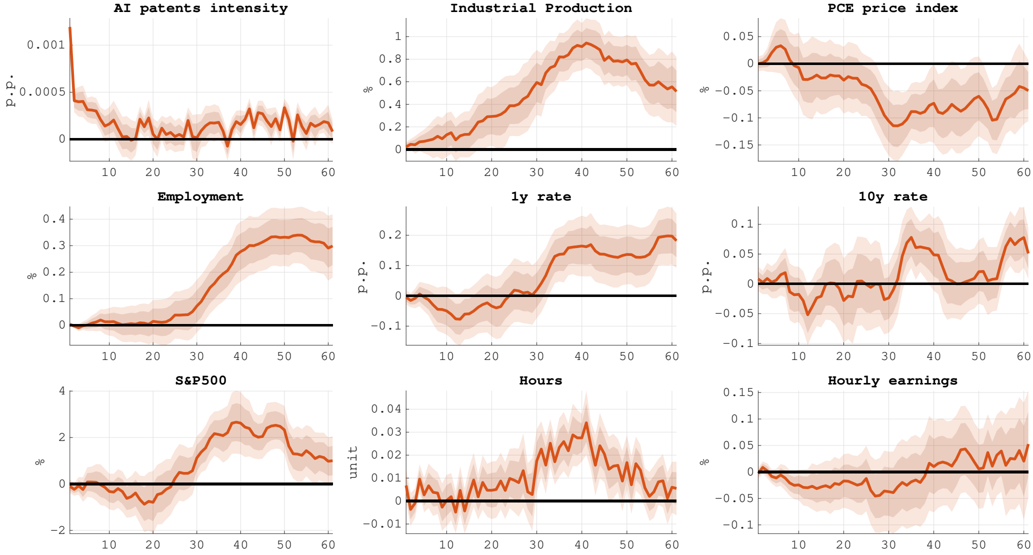
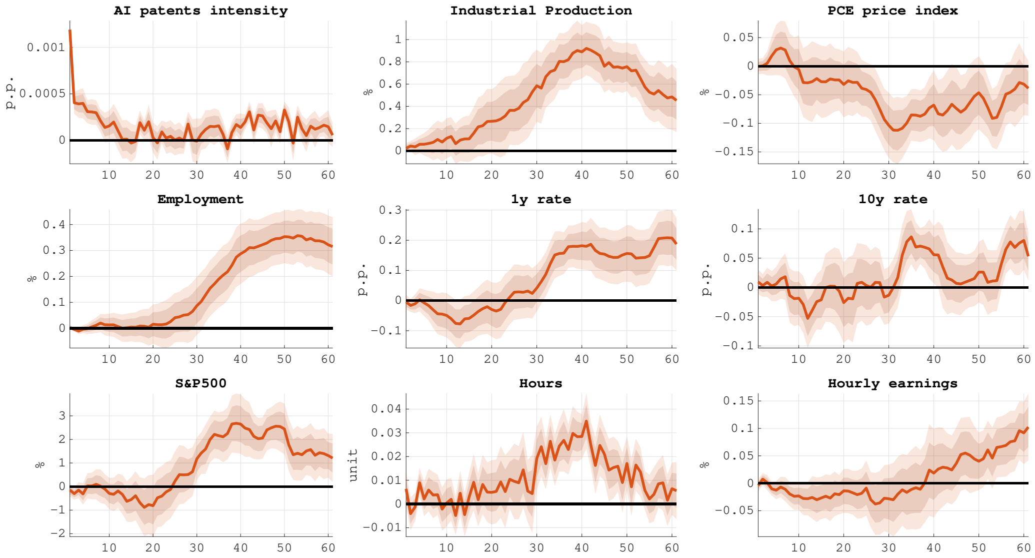
Detrended (quadratic) *AIint*



Note. The figure displays the IRFs to a shock to a AIint. Sample 1980-2019. The estimates are based on local projections with Newey-West standard errors. Point estimate and 68%-90% confidence bands. Back

Trend in LP



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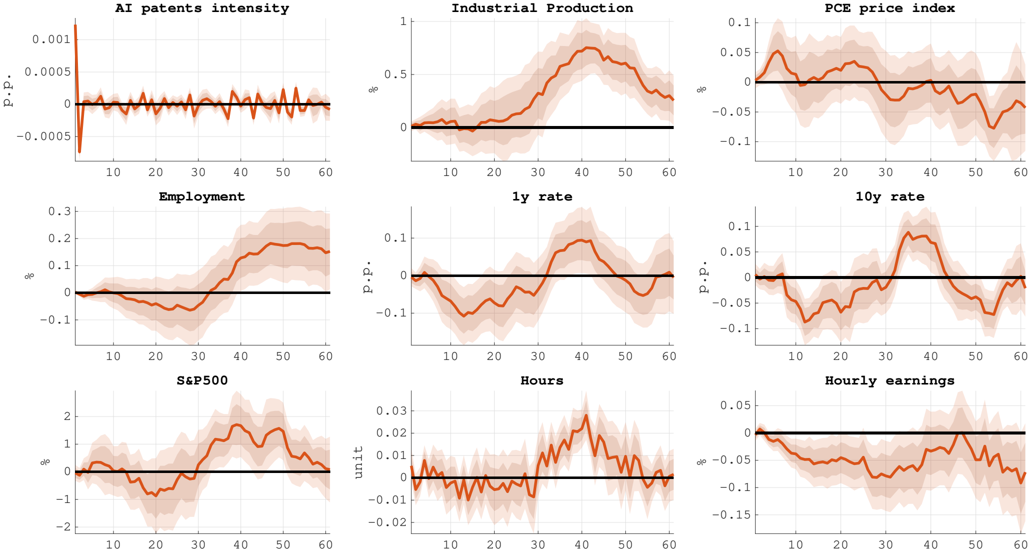
AIint in growth rate



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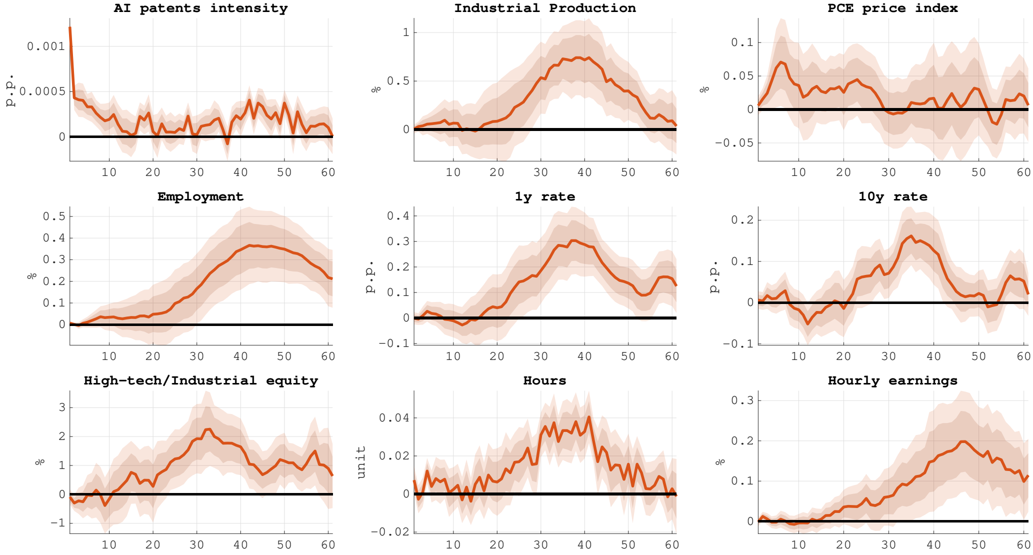
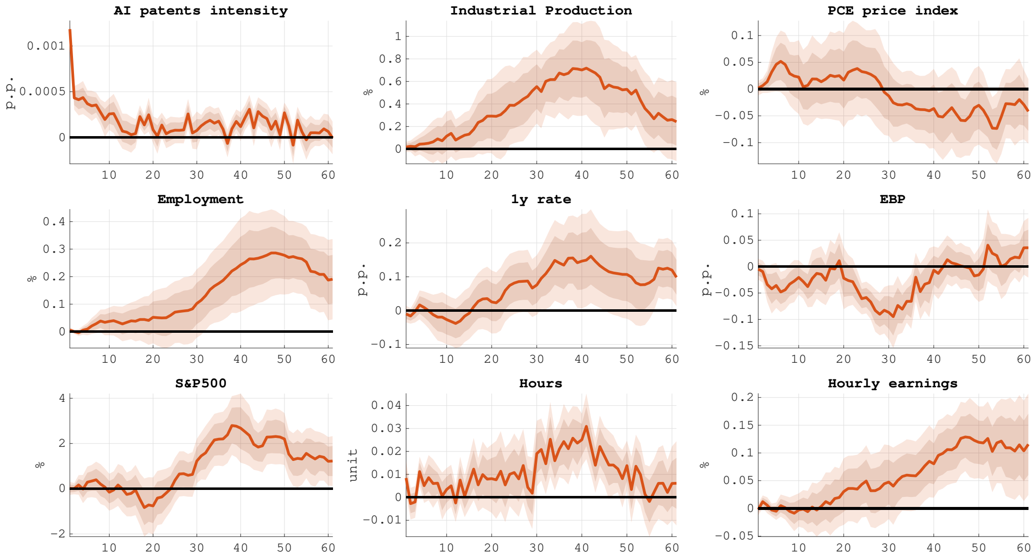
High tech vs industrial stocks



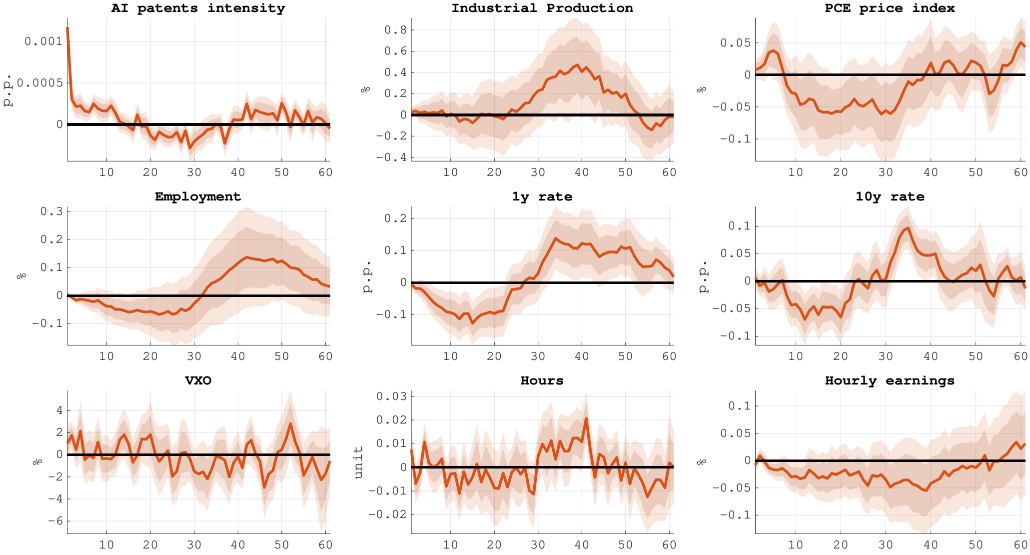
Note. The figure displays the IRFs to a shock to a AIint. Sample 1980-2019. The estimates are based on local projections with Newey-West standard errors. Point estimate and 68%-90% confidence bands. Back

Controlling for EBP



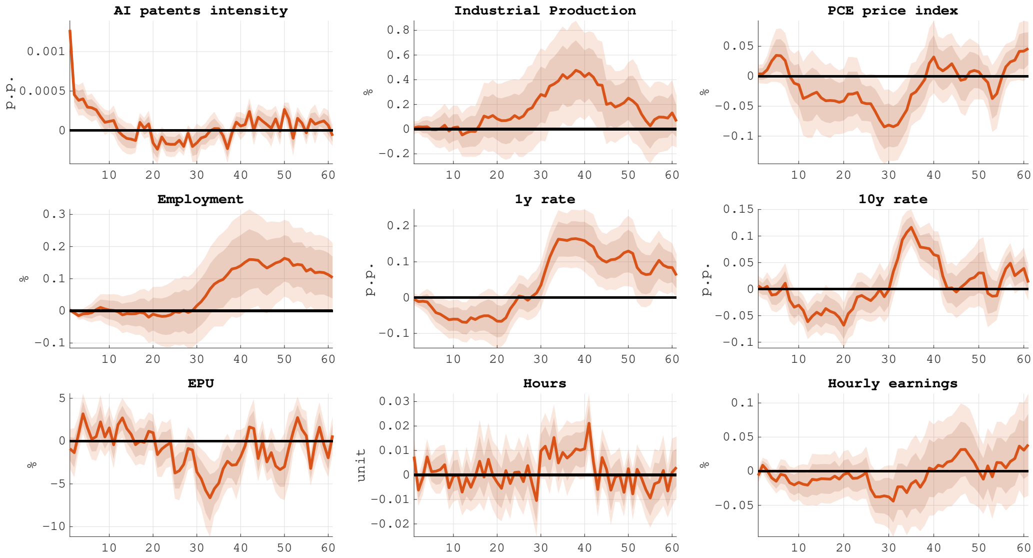
Note. The figure displays the IRFs to a shock to a AIint. Sample 1980-2019. The estimates are based on local projections with Newey-West standard errors. Point estimate and 68%-90% confidence bands. Back

Controlling for VXO



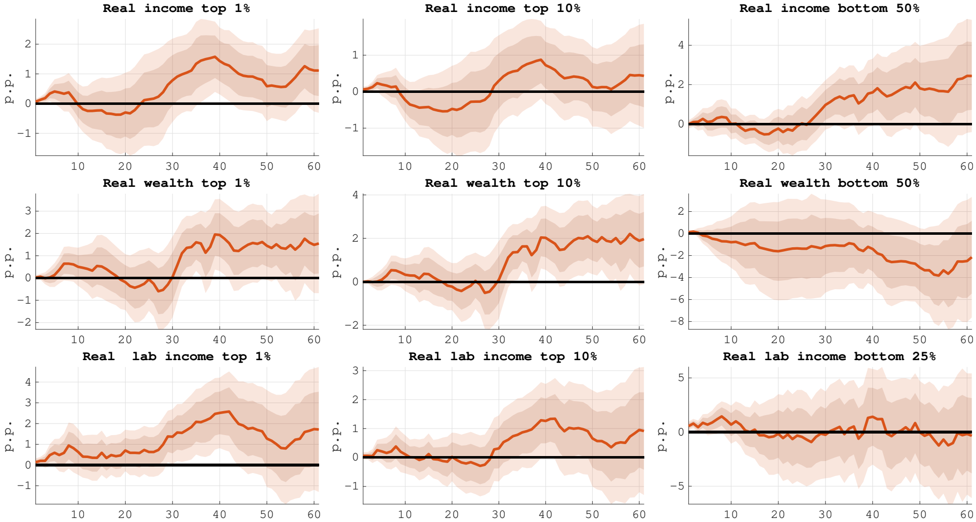
Note. The figure displays the IRFs to a shock to a AIint. Sample 1985-2019. The estimates are based on local projections with Newey-West standard errors. Point estimate and 68%-90% confidence bands. Back

Controlling for EPU



Note. The figure displays the IRFs to a shock to a AIint. Sample 1986-2019. The estimates are based on local projections with Newey-West standard errors. Point estimate and 68%-90% confidence bands. Back

Absolute response of income and wealth



Note. The figure displays the IRFs to a Alint shock. Sample 1980-2019. The estimates are based on local projections with Newey-West standard errors. Point estimate and 68%-90% confidence bands. Back

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