The macroeconomic effects of AI innovation

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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

- Release of AI chatbots like ChatGPT spurred debate on the **economic effects of AI**
- Empirical analyses focus on sectoral/labor market implications

Research Question

What are the *macroeconomic effects* of AI adoption? Views are polarized:

→ AI as **game changer** (Bresnahan & Trajtenberg 1995, Brynjolfsson et al. 2023, etc)...
→ ......or **low return-high risk** tech (Acemoglu, 2024, etc) ?

Literature review

This paper

- Studies empirically the **effects of AI innovation** in historical perspective
- Constructs an index of **AI intensity in US innovation** from 1980 to 2019 using **patent data**
- Estimates its impacts on industrial production, consumer prices, labor markets, inequality

Preview of the results

- An increase in the intensity of AI in tech is **expansionary** as positive **technology shocks**
- The downside is an increase in **inequality**

Data and methods

- **Artificial Intelligence Patent Dataset** by Gizcy et al 2022
  - all filed patents at the United States Patent and Trademark Office in 1980-2020
  - **Score of the AI content of the patented tech** (from 0= no AI involved to 1= fully AI-based)
  - Based on separate scores on **8 AI domains** (detected through ML and manual validation)

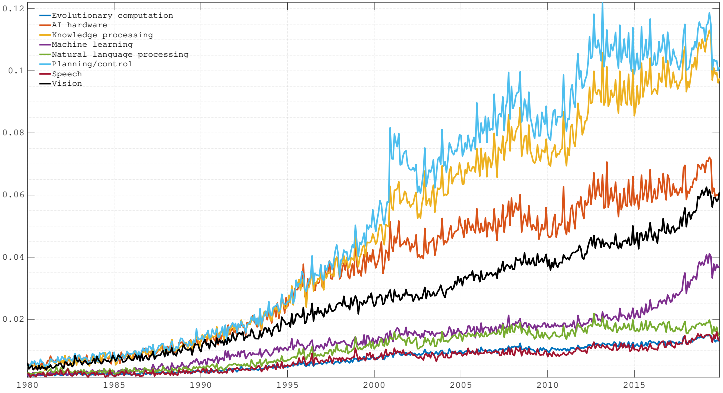
- **AI intensity in US innovation** = simple score average in the month patents are *filed*

- Economics: filing date is when the news of the future tech is first disclosed (*news shock*)

Impacts of *shifts of US innovation towards AI* up to 5y ahead using **local projections**

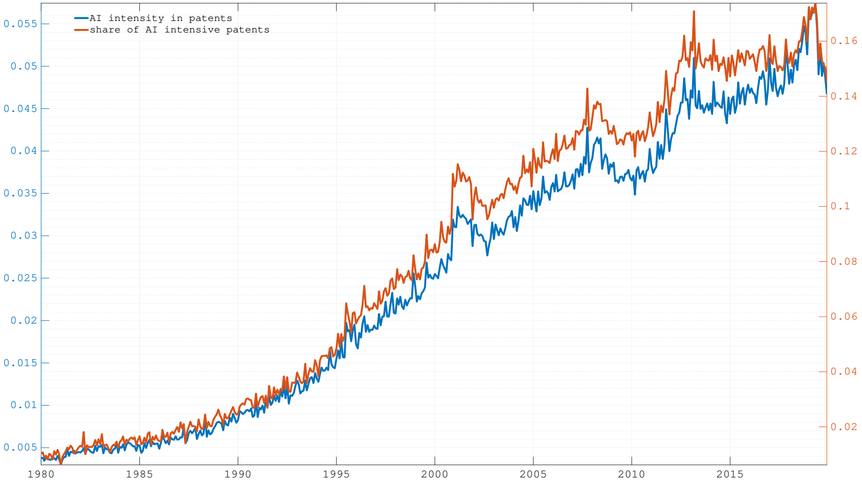
Pre-estimation analysis

AI domains and examples

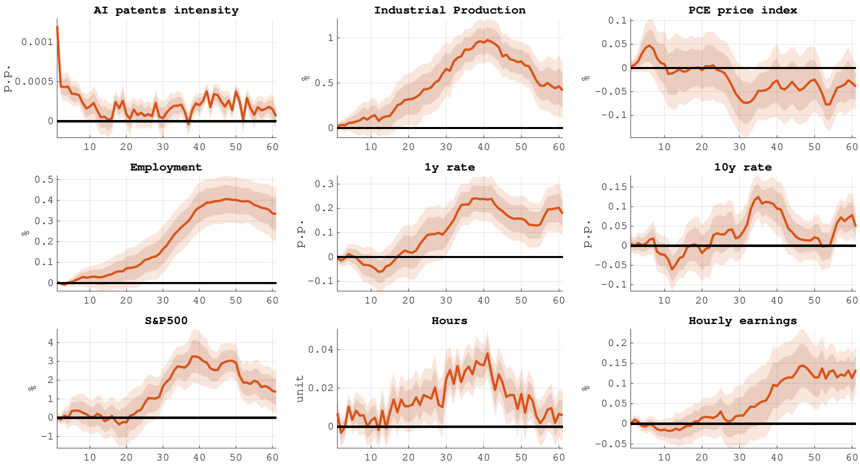


- **Knowledge processing**: representing and deriving facts about the world and using this information in automated systems.
- **Speech recognition**: includes techniques to understand a sequence of words given an acoustic signal.
  Apple's **Siri**, Amazon's **Alexa**, or Microsoft's **Cortana**
- **Machine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

AI intensity of US innovation

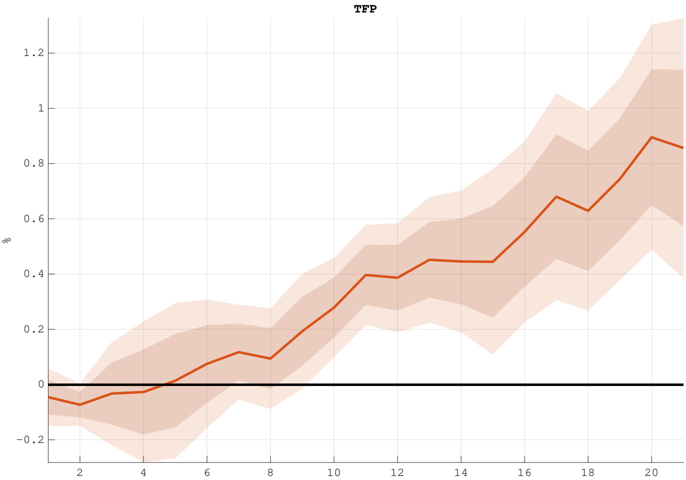


Baseline Impulse Response Functions



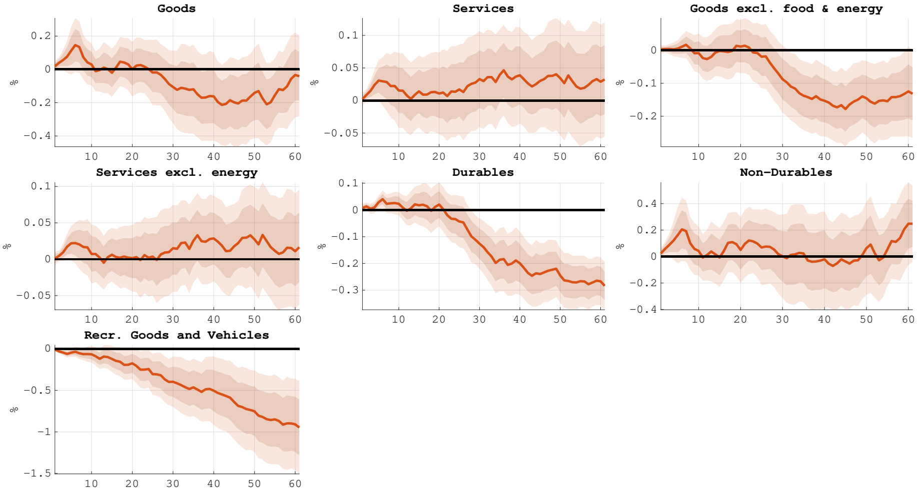
- IP, employment and wages up after 2y, prices go down mildly. MoPo responds
- Variance explained by AI not trivial Variance decomposition

Total factor productivity



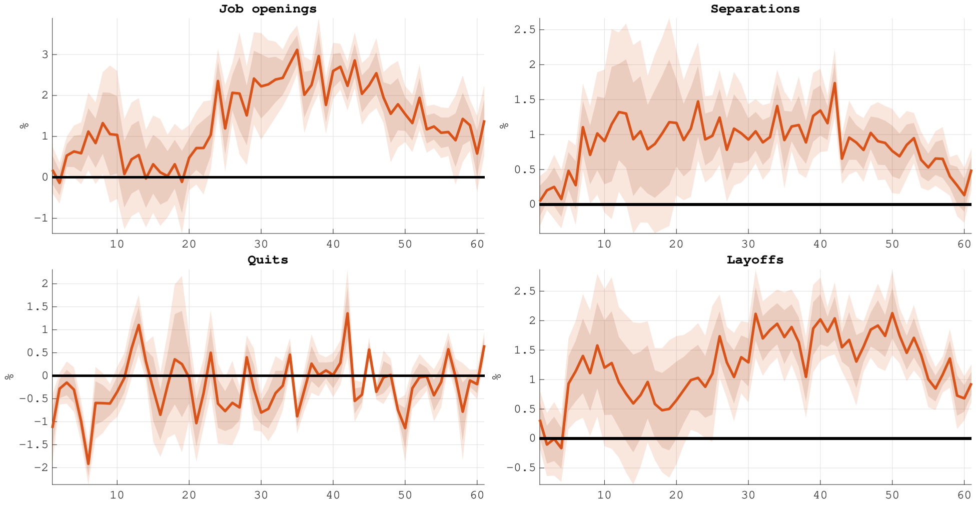
AI enhances long-run productivity growth

Focus on consumer prices



- Core prices decrease more strongly, driven by durables
- prices of high-tech durables decline persistently

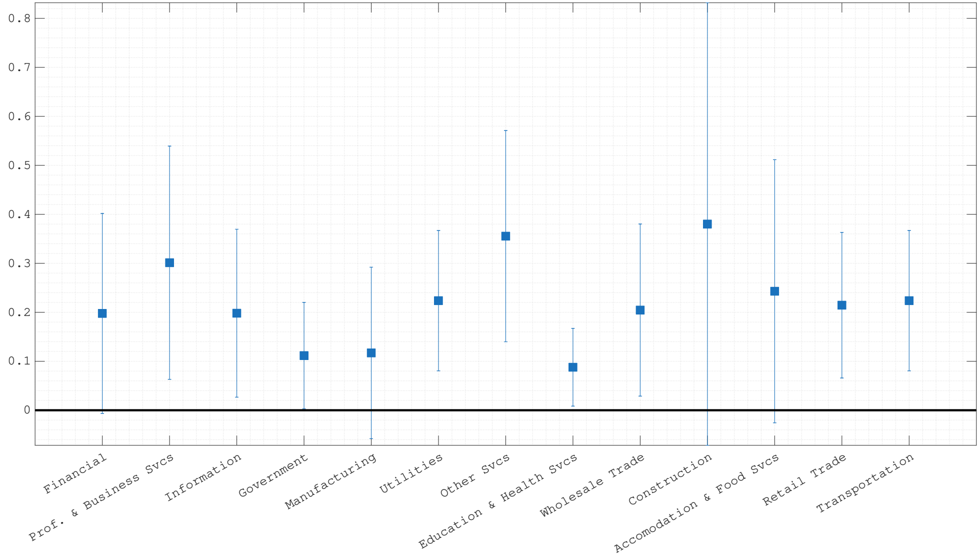
Labor market flows (from BLS)



- Openings rise more than separations (driven by layoffs)

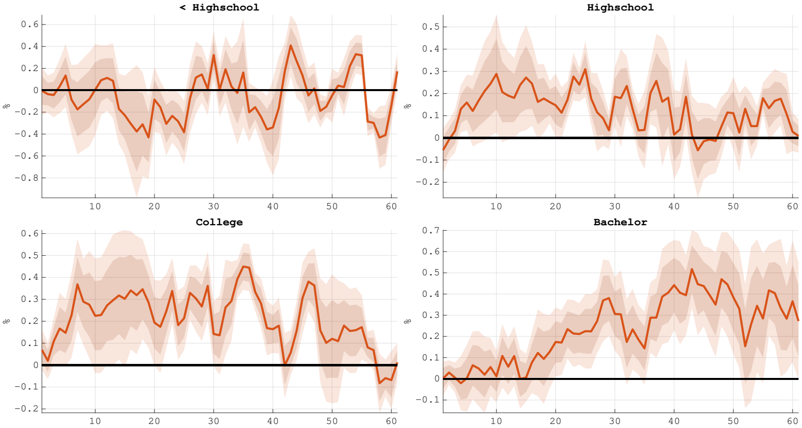
No big difference b/w high vs low AI-exposed sectors

(a) Employment



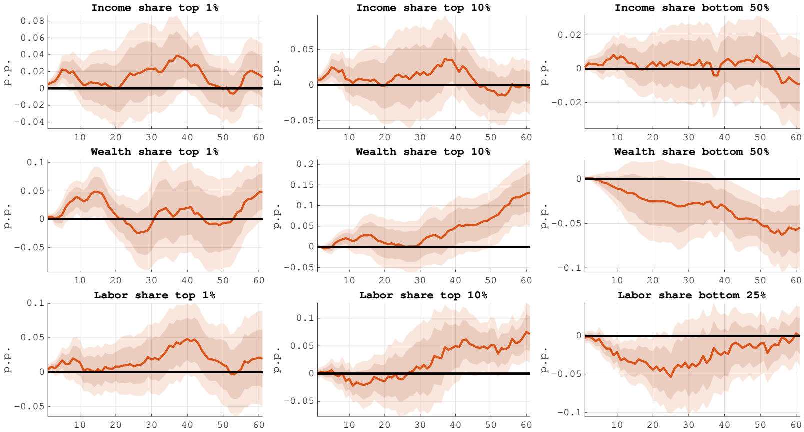
hours, wages, etc

Employment by education



Employment increases for educated people

Inequality



- From Real-time inequality database (Blanchet et al. 2022)
- Wealth inequality increases (e.g., asset return channel as in Moll et al 2022)
- In levels: income rises for all, not the same for wealth Absolute

Robustness and additional results

- Use share of AI-intense patents (scores$>$0.5) instead of baseline index Share
- Include alternative price indexes PCE core CPI CPI core
- Alternative stock prices Nasdaq High tech vs industrials
- Stationary version of the index of AI intensity Linear detrending Qudratic detrending Trend in LP
- Estimates based on iid shocks iid shocks
- Controlling for # patents # patents
- **No overlap with robotics innovation** - include robotics patents Table # rob patents % rob patents
- Controlling for financial/uncertainty conditions EBP VXO EPU

Conclusions

- Implications of Generative AI very uncertain
- Recent history of US **patenting** suggests AI pays off at the macro level
- AI innovation growth-enhancing in the medium run
  - Boosts productivity
  - Creates new opportunities in the labor market (complementarity AI-human work?)
- Widening of wealth inequality calls for the design of appropriate redistributive policies

Background

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

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:

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

where h = horizon of the response, α = 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; ε_{t+h} = residual with moving average structure across $h \Rightarrow$ the inference is based on Newey and West (1994) standard errors.

Variance decomposition

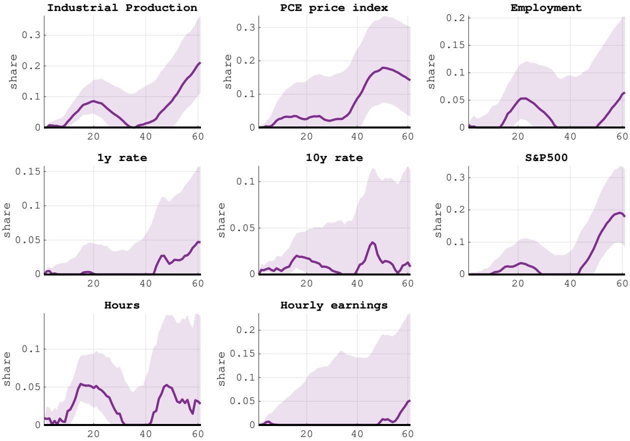
- Quantitative contribution of $\mathcal{AI}int_t$ shock $\Rightarrow$ forecast error variance decomposition
- Follow Gorodnicenko and Lee (2020, JBES) $\Rightarrow$ R^2 approach

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

$$\widehat{\varepsilon}_{j,t+h|t-1} = \omega_{z,0}\widehat{\varepsilon}_{AI,t+h} + \cdots + \omega_{z,h}\widehat{\varepsilon}_{AI,t} + \tilde{v}_{t+h|t-1} \qquad \forall j = \text{endog. vars} \tag{3}$$

- R^2 from regression in Equation (3) yields variance contribution of $\mathcal{AI}int_t$ to y
- Inference based on bootstrap

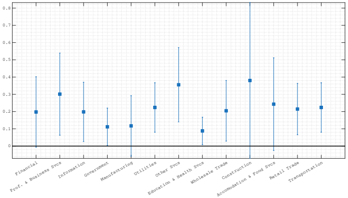
How much is explained by AI tech? Variance decomposition



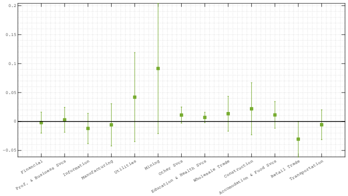
20% of IP and consumer prices at 5y-horizon

Sectoral effects

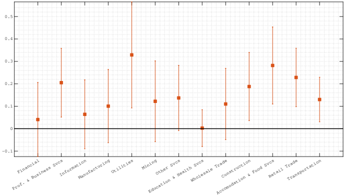
(a) Employment



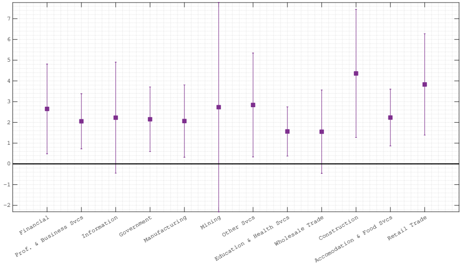
(b) Hours



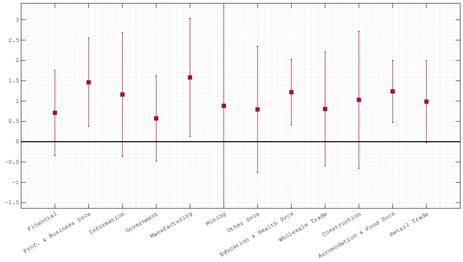
(c) Real wage



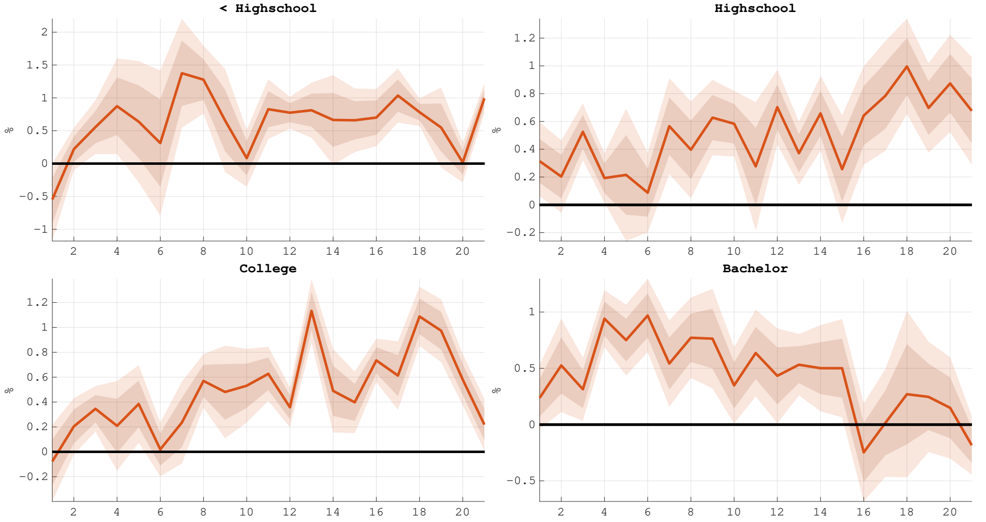
(d) Openings



(e) Separations

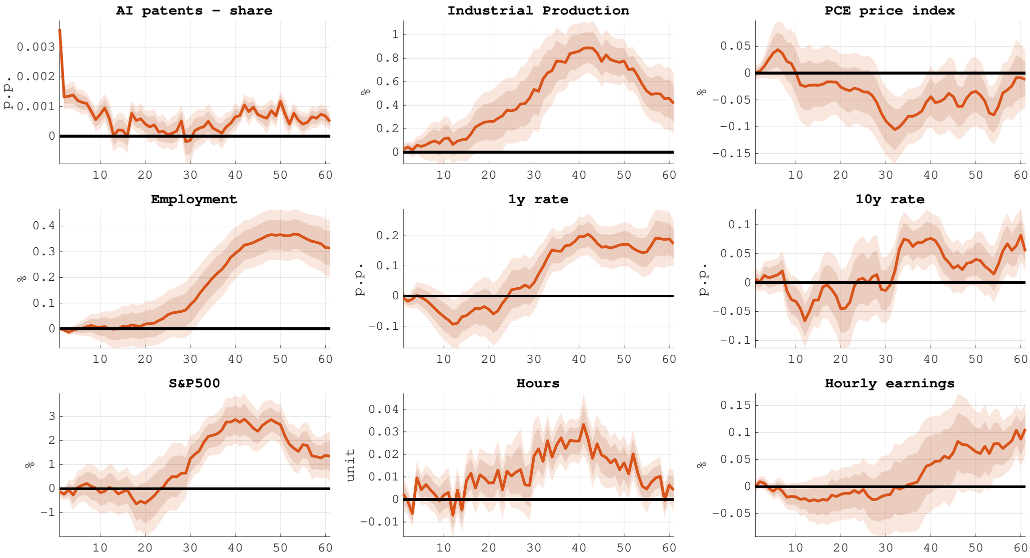


Earnings by education



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.

AI share



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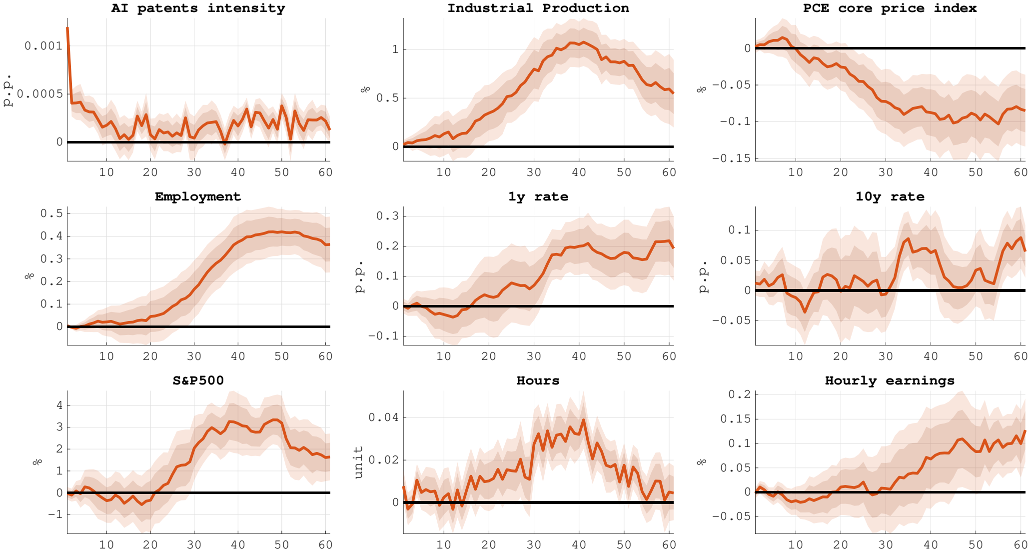
Core PCE



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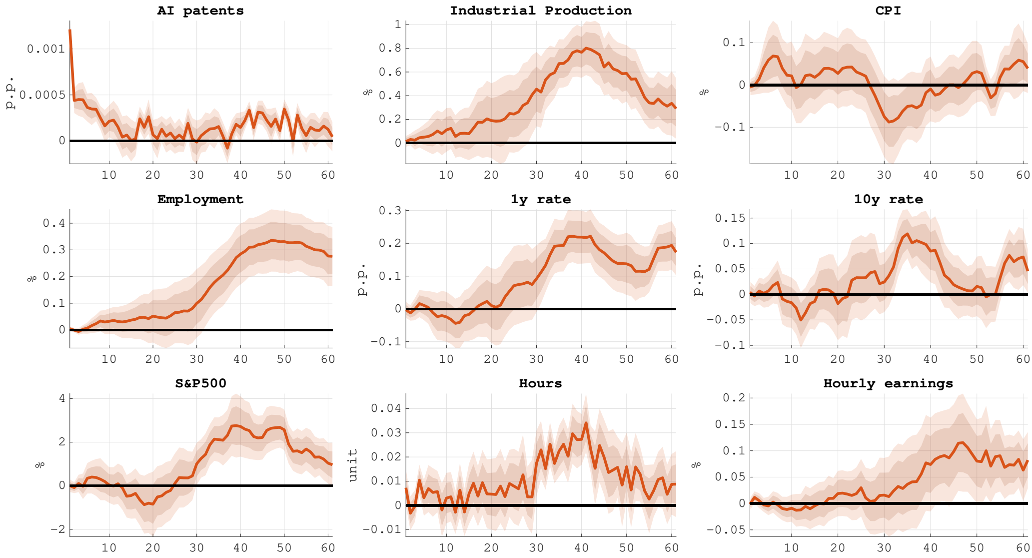
CPI



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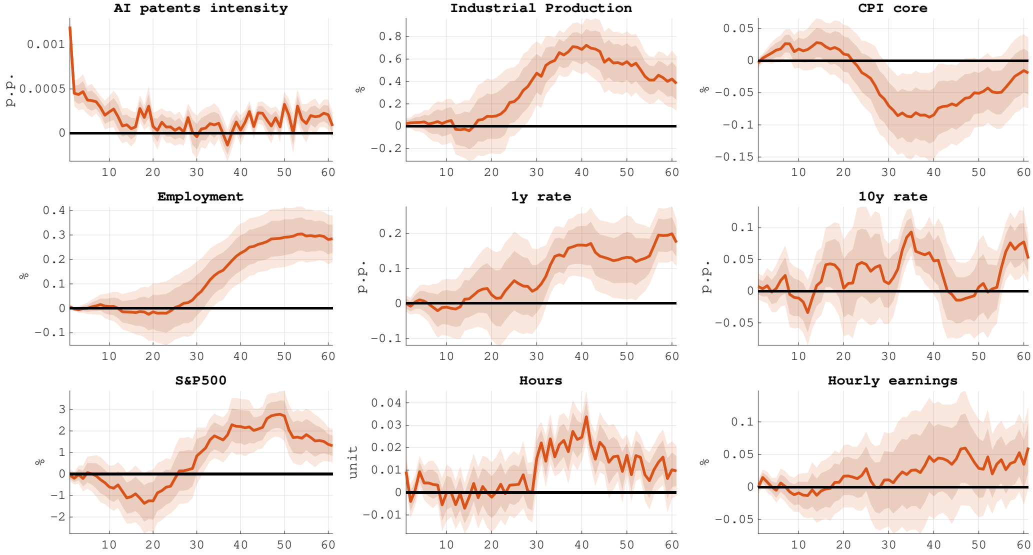
Core CPI



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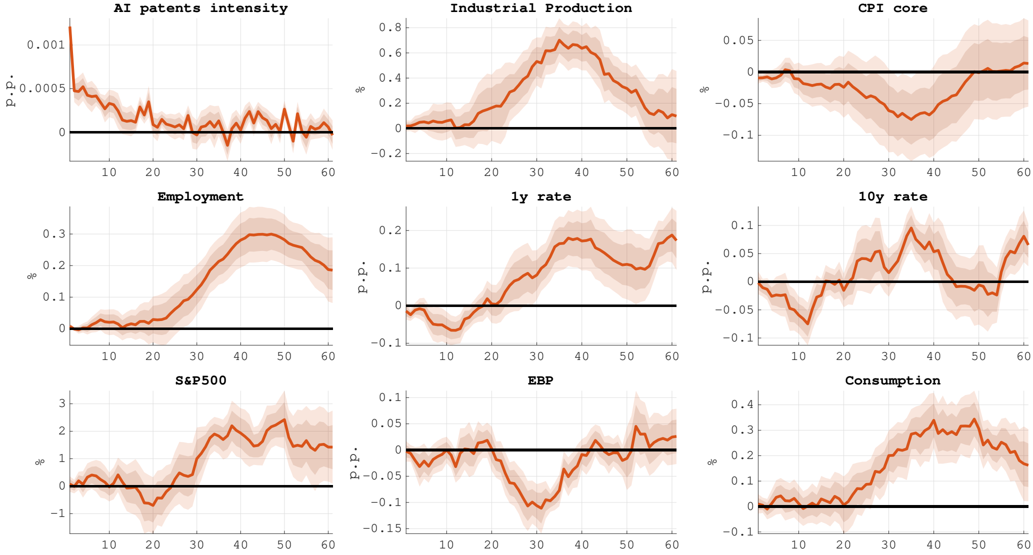
EBP and consumption



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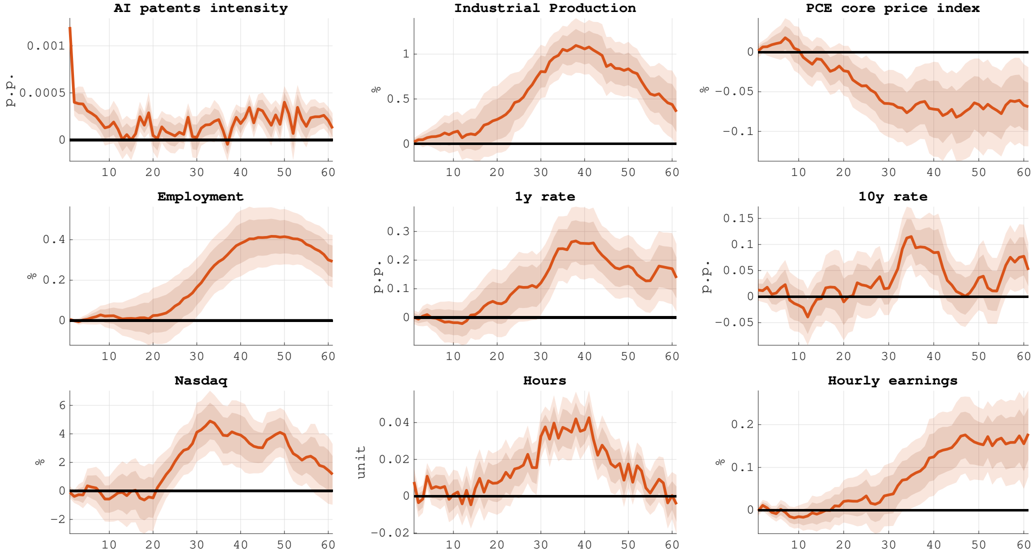
Nasdaq



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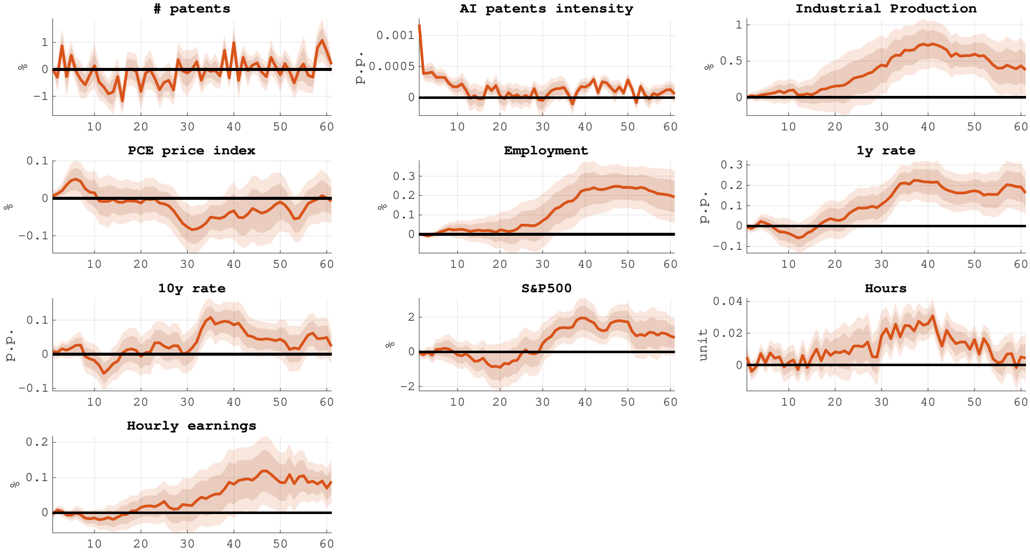
Controlling for patents



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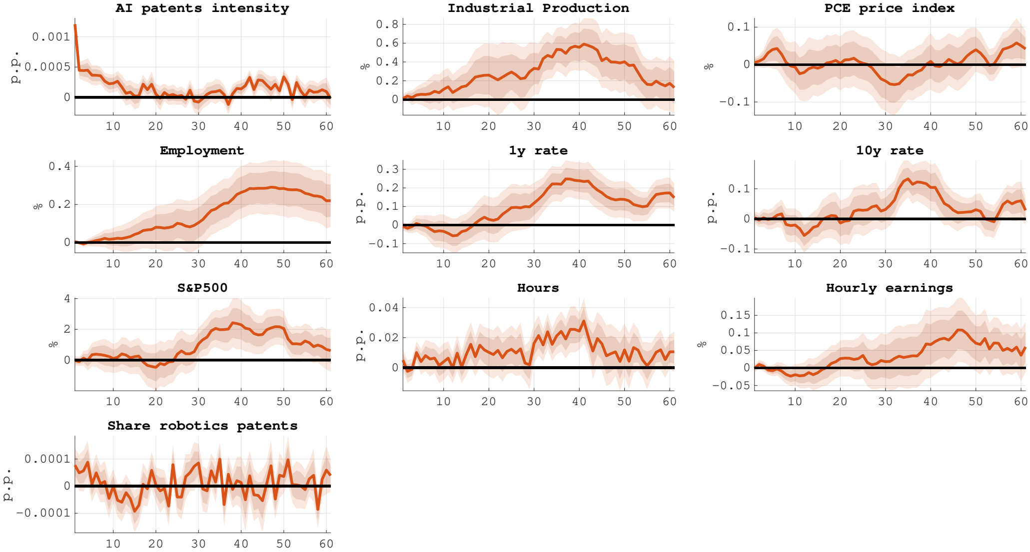
AI intensity in robotic patents

	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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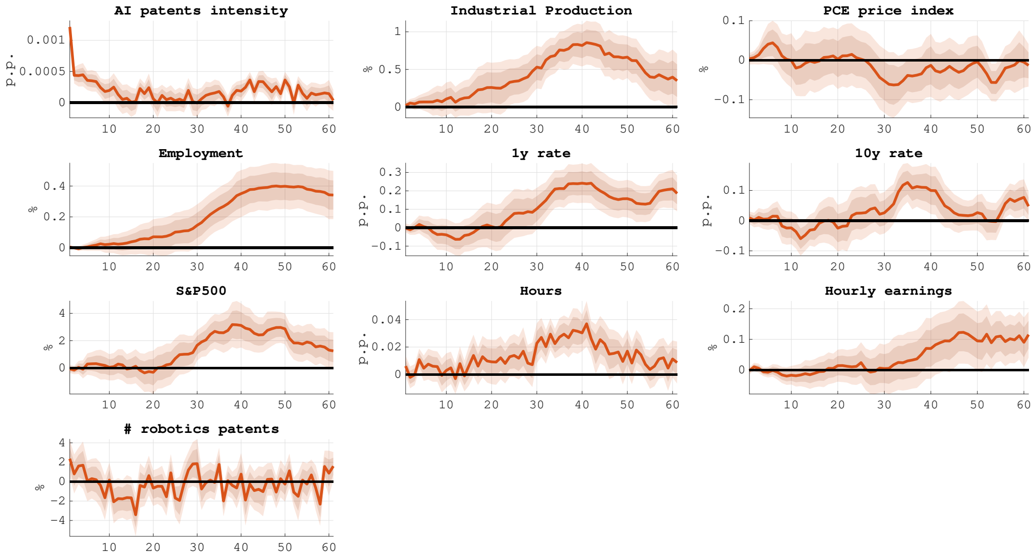
Controlling for # of robotics patents



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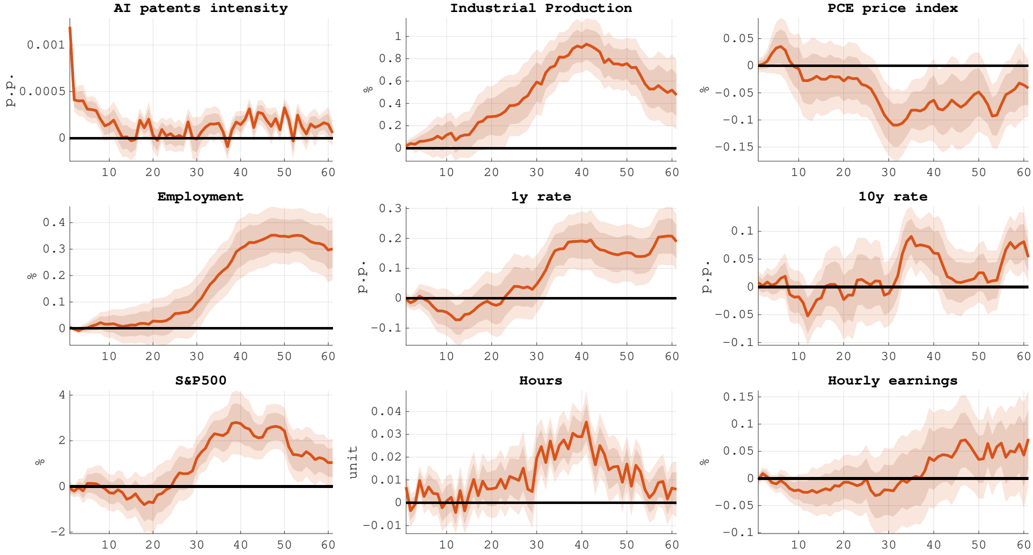
Detrended *AIint*



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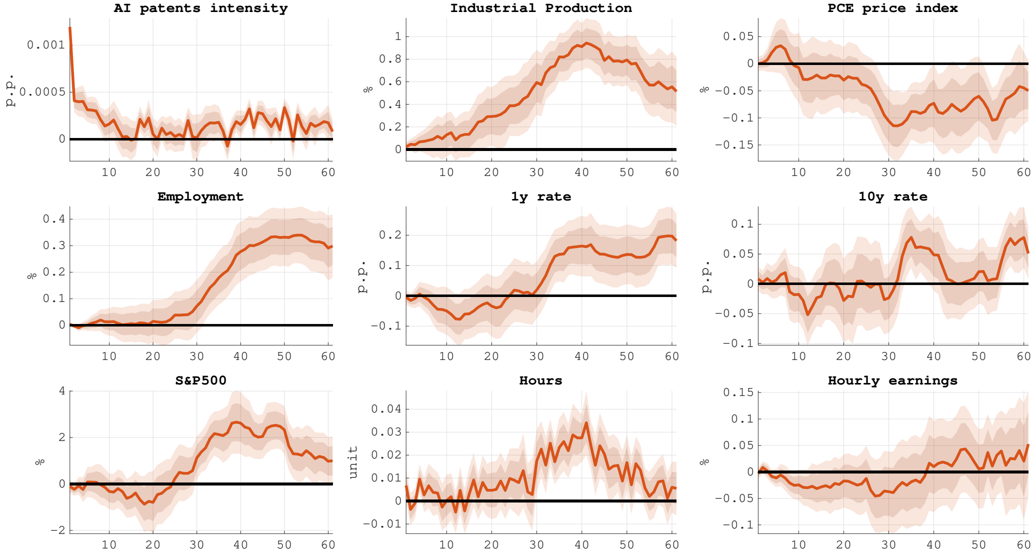
Detrended (quadratic) *AIint*



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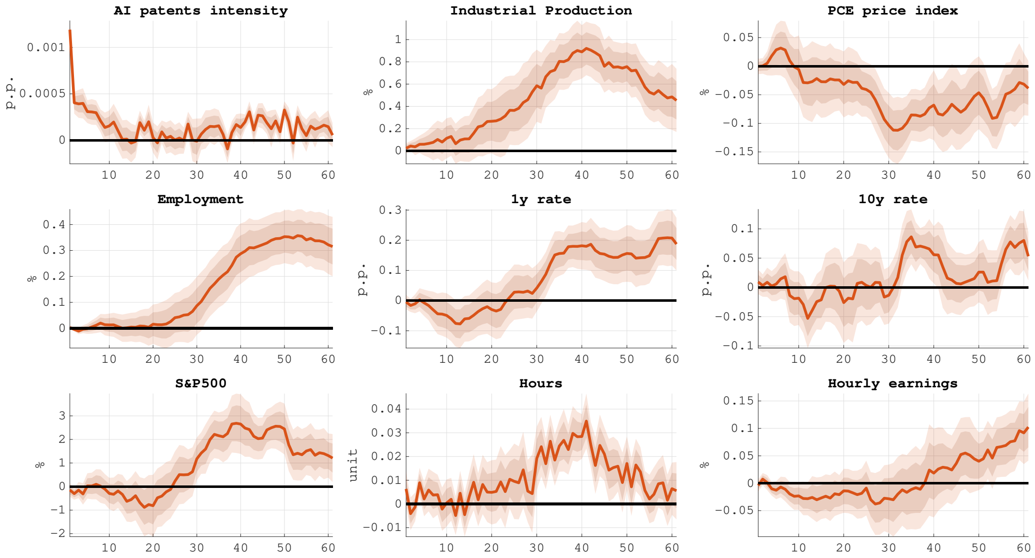
Trend in LP



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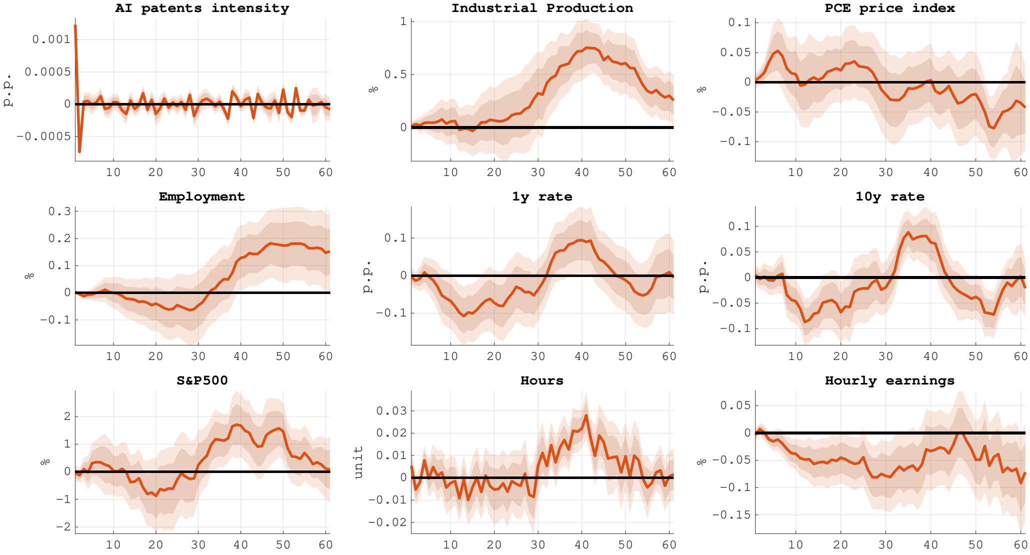
AIint in growth rate



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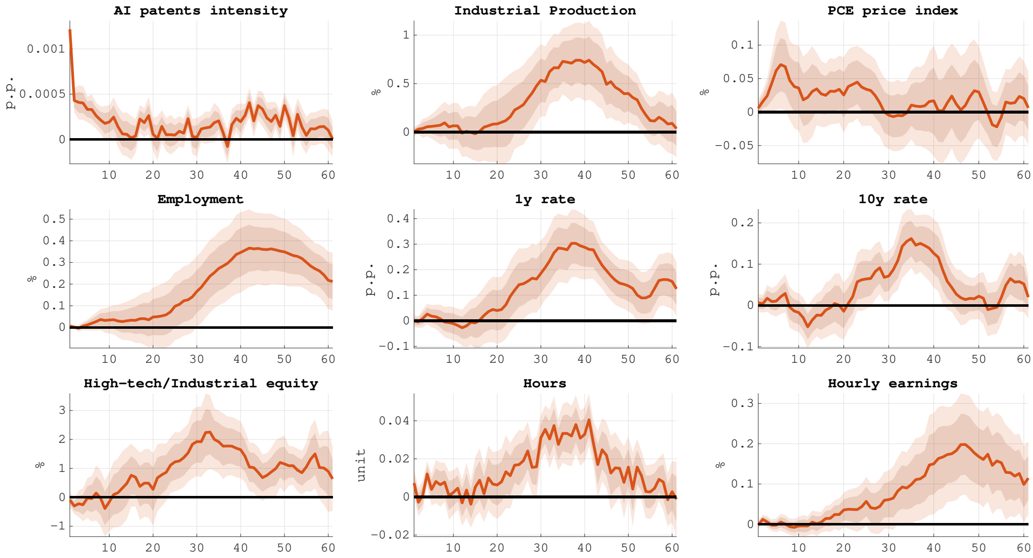
High tech vs industrial stocks



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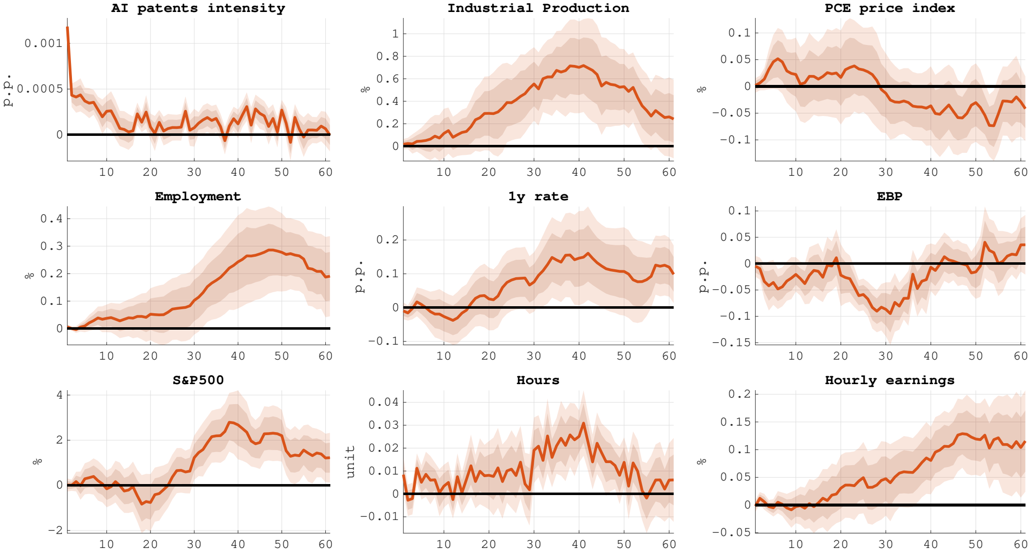
Controlling for EBP



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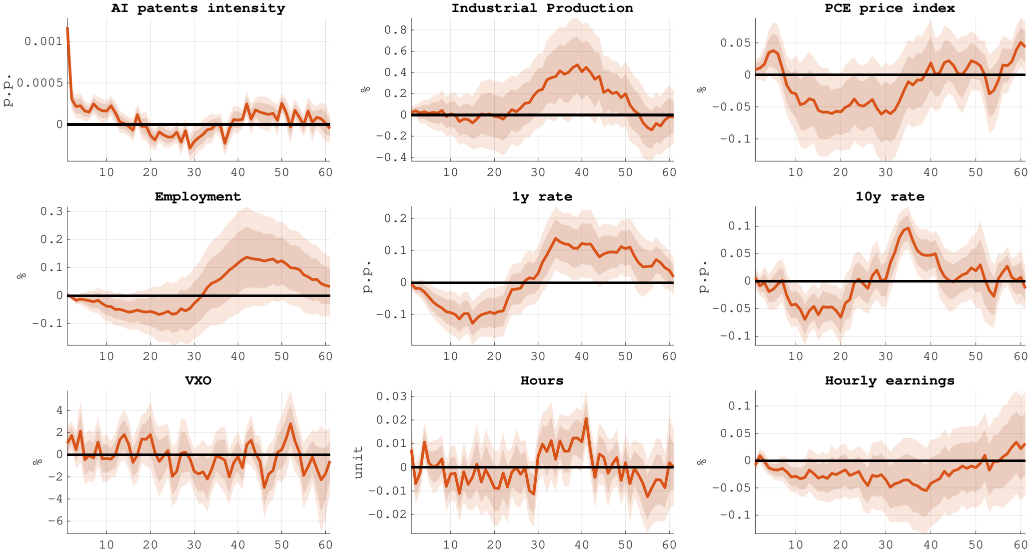
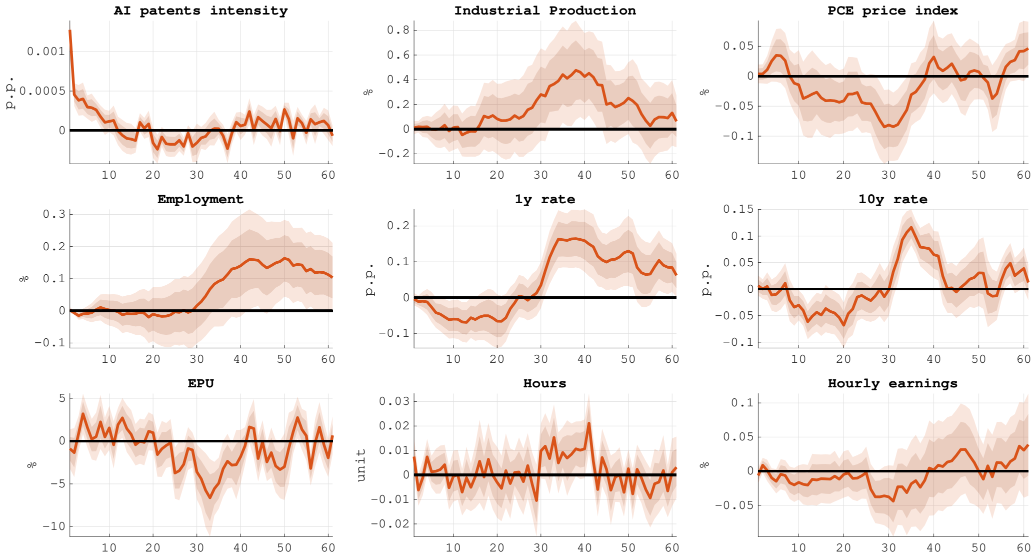
Controlling for VXO



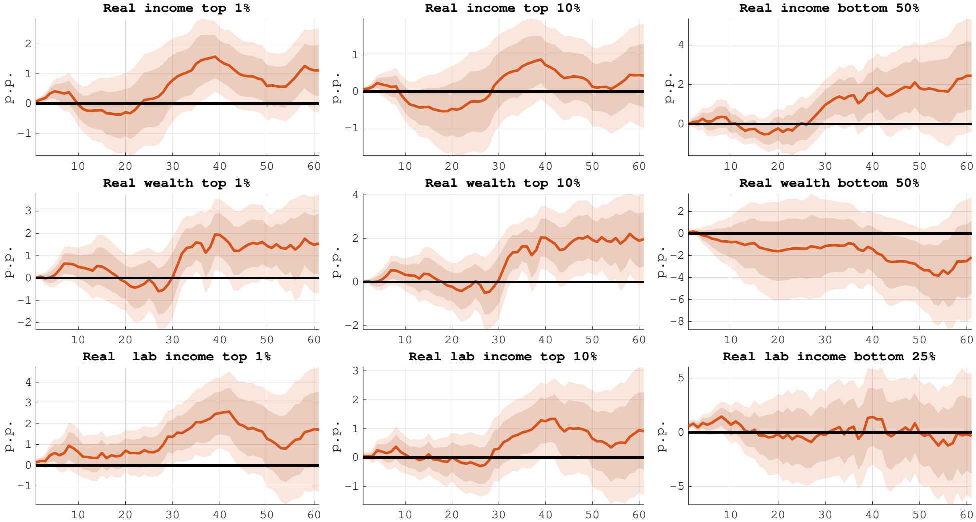
Note. The figure displays the IRFs to a shock to a AIint. Sample 1985-2019. The estimates are based on local projections with Newey-West standard errors. Point estimate and 68%-90% confidence bands. Back

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

References I

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *The quarterly journal of economics*, 131(4):1593–1636.

Barsky, R. B. and Sims, E. R. (2011). News shocks and business cycles. *Journal of monetary Economics*, 58(3):273–289.

Basu, S., Fernald, J. G., and Kimball, M. S. (2006). Are technology improvements contractionary? *American Economic Review*, 96(5):1418–1448.

Baumeister, C. and Hamilton, J. D. (2019). Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks. *American Economic Review*, 109(5):1873–1910.

Beaudry, P. and Portier, F. (2014). News-driven business cycles: Insights and challenges. *Journal of Economic Literature*, 52(4):993–1074.

Bloom, N. (2009). The impact of uncertainty shocks. *econometrica*, 77(3):623–685.

Fisher, J. D. and Peters, R. (2010). Using stock returns to identify government spending shocks*. *The Economic Journal*, 120(544):414–436.

References II

Gertler, M. and Karadi, P. (2015). Monetary policy surprises, credit costs, and economic activity. *American Economic Journal: Macroeconomics*, 7(1):44–76.

Gilchrist, S. and Zakrajšek, E. (2012). Credit spreads and business cycle fluctuations. *American economic review*, 102(4):1692–1720.

Känzig, D. R. (2021). The macroeconomic effects of oil supply news: Evidence from opec announcements. *American Economic Review*, 111(4):1092–1125.

Känzig, D. R. (2022). The unequal economic consequences of carbon pricing. *Available at SSRN 3786030*.

Kurmann, A. and Otrok, C. (2013). News shocks and the slope of the term structure of interest rates. *American Economic Review*, 103(6):2612–2632.

McCracken, M. W. and Ng, S. (2016). Fred-md: A monthly database for macroeconomic research. *Journal of Business & Economic Statistics*, 34(4):574–589.

Mertens, K. and Ravn, M. O. (2013). The dynamic effects of personal and corporate income tax changes in the united states. *American economic review*, 103(4):1212–1247.

References III

Newey, W. K. and West, K. D. (1994). Automatic lag selection in covariance matrix estimation. *The Review of Economic Studies*, 61(4):631–653.

Ramey, V. A. (2011). Identifying government spending shocks: It's all in the timing. *The Quarterly Journal of Economics*, 126(1):1–50.

Romer, C. D. and Romer, D. H. (2004). A new measure of monetary shocks: Derivation and implications. *American economic review*, 94(4):1055–1084.

Romer, C. D. and Romer, D. H. (2010). The macroeconomic effects of tax changes: estimates based on a new measure of fiscal shocks. *American Economic Review*, 100(3):763–801.

Smets, F. and Wouters, R. (2007). Shocks and frictions in us business cycles: A bayesian dsge approach. *American economic review*, 97(3):586–606.