Reshoring, Automation, and Labor Markets under Trade Uncertainty

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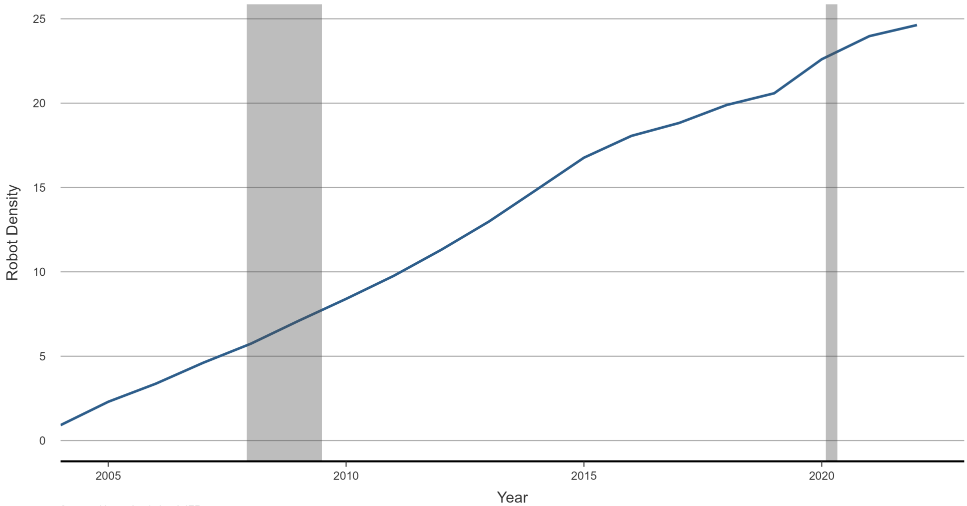
Reshoring has been rising in the past decade

Source: OECD via Haver Analytics

Reshoring and Automation

- Reshoring is easier when automation technologies are available
  - De Backer et al. (2018); Artuc et al. (2019); Stemmler (2019); Faber (2020); Carbonero et al. (2020); Krenz et al. (2021); Bonfiglioli et al. (2022); Faber et al. (2023)

Automation is also rising

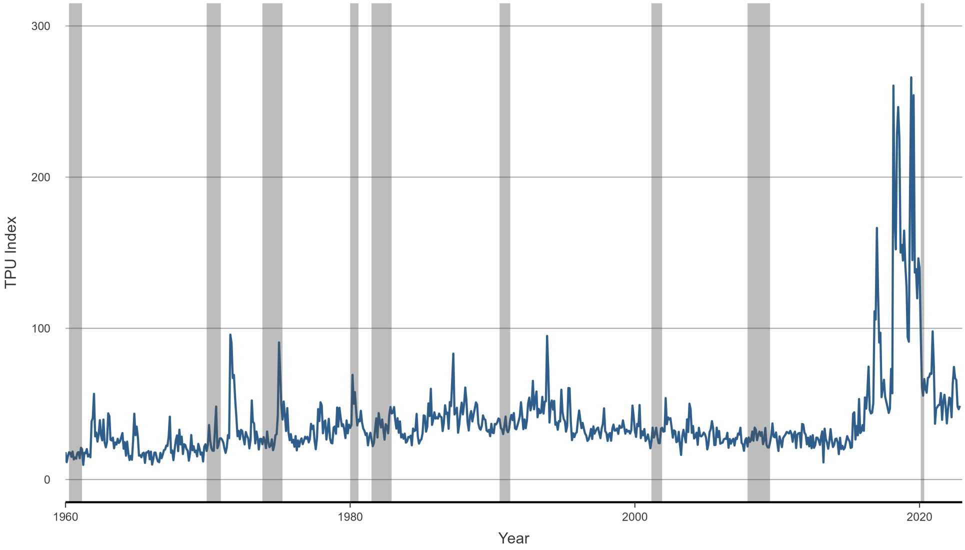


Source: Haver Analytics & IFR

Trade uncertainty and reshoring

- The presence of automation may reduce the benefits of reshoring for workers
- Can reshoring induced by trade uncertainty “bring jobs back” and redue skill premium?

Trade policy uncertainty surged in recent years



Source: Caldara et al. (2020)

details

This paper

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- Domestic production uses two types of technologies:
  1. Worker-only technology: uses low-skilled workers, subject to DMP search frictions
  2. Automation: uses robots and high-skilled workers

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- Domestic production uses two types of technologies:
  1. Worker-only technology: uses low-skilled workers, subject to DMP search frictions
  2. Automation: uses robots and high-skilled workers
- Trade uncertainty
  - stochastic volatility in trade costs

Model mechanism

- Rise in automation complicates effects of reshoring, especially in frictional labor markets
  - Threat of automation weakens worker bargaining position and contains wage increases
  - By raising productivity and reducing labor costs, automation encourages reshoring

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  - Threat of automation weakens worker bargaining position and contains wage increases
  - By raising productivity and reducing labor costs, automation encourages reshoring
  - Reshoring may (or may not) reduce low-skilled employment because
    - automation is labor substituting
    - less incentive to hire workers in frictional labor markets under trade uncertainty
    - depending on trade uncertainty persistence and response of automation

Model mechanism (cont.)

- Trade uncertainty affects automation through 3 channels
  - Expenditure-switching: less imports, more domestic production (reshoring)
  - Precautionary savings: lower real rate, more automation
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  - higher U for low-skilled workers
- Model predictions in line with industry-level evidence

Related literature

Reshoring and global supply chains: Fajgelbaum et al. (2021); Alfaro and Chor (2023); Grossman et al. (2023); Utar et al. (2023)

Automation and trade: De Backer et al. (2018); Dachs et al. (2019); Stemmler (2019); Faber (2020); Carbonero et al. (2020); Krenz et al. (2021); Bonfiglioli et al. (2022); Mandelman and Zlate (2022); Artuc et al. (2023); Baur et al. (2023)

(Trade policy) uncertainty: Handley and Limao (2015, 2017, 2022); Feng et al. (2017); Crowley et al. (2018); Alessandria et al. (2019); Greenland et al., (2019); Caldara et al. (2020); Novy and Taylor (2020); Poilly and Tripier (2023); Alessandria et al. (2021, 2024); Choi et al. (2023); Faber et al. (2023); Rodrigue et al. (2024); Dur et al., (2024); Kim and Lee, (2024)

Our contribution: We highlight how trade uncertainty can drive 3-way interactions between reshoring, automation, and labor markets.

Presentation Outline

1. The Model
2. Calibration
3. Macroeconomic Effects of Trade Uncertainty
4. Supporting Evidence

Open-economy DMP model with automation

- Final goods use domestic input (Y_{dt}) and imported input (Y_{ft}), with delivery lags

$$Y_t = \left[\alpha_d^{\frac{1}{\theta}} Y_{dt}^{\frac{\theta-1}{\theta}} + (1-\alpha_d)^{\frac{1}{\theta}} Y_{f,t-1}^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}}$$

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- Domestic goods use inputs produced by workers only (Y_{nt}) and by automation (Y_{at})

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  - Trade uncertainty: second-moment shocks to iceberg costs

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- Y_{nt} uses unskilled labor, subject to random search frictions
- Y_{at} uses skilled labor and robots
- Perfectly competitive goods market

Representative household

- Utility function

$$\mathbb{E}\sum_{t=0}^{\infty}\beta^{t}\left(\ln C_t - \chi N_t\right)$$

- Budget constraint

$$C_t + B_t = r_{t-1}B_{t-1} + w_{nt}N_t + w_{st}\bar{s} + \phi(1 - N_t) + d_t - T_t$$

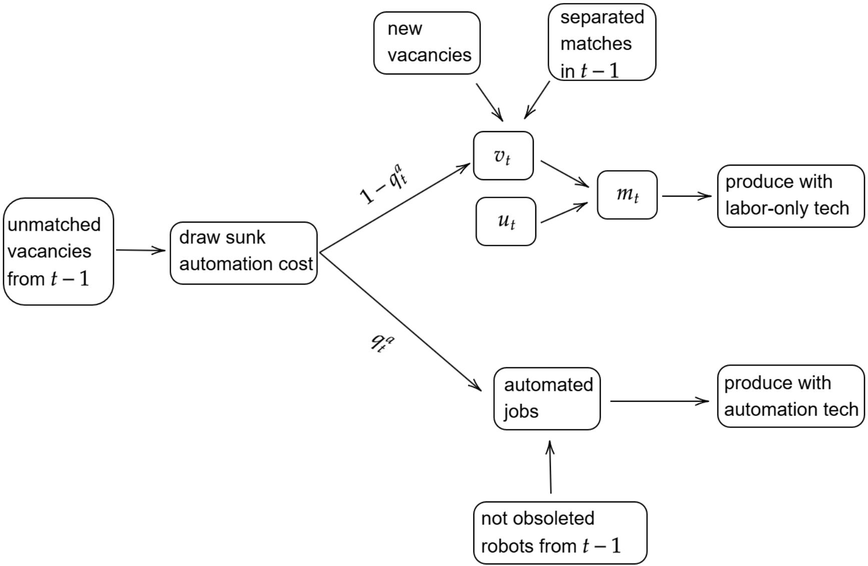
- Optimization problem

$$V_t(B_{t-1}, N_{t-1}) \equiv \max_{C_t, N_t, B_t} \ \ln C_t - \chi N_t + \mathbb{E}_t D_{t,t+1} V_{t+1}(B_t, N_t)$$

- Employment law of motion

$$N_t = (1-\delta)N_{t-1} + q_t^u u_t$$

Model overview: production



Labor market

- Matching technology

$$m_t = \mu u_t^{\alpha} v_t^{1-\alpha}$$

- Job seekers

$$u_t = 1 - (1-\delta)N_{t-1}$$

- Vacancies

$$v_t = (1 - q_{t-1}^v)(1 - q_t^a)v_{t-1} + \delta N_{t-1} + \eta_t$$

  - vacancy filling rate: $q_t^v = \frac{m_t}{v_t}$
  - automation prob: q_t^a
  - new vacancies: η_t

Vacancy creation

- Entry cost for a new vacancy: e
  - $i.i.d.$ from $F(e)$

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$$J_t^v = -\kappa + q_t^v J_t^e + (1 - q_t^v)\mathbb{E}_t D_{t,t+1}\left\{q_{t+1}^a J_{t+1}^a - \int_0^{\nu_{t+1}^*} \nu dG(\nu) + (1 - q_{t+1}^a)J_{t+1}^v\right\}$$

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- Value of a filled position

$$J_t^e = p_{nt} Z_t - w_{nt} + \mathbb{E}_t D_{t,t+1} \left\{ (1 - \delta) J_{t+1}^e + \delta J_{t+1}^v \right\}$$

Vacancy creation

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- New vacancy created if net value of entry is non-negative ($e \leq J_t^v$)
- Measure of newly created vacancies

$$\eta_t = F(J_t^v)$$

Automation decision

- Sunk cost of adopting automation equipment: ν
  - $i.i.d.$ from $G(\nu)$

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- Value of automating

$$J_t^a = \pi_t^a(1-\kappa_a) + (1-\rho^o)\mathbb{E}_t D_{t,t+1} J_{t+1}^a$$

  - $\pi_t^a \equiv \max_{s_t} p_{at} Z_t \zeta^{\gamma_a} s_t^{1-\gamma_a} - w_{st} s_t$

Automation decision

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- Net benefit of automation: $\nu_t^* \equiv J_t^a - J_t^v$

- Automate iff cost lower than net benefit (i.e., $\nu \leq \nu_t^*$) $\Rightarrow$ Prob of automating

$$q_t^a = G(\nu_t^*)$$

Automation decision

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- Law of motion for robots

$$A_t = (1-\rho^o)A_{t-1} + q_t^a(1-q_{t-1}^v)v_{t-1}$$

Wage determination

- Wages are determined by Nash bargaining

$$\max_{w_t} \left(S_t^H\right)^b (J_t^e - J_t^v)^{1-b}$$

employment surplus

- Steady state wage

$$w^N = \phi + \frac{\chi}{\Lambda} + \frac{b}{1-b}[1 - \beta(1-q^u)(1-\delta)](J^e - J^v)$$

  - Wage increases with both worker reservation value $\phi + \frac{\chi}{\Lambda}$ and worker bargaining power b
  - Wage decreases with firm reservation value J^v
  - Threat of automation (q^a) raises J^v and thus lowers wage

Government policy and search equilibrium

- Government policy: $\phi(1 - N_t) = T_t$

- Goods market clear

$$C_t + \kappa v_t + \kappa_a \gamma_a p_{at} Y_{at} + (1 - q^v_{t-1}) v_{t-1} \int_0^{\nu_t^*} \nu dG(\nu) + \int_0^{J_t^v} edF(e) = Y_t$$

- Financial autarky and balanced trade: $\tau_t p_{dt} X_t = p_{ft} Y_{ft}$

- Results are robust to allowing for capital flows

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1. The Model
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Calibration

- Calibrate parameters to match observations in the U.S. labor market calibrated parameters

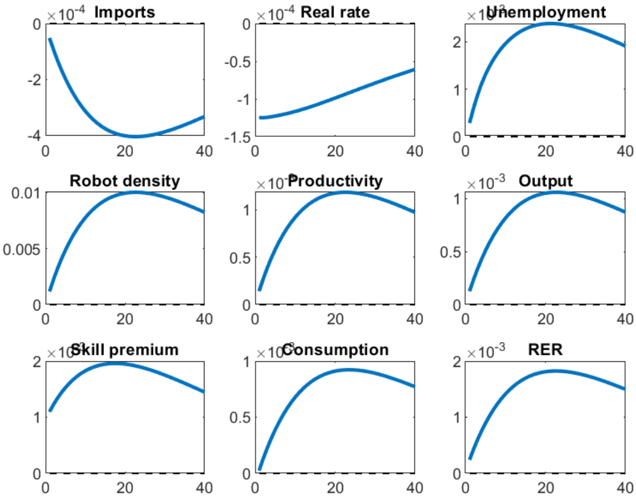
- Trade-related parameters:
  - Short-run trade elasticity: $\theta = 0.8$ (Boehm et al., 2023; di Giovanni et al., 2023)
  - Iceberg cost: $\bar{\tau} = 1.74$ (Anderson and van Wincoop, 2004)
  - First- and second-moment shocks to trade cost: Caldara et al. (2020) details

Automation-related parameters

- Follow Firooz, Liu, and Wang (2023)
- Labor-robots substitution elasticity $\sigma = 2$
  - Robot density $\uparrow$ 300% when robot prices $\downarrow$ 40%
  - Cheng et al. (2021): $\sigma \sim 3 - 4.5$
- Share of worker-produced intermediate goods $\alpha_n^{1/\sigma} = 0.63$
  - Matching robot density of 0.02

Presentation Outline

Macroeconomic effects of trade uncertainty



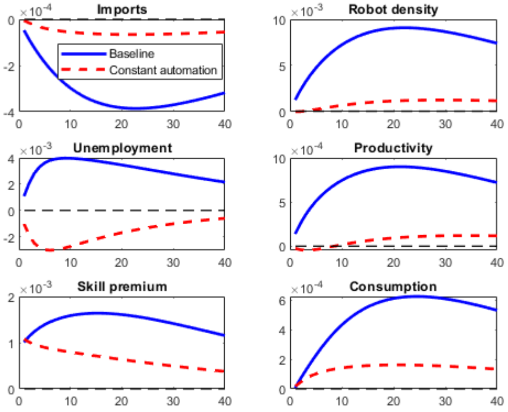
Why imports fall?

Transmission channels

- Counterfactual exercises to explore model mechanics

1. No endogenous response in automation probability
2. Higher openness
3. More persistent uncertainty

Automation amplifies effects of trade uncertainty

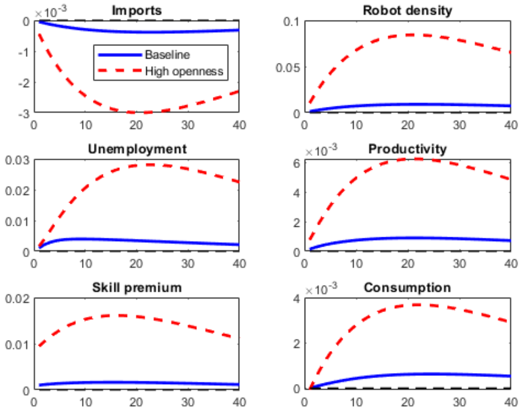


- Constant automation prob (q^a) $\rightarrow$ reshoring less attractive $\rightarrow$ smaller decline in imports
- Absent automation, expenditure switching boosts labor demand and lowers U ("China shock" reversal)
- Endogenous automation prob amplifies trade uncertainty

Openness to trade amplifies trade uncertainty

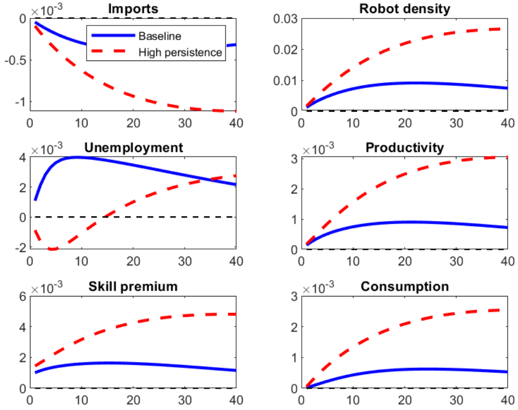
$$Y_t = \left[\alpha_d^{\frac{1}{\theta}} Y_{dt}^{\frac{\theta-1}{\theta}} + (1-\alpha_d)^{\frac{1}{\theta}} Y_{f,t-1}^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}}$$

Openness to trade amplifies trade uncertainty



- More openness → stronger expenditure switching, larger decline in imports → amplifying effects of trade uncertainty

Higher persistence of trade uncertainty leads to larger effects



capital flows | imported automation equipment | no delivery lags | wage rigidity | TFP uncertainty | 1st moment trade cost | 1st moment TFP

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Testable model implications

- Trade uncertainty reduces imports and stimulates automation
- Trade uncertainty raises labor productivity, value added, and skill premium, but reduces employment of low-skilled workers
- Macro effects of trade uncertainty works through automation channel

Data

- TPU index
  - Caldara et al. (2020) details
- Robot density: operational stock of industrial robots per thousand manufacturing employees in 2-digit industries robot def.
  - IFR, NBER-CES
- Offshoring measured by share of imported intermediate goods in gross output
  - OECD Trade in Value Added, BEA
- Skill premium
  - CPS
- Industry-level tariffs
  - World Integrated Trade Solution (WITS)

summary statistics IFR industries

Empirical specification

$$\ln Y_{jt} = \alpha_0 + \alpha_1 ImpShare_j \times \ln TPU_t + \alpha_2 \ln(1 + Tariff_{jt}) + \eta_j + \theta_t + \varepsilon_{jt},$$

- Y_{jt}: intermediate import share or robot density, industry j time t
- Trade uncertainty exposures measured by $ImpShare_j \times \ln TPU_t$
  - TPU_t: trade policy uncertainty
  - $ImpShare_j$: initial share of imported intermediate goods in gross output, industry j
- η_j and θ_t: industry and time FE
  - cross-industry variations, not macro effects (e.g., precautionary effect)
- $\ln(1 + Tariff_{jt})$: Control for industry-level tariffs

Trade uncertainty reduces offshoring and boosts automation

	(1) log(Robot density)	(2) log(Import share)
Initial import share × log(TPU)	5.251***	-1.001**
	(1.369)	(0.425)
log(1+Tariff)	18.21	-7.598
	(85.48)	(8.167)
Industry fixed effect	✓	✓
Time fixed effect	✓	✓
Observations	161	308
R^2	0.917	0.956
Years	2004:2018	1997:2018
No. of industries	12	14

- One SD (0.25) increase in trade uncertainty exposures associated with
  - increases in robot density of 1.3 log points (1/2 of its SD)
  - decreases in import share of 0.25 log points (1/3 of its SD)

Import origins

Trade uncertainty raises labor productivity and skill premium

	(1) log(Labor productivity)	(2) log(Employment)	(3) log(Value Added)	(4) log(Skill premium)
Initial import share × log(TPU)	0.326**	-0.168	0.158	0.143**
	(0.125)	(0.201)	(0.193)	(0.0531)
log(1+Tariff)	-1.088	8.739	7.651	0.983
	(4.409)	(16.85)	(15.11)	(1.757)
Industry fixed effect	✓	✓	✓	✓
Time fixed effect	✓	✓	✓	✓
Observations	264	264	264	308
R^2	0.970	0.943	0.961	0.790
Years	1997:2018	1997:2018	1997:2018	1997:2018
No. of industries	12	12	12	14

- One SD increase in trade uncertainty exposures associated with
  - increases in labor productivity of 0.08 log points (16% of its SD)
  - increase in skill premium of 0.04 log points (35% of its SD)

Automation channel of trade uncertainty: two-stage approach

	(1) log(Labor productivity)	(2) log(Employment)	(3) log(Value Added)	(4) log(Skill premium)
Predicted log(Robot density)	0.0608***	-0.0429*	0.0179	0.0389**
	(0.0201)	(0.0229)	(0.0265)	(0.0173)
log(1+Tariff)	-17.75**	-6.568	-24.32***	2.209
	(7.690)	(4.590)	(8.989)	(5.783)
Industry fixed effect	✓	✓	✓	✓
Time fixed effect	✓	✓	✓	✓
Observations	161	161	161	161
Years	2004:2018	2004:2018	2004:2018	2004:2018
No. of industries	12	12	12	12

- Examine automation channel of trade uncertainty using two-stage procedure as in Bertrand and Mullainathan (2001)
- First stage: regress robot density on trade uncertainty exposure
- Second stage: regress macro variable on predicted robot density from first stage

Conclusion

- We study macro effects of trade uncertainty in an open-economy model with automation and search frictions
- Model predicts that
  1. Trade uncertainty discourages offshoring and boosts automation; by containing costs, automation facilitates reshoring
  2. Reshoring induced by trade uncertainty boosts domestic production but not necessarily domestic employment
  3. Automation induced by trade uncertainty raises labor productivity and skill premium
  4. Effects are stronger with endogenous response in automation, higher openness, or more persistent trade uncertainty shock
- Model predictions broadly in line with industry-level evidence

Thank You!

Additional slides

TPU index

- Aggregate TPU index from Caldara et al. (2020)
- Searches of newspaper articles that discuss trade policy uncertainty
  - 7 newspapers: Boston Globe, Chicago Tribune, Guardian, Los Angeles Times, New York Times, Wall Street Journal, and Washington Post.
- Trade policy terms appear along with uncertainty terms
- Trade policy terms: tariff, import dut, import barrier, trade treat, trade polic, trade act, dumping, import fee, tax (within ten words of foreign good, foreign oil, or import), and import (within 10 words of surtax or surcharge).
- Uncertainty words: uncertain, risk, potential, danger, dubious, unclear, probabl, and predict.

back-intro back-data

Employment surplus

- Employment surplus

$$S_t^H \equiv \frac{1}{\Lambda_t} \frac{\partial V_t(B_{t-1}, N_{t-1})}{\partial N_t}$$

  - Λ_t: Lagrange multiplier for the budget constraint

- Employment optimization delivers

$$S_t^H = w_{nt} - \phi - \frac{\chi}{\Lambda_t} + \mathbb{E}_t D_{t,t+1}(1 - q_{t+1}^u)(1-\delta)S_{t+1}^H$$

  - employment relation survives with prob. $1 - \delta$
  - adding a worker today $\rightarrow$ reduce unemployment pool tomorrow, a fraction q_{t+1}^u of whom find a job

back

Calibrated parameters

	Parameter Description	value
β	Subjective discount factor	0.99
α	Elasticity of matching function	0.50
ϕ	Unemployment benefit	0.25
b	Nash bargaining weight	0.50
δ	Job separation rate	0.10
ρ^o	Automation obsolescence rate	0.03
κ_a	Flow cost of automated production	0.98
μ	Matching efficiency	0.6606
κ	Vacancy posting per-period fixed cost	0.1128
α_n	Share of worker-produced intermediate goods	0.39
σ	Elasticity of substitution between domestic intermediate goods	2.03
$\bar{e}$	Scale of vacancy creation cost distribution	3.07
$\bar{\nu}$	Scale of automation cost distribution	8.57
α_d	weight on domestic intermediate input (home bias)	0.85
θ	Substitution elasticity between domestic and imported goods	0.8
$\bar{\tau}$	Average iceberg trade cost	1.74
$\bar{Z}$	Average level of TFP	1
$\bar{s}$	Supply of skilled workers	0.3
γ_a	Share of automation equipment in production	0.32
ζ	Automation-specific productivity	3.4422
χ	Disutility of working	0.3741
ρ_z	Persistence of TFP shock	0.95
σ_z	Volatility of TFP shock	0.01
ρ_τ	Persistence of first-moment trade cost shock	0.99
σ_τ	Volatility of first-moment trade shock	0.00215
$\rho_{\sigma\tau}$	Persistence of trade uncertainty shock	0.96
η_τ	Volatility of trade uncertainty shock	0.37

back

Calibration details

- Matching function elasticity α: Blanchard and Gali (2010)
- Bargaining weight b and unemployment benefit ϕ: Hall and Milgrom (2008)
- Job separation rate δ: JOLTS
- Automation depreciation ρ^o: IFR
- Flow cost of automation κ_a & vacancy creation cost distribution parameter $\bar{e}$: Leduc and Liu (2024)
- Vacancy posting fixed cost κ: implies flow cost of vacancy posting is 1% of GDP
- Matching efficiency μ: implies quarterly job filling rate 0.71 (den Haan et al., 2000)
- Automation cost distribution parameter $\bar{\nu}$: implies automation probability of 38%
  - ABS: automation exposure 52% (manuf.) and 28% (whole)
- Skilled workers $\bar{s}$: relative employment of college-educated workers
- Automation-specific productivity ζ: skill premium of 55%
- Export demand shifter: export share of 10.8%
- Disutility of working χ: unemployment rate of 5.9%

Trade uncertainty shock

- First- and second-moment shocks to trade cost calibrated following Caldara et al. (2020)
- First-moment shock:

$$\ln(\tau_t) = (1 - 0.99)\ln(1.74) + 0.99\ln(\tau_{t-1}) + \sigma_{\tau t}\varepsilon_{\tau t}$$

where $\varepsilon_{\tau t} \sim N(0, 1)$

- Second-moment shock (uncertainty):

$$\sigma_{\tau t} = (1 - 0.96)0.002 + 0.96\sigma_{\tau,t-1} + 0.37u_{\tau t}$$

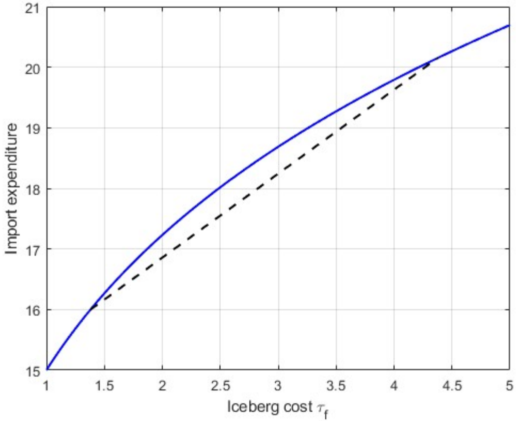
where $u_{\tau t} \sim N(0, 1)$ and independent of $\varepsilon_{\tau t}$

back

Expenditure-switching effect of trade uncertainty

Import expenditure (no delivery lag, $\theta < 1$):

$$p_f Y_f = (1 - \alpha_d) Y (p_f)^{1-\theta}, \quad p_f = \tau_f Q$$



back

Trade uncertainty and capital flows

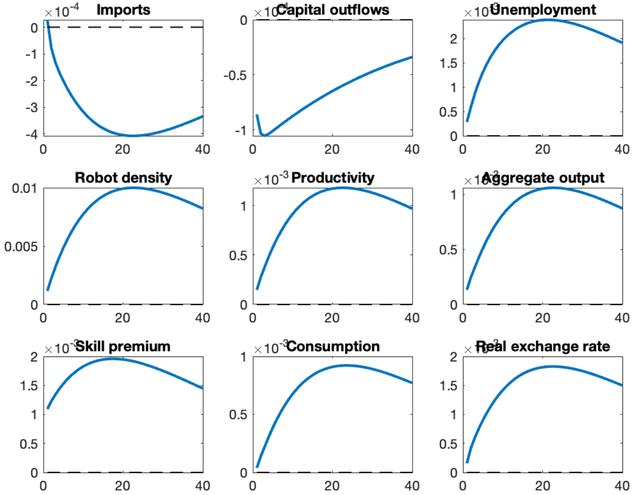
- HH budget constraint:

$$C_t + \mathcal{Q}_t B_t^* + \frac{\psi}{2}\mathcal{Q}_t(B_t^* - \bar{B}^*)^2 = r_{t-1}^* \mathcal{Q}_t B_{t-1}^* + w_{nt} N_t + w_{st}\bar{s} + \phi(1 - N_t) + d_t - T_t$$

- Balance of payments:

$$\mathcal{Q}_t(B_t^* - B_{t-1}^*) = \tau_t p_{dt} X_t - p_{ft} Y_{ft} + (r_t^* - 1)\mathcal{Q}_t B_{t-1}^*$$

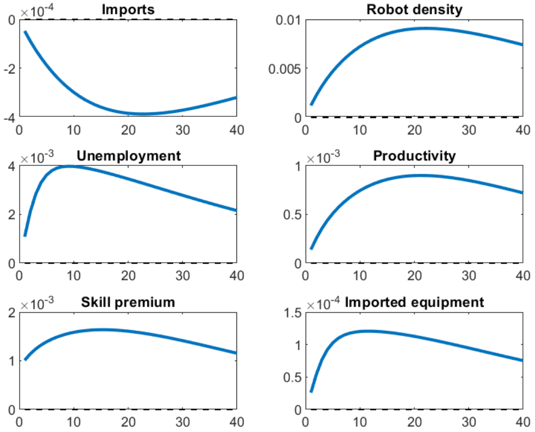
Trade uncertainty in a model with capital flows



back

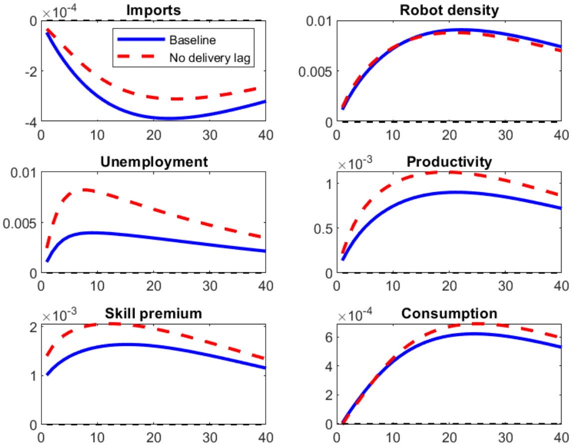
Trade uncertainty in a model with imported automation equipment

$$y_{at} = Z_t \left(\zeta^{1-\gamma_f} x_{at}^{\gamma_f}\right)^{\gamma_a} s_t^{1-\gamma_a}$$



back

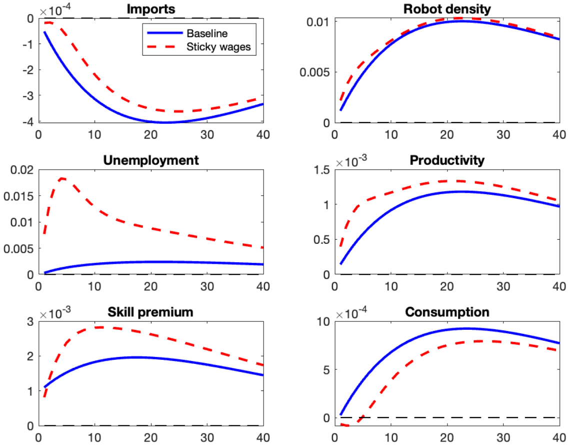
Trade uncertainty in a model with no delivery lags



back

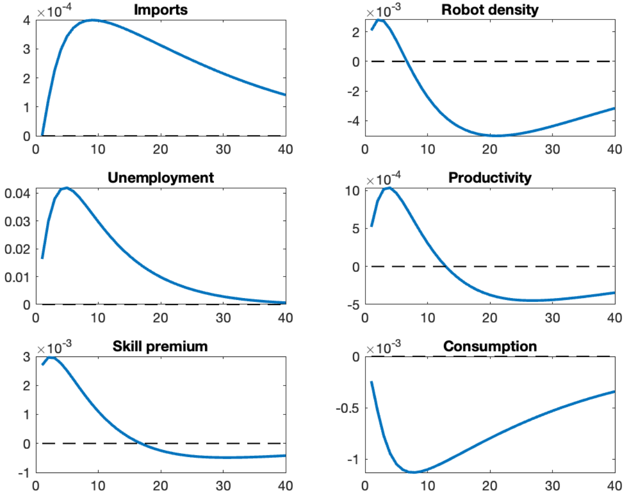
Trade uncertainty in a model with wage rigidity

$$w_{nt} = w_{n,t-1}^{\gamma_w} w_{nt}^{N\ 1-\gamma_w}$$



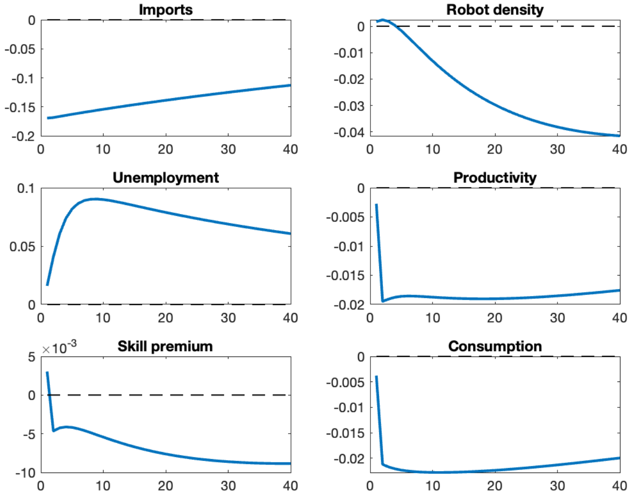
back

Macro effects of TFP uncertainty



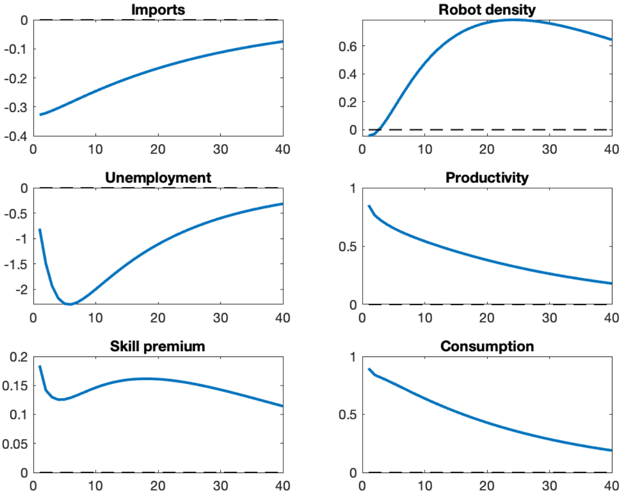
back

Macro effects of first-moment shock to trade costs



back

Macro effects of TFP shock



back

IFR Definition of Robots

Industrial robots are automatically controlled, reprogrammable, and multipurpose manipulators with several axes.

back

Summary statistics

	Mean	Count	SD	Min	Max	IQR
log Robot density	.615	161	2.731	-6.570	6.040	3.520
log $TPU \times$						
Initial share of intermediate imports	.345	264	.246	.059	1.553	.152
log Share of intermediate imports	-2.234	264	.684	-4.188	-.961	.708
log Labor Productivity	5.176	264	.488	4.136	6.522	.628
log Employment	6.476	264	.611	5.174	7.630	1.070
log Real Value-Added	11.652	264	.769	10.055	13.563	.920
log Skill premium	.484	264	.101	.247	.768	.139
log(1+Tariff)	.200	264	.023	0	.113	.0124

back

IFR industries

Code	Label
10-12	Food products and beverages; Tobacco products
13-15	Textiles, leather, wearing apparel
16	Wood and wood products (incl. furniture)
17-18	Paper and paper products, publishing & printing
19-22	Plastic and chemical products
23	Glass, ceramics, stone, mineral products n.e.c. (without automotive parts)
24	Basic metals (iron, steel, aluminum, copper, chrome)
25	Metal products (without automotive parts), except machinery and equipment
26-27	Electrical/electronics
28	Industrial Machinery
29	automotive
30	Other transport equipment

back

Import share from different origins

	(1) log(Mexico imp. share)	(2) log(Canada imp. share)	(3) log(China imp. share)
Initial imp. share × log(TPU)	-1.443	-0.244	-1.594***
	(1.072)	(0.211)	(0.318)
Industry FE	✓	✓	✓
Time FE	✓	✓	✓
Observations	323	330	308
R^2	0.986	0.984	0.887
Years	1997:2018	1997:2018	1997:2018
No. of industries	15	15	14

back