The Innovation Long-Run Risk Component

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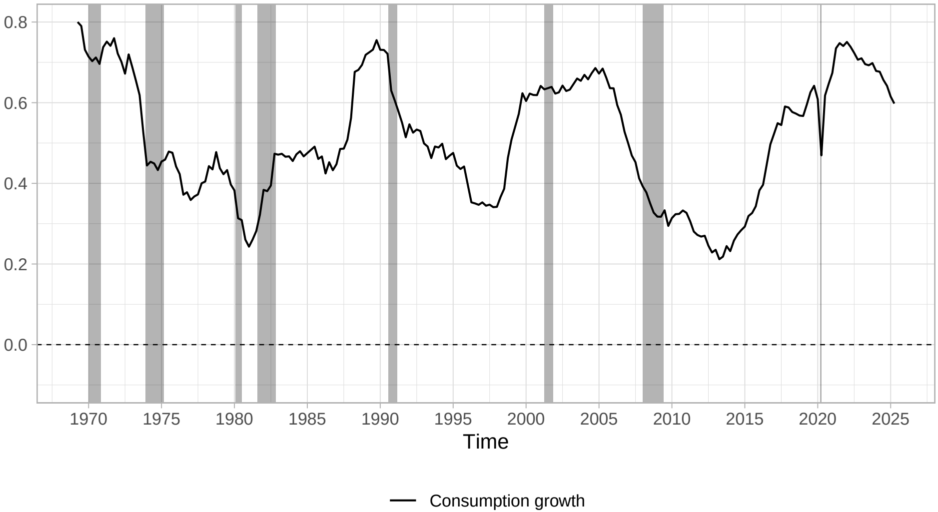
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1975
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2005
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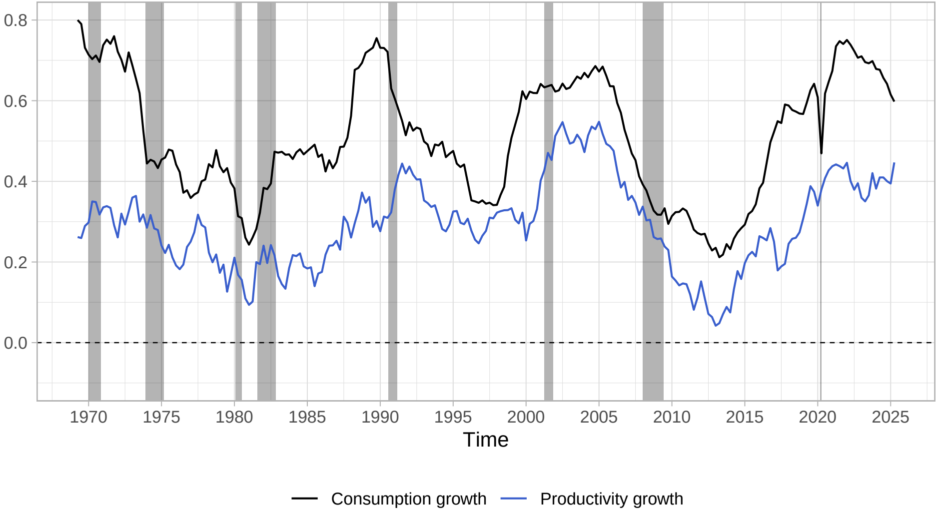
2020
2025
Time
Consumption growth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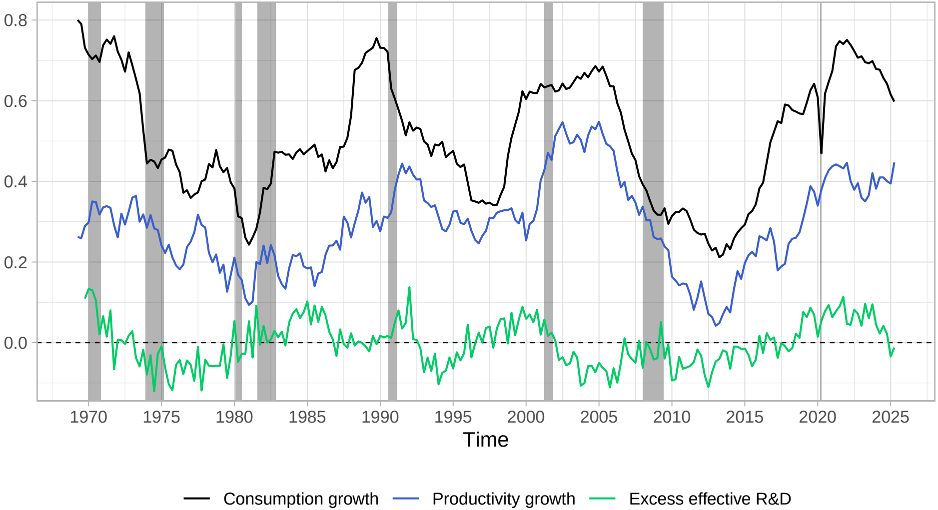
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- R&D shocks are significantly priced risk in assets cross-section
- Key channel of heterogeneous R&D-exposure cash-flow sensitivities

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Macroeconomic risk factors Lettau and Ludvigson (2001); Bansal et al. (2005); Savov (2011); Melone (2021); ...

Contribution: first risk factor (1) related to aggregate R&D; (2) based on structural shocks

Roadmap

Theoretical Framework

From Theory to Data

The Empirical Innovation Component

The Long-Run Risk from Innovation

The Innovation Risk Premium

Conclusions and Next Steps

Theoretical Framework

The Innovation Component

Aggregate productivity depends on ideas,

$$Z_t = I_t^{\xi} \cdot \exp[a_t] \tag{1}$$

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$$Z_t = I_t^{\xi} \cdot \exp[a_t] \tag{1}$$

$$I_t = (1-\phi) I_{t-1} + \chi \cdot S_{t-1}^{\eta} I_{t-1}^{\psi} Q_{t-1}^{-\omega} \tag{2}$$

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Key implication:

▸ Details

$$\Delta \ln Z_{t+1} \approx \gamma_0 + \gamma_1 \left(\ln S_t - \frac{1-\psi}{\eta} \ln I_t - \frac{\omega}{\eta} \ln Q_t \right) + \Delta a_{t+1} \tag{3}$$

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» ***effective R&D***

$$s_t \equiv \ln S_t - \frac{1-\psi}{\eta} \ln I_t - \frac{\omega}{\eta} \ln Q_t \tag{4}$$

Stationary $\Delta \ln Z_t$ and Δa_t $\implies$ Stationary s_t

The Long-Run Risk from Innovation

Assuming stationarity of productivity and effective R&D:

▸ $\Delta \ln Z$ stationarity

excess effective R&D $$\tilde{s}_t = s_t - \bar{s} \tag{5}$$

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$$E_t \left[\Delta \ln Z_{t+1}\right] \approx \mu + \gamma_1 \cdot \tilde{s}_t + E_t \left[\Delta a_{t+1}\right] \tag{6}$$

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» Assuming $\tilde{s}_t = \rho_s \tilde{s}_{t-1} + \tilde{\varepsilon}_t$ Long-Run impact of R&D shocks:

$$\{E_{t+1} - E_t\} \sum_{j=0}^{\infty} \Delta \ln Z_{t+1+j} = \frac{\rho_s}{1-\rho_s} \tilde{\varepsilon}_{t+1} \tag{7}$$

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(assuming $C_t \propto Z_t$) $$\propto \{E_{t+1} - E_t\} \sum_{j=1}^{\infty} \Delta \ln C_{t+j} \quad (8)$$

The (Innovation?) Long-Run Risk Premium

Fundamental asset pricing equation:

$$\mathrm{E}\left[R^i_{t+1}\right] - R^f_t = -R^f_t \cdot \mathrm{Cov}\left[M_{t+1}, R^i_{t+1}\right]$$

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Recursive preferences:

$$\ln M_{t+1} = E_t\left[\ln M_{t+1}\right] - b_c\, \varepsilon_{c,t+1} - b_x\, \varepsilon_{x,t+1}$$

where $\varepsilon_{c,t+1} = \ln C_{t+1} - E_t\left[\ln C_{t+1}\right]$ and $\varepsilon_{x,t+1} = \{E_{t+1} - E_t\} \sum_{j=1}^{\infty} \kappa_x^j \Delta \ln C_{t+1+j}$

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» Resulting pricing factor model:

$$E_t\left[R^i_{t+1}\right] - R^f_t = \lambda_c \beta^i_c + \lambda_x \beta^i_x \tag{9}$$

Calibrated DSGE models say $\lambda_x > 0$ explains more than 80% of US market's return.

From Theory to Data

A feasible measure

Theoretical definition to be mapped to the data

$$\ln S_t - \alpha_I \ln I_t - \alpha_Q \ln Q_t = \bar{s} + \tilde{s}_t \tag{10}$$

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$$\ln S_t - \alpha_Z \ln Z_t - \alpha_L \ln L_t = \bar{s} + \tilde{s}_t - \alpha_Z a_t \tag{10}$$

- Products variety log-proportional to labor force: $\ln Q_t \; = \; \kappa \cdot \ln L_t$
- Ideas limit sample timespan and fragile to misspecification: $\ln I_t \; = \; (\ln Z_t - a_t)/\xi$

gross effective R&D: $\quad \hat{s}_t \equiv \tilde{s}_t - \alpha_Z a_t$

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- Timing issue: single-equation estimation over system models

More structure is required, besides $\Delta \ln Z_{t+1} \approx \mu + \gamma_1 \cdot \tilde{s}_t + \Delta a_{t+1}$:

$$\tilde{s}_{t+1} = \rho_s \tilde{s}_t \tag{11a}$$

(11b)

(11c)

Identifying the Innovation Component and its Long-Run Impact

More structure is required, besides $\Delta \ln Z_{t+1} \approx \mu + \gamma_1 \cdot \tilde{s}_t + \Delta a_{t+1}$:

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1. a_t dynamic structure
2. feedback effects

$$\tilde{s}_{t+1} = \rho_s \tilde{s}_t + \theta_a a_t \tag{11a}$$

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$$\tilde{s}_{t+1} = \rho_s \tilde{s}_t + \theta_a a_t + b_{as} \varepsilon_{a,t+1} + b_{ss} \varepsilon_{s,t+1} \quad (11a)$$

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$$\Delta \ln Z_{t+1} - \mu = (\gamma_1 + \theta_s) \tilde{s}_t + (\rho_a - 1) a_t + b_{aa} \varepsilon_{a,t+1} \tag{11c}$$

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» $\tilde{s}_t$ can be identified in levels $\Leftarrow$ if $\theta_s \approx 0$, γ_1 can be identified $(\kappa_a \equiv 1 - \alpha_Z \gamma_1)$

$$\tilde{s}_t = \alpha_Z \left(\sum_{j=0}^{t-1} \kappa_a^j (\Delta \ln Z_{t-j} - \mu) \right) + \sum_{j=0}^{t-1} \kappa_a^j \Delta \hat{s}_{t-j} + \kappa_a^t \tilde{s}_0 \tag{12}$$

The Empirical Innovation Component

Gross Effective R&D: Specification, Method and Data

Theory: $\hat{s}_t$ stationary,* formed by a linear combination of non-stationary variables

$$\ln S_t - \alpha_Z \ln Z_t - \alpha_L \ln L_t = \bar{s} + \hat{s}_t \tag{10}$$

Empirical model: $\hat{s}_t$ is represented by the Error Correction Term (ECT) e_t from the regression

$$\ln S_t = b_{0,S} + b_Z \ln Z_t + b_L \ln L_t + e_t \tag{13}$$

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Data:

S_t US Private R&D from BEA, 1947q1–2025q1 (robustness: Total R&D)

Z_t US Total Factor Productivity (TFP) from Fernald (2012) — utilization-adjusted and excluding R&D capital, 1947q1–2023q1 (robustness: raw TFP)

L_t US Total Employment Level from BLS, 1948q1–2025q1 (robustness: Non-farm Employment)

Gross Effective R&D: Results

▸ ΔZ Stationarity

$$\ln S_t = b_0 + b_Z \ln Z_t + b_L \ln L_t + e_t$$

	Baseline	S: Tot. R&D	Z: Raw TFP	Q: N.F. Empl.	Est. Meth.: IM
b_Z	3.526^{***}	4.197^{***}	3.655^{***}	3.349^{***}	2.821^{***}
b_L	0.909^{***}	-0.354	0.956^{***}	0.953^{***}	1.387^{***}
			$\hat{s}_t = e_t$		
$\sigma_{\hat{s}}$	0.130	0.144	0.128	0.129	0.253
tt	−0.00	−0.00	−0.00	−0.00	0.00
tt^2	0.00	−0.00	0.00	0.00	−0.00
ADF	-2.57^{**}	-2.45^{**}	-2.92^{***}	-2.45^{**}	-9.18^{***}
KPSS	0.09	0.09	0.09	0.10	0.29
AR(1)	0.96	0.96	0.95	0.97	0.15
HL low	2.6	2.7	2.1	2.7	0.1
HL high	21.0	23.6	12.0	25.1	0.1
T	309	309	309	309	309

$^{*}\, p < 0.1$, $^{**}\, p < 0.05$, $^{***}\, p < 0.01$

- Stationary but persistent
- Minor differences across specifications

▸ All ECTs plot

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$$\ln S_t = b_0 + b_Z \ln Z_t + b_L \ln L_t + e_t$$

	Baseline	S: Tot. R&D	Z: Raw TFP	Q: N.F. Empl.	Est. Meth.: IM
b_Z	3.526^{***}	4.197^{***}	3.655^{***}	3.349^{***}	2.821^{***}
b_L	0.909^{***}	-0.354	0.956^{***}	0.953^{***}	1.387^{***}
			$\hat{s}_t = e_t$		
$\sigma_{\hat{s}}$	0.130	0.144	0.128	0.129	0.253
tt	−0.00	−0.00	−0.00	−0.00	0.00
tt^2	0.00	−0.00	0.00	0.00	−0.00
ADF	-2.57^{**}	-2.45^{**}	-2.92^{***}	-2.45^{**}	-9.18^{***}
KPSS	0.09	0.09	0.09	0.10	0.29
AR(1)	0.96	0.96	0.95	0.97	0.15
HL low	2.6	2.7	2.1	2.7	0.1
HL high	21.0	23.6	12.0	25.1	0.1
T	309	309	309	309	309

$^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

- Stationary but persistent
- Minor differences across specifications

▸ All ECTs plot

Net Effective R&D: Specification, Method and Data

Theory: (1) need to assume negligible feedback R&D $\longrightarrow$ external component

$$\Delta \ln Z_{t+1} = \mu + (\gamma_1 + \theta_s)\,\hat{s}_t + (\rho_a + (\gamma_1 + \theta_s)\alpha_Z - 1)a_t + b_{aa}\varepsilon_{a,t+1} \tag{11c}$$

(2) recursive expression of $\tilde{s}_t$ from (12)

Empirical model: (1) regression including macroeconomic factors f_t spanning a_t

$$\Delta \ln Z_{t+1} = b_{0,z} + b_s\hat{s}_t + \mathbf{b}_f'\mathbf{f}_t + u_{t+1} \tag{14}$$

(2) expression in (12), omitting initial condition

Estimation method: (1) OLS (2) Plug-in estimation (estimates replace $\{\alpha_Z, \gamma_1, \hat{s}_t\}$, ▸ Delta method inference)

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Estimation method: (1) OLS (2) Plug-in estimation (estimates replace $\{\alpha_Z, \gamma_1, \hat{s}_t\}$, ▸ Delta method inference)

Data: f_t LN Factors from Ludvigson and Ng (2009) — 9 factors extracted from >100 macroeconomic series, 1960q1–2025q1 (robustness: BS Factors, expanding Bansal and Shaliastovich (2013) — US CAPE, 3m/3y/5y/10y Treasury yields, integrated market volatility, corporate liquid-assets/profits growth, labor force growth; 1951q4–2025q1)

Net Effective R&D: Results

$$\Delta \ln Z_{t+1} = b_0 + b_s \hat{s}_t + \mathbf{b}_f' \mathbf{f}_t + u_{t+1}$$

	Baseline	S: Tot. R&D	Z: Raw TFP	Q: N.F. Empl.	$\mathbf{f}$: BS
b_s (%)	1.55^{***}	1.22^{***}	0.79^{**}	1.52^{***}	1.56^{***}
$W(\mathbf{f})$	61.0^{***}	50.3^{***}	2775.1^{***}	62.0^{***}	80.0^{***}
R^2 (%)	12.4	11.8	41.7	12.2	9.5
T	261	261	260	261	292
κ_a	0.971	0.949	0.945	0.949	0.964
	(0.013)	(0.012)	(0.012)	(0.012)	(0.014)
$\tilde{s}_t \quad (\kappa_a^t < 0.01)$					
$\sigma_{\tilde{s}}$	0.057	0.065	0.062	0.055	0.058
ADF	-3.95^{***}	-3.49^{***}	-3.50^{***}	-3.56^{***}	-3.91^{***}
KPSS	0.09	0.13	0.19	0.14	0.09
AR(1)	0.70	0.68	0.70	0.70	0.71
$T_{\tilde{s}}$	225	220	151	219	226

$^{*}\,p < 0.1$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$

- Significant predictive power of both R&D and external factors
- Stationary effective R&D, low persistence

▸ κ decay ▸ All $\tilde{s}$ plot

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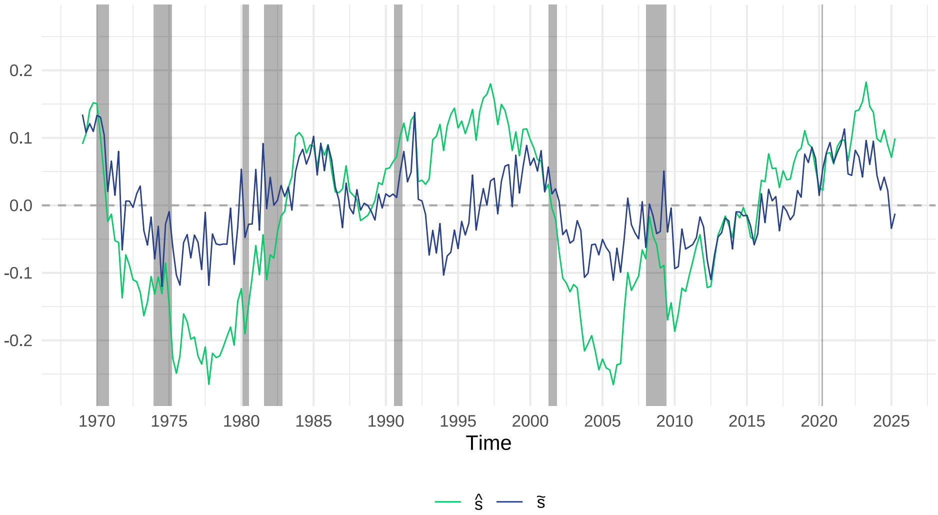

0.2
0.1
0.0
-0.1
-0.2
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025
Time
$\hat{s}$
$\tilde{s}$

The Long-Run Risk from Innovation

Theory: VARMA(2,1) from taking a_t out from (11):

$$\begin{bmatrix} \Delta \ln Z_t \\ x_t \end{bmatrix} = \Gamma_x' \begin{bmatrix} \Delta \ln Z_{t-1} \\ x_{t-1} \\ x_{t-2} \end{bmatrix} + \Theta_x' \begin{bmatrix} \varepsilon_{a,t} \\ \varepsilon_{s,t} \\ \varepsilon_{a,t-1} \end{bmatrix} \qquad x \in \{ \tilde{s}, \hat{s} \} \tag{15}$$

Effective R&D Shocks: Specification and Method

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Empirical model: Structural VAR(Q)

$$\begin{bmatrix} \Delta \ln Z_t \\ x_t \end{bmatrix} = \sum_{q=1}^{Q} A'_{x,q} \begin{bmatrix} \Delta \ln Z_{t-q} \\ x_{t-q} \end{bmatrix} + \begin{bmatrix} b_{aa} & 0 \\ b_{ax} & b_{xx} \end{bmatrix} \begin{bmatrix} \varepsilon_{a,t} \\ \varepsilon_{s,t} \end{bmatrix} \qquad x \in \{\tilde{s}, \hat{s}\} \tag{16}$$

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Estimation method: OLS and Cholesky decomposition

Effective R&D Shocks: Results

	Baseline	S: Tot. R&D	Z: Raw TFP	Q: N.F. Empl.	s: Net
N. Obs.	305	305	306	305	223
N. Lags	3	3	2	3	2
$R^2_{\Delta Z}$ (%)	5.3	4.4	4.8	5.3	2.8
$\max\lvert\text{roots}\rvert$	0.92	0.90	0.93	0.92	0.93
F-GC(s)	5.3***	6.5***	6.1***	5.5***	1.7
H-LM(z, 4)	3.2	2.3	22.6***	3.3	4.9
H-LM(s, 4)	30.2***	27.0***	33.2***	29.4***	6.4
AC-LM(1)	5.8	6.3	6.2	5.1	7.2
AC-LM(8)	29.4	37.9	41.9	26.7	37.5
AC-LM(16)	69.6	68.6	69.3	69.6	69.1
AC-LM(40)	169.4	155.7	166.9	165.9	154.7

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

- R&D: significant predictive power
- Residuals: heteroskedastic, but not auto-correlated

All ε_S plot

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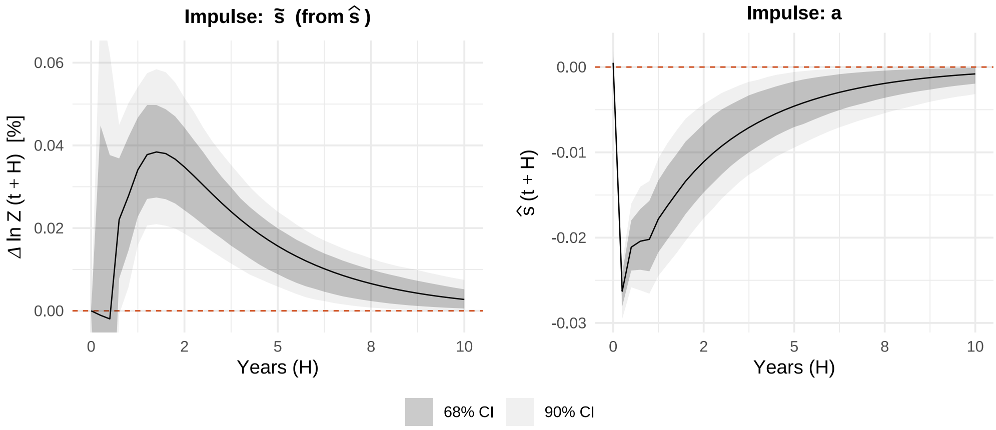
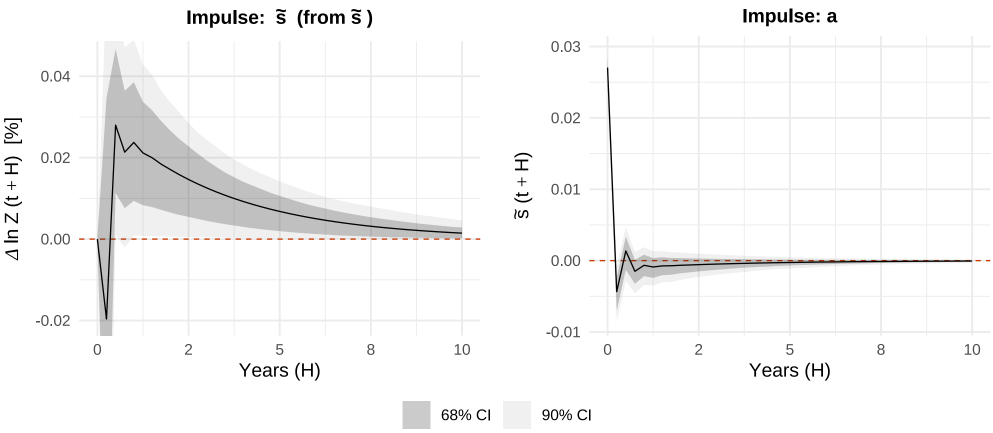
All ε_s plot

Productivity Gains from Innovation (VAR IRF's — Gross Effective R&D)



- R&D shocks impact: persists longer than 8 years
- External shocks impact: negative, on Gross Effective R&D

Productivity Gains from Innovation (VAR IRF's — Net Effective R&D)



- R&D shocks impact: noisier estimate, but persists longer than 8 years
- External shocks impact: positive, on Net Effective R&D

Theory: Long-Run Predictions of Consumption growth are proportional to Effective R&D shocks

$$\{E_{t+1} - E_t\} \sum_{j=1}^{\infty} \Delta \ln C_{t+j} \quad \propto \quad \varepsilon_{s,t+1} \tag{7}$$

I do *not* assume a realistic structure for Consumption dynamics

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$$\Downarrow$$

Estimation method: Local Projection — Montiel Olea and Plagborg-Møller (2021)

Estimation model:

$$\sum_{j=1}^{H} \Delta \ln C_{t+j} = b_{c,H,0} + b_{c,H,s} \cdot \varepsilon_{s,t} + \sum_{l=0}^{k} \{\mathbf{b}'_{c,H,f,l} \mathbf{f}_{t-l} + b_{cc,H,l} \cdot \ln C_{t-l}\} + \nu_{c,H} \tag{17}$$

Long-Run Risk from Innovation: Specification, Method and Data

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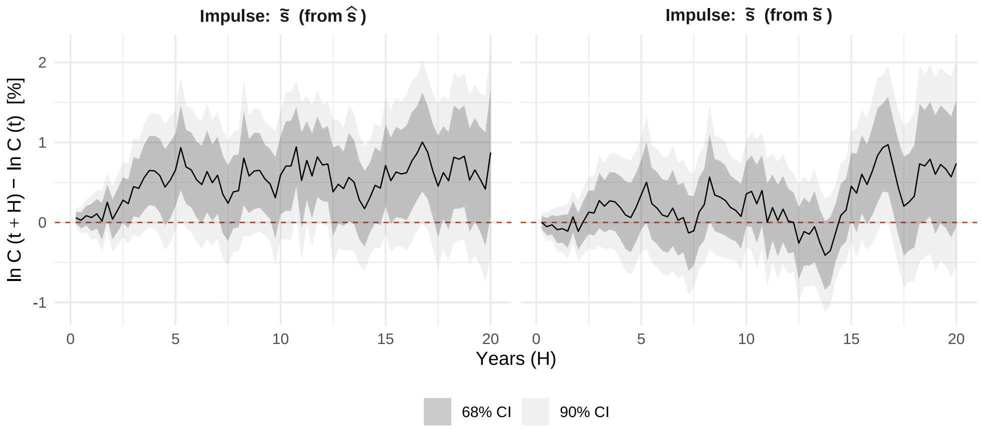
Data: C_t is US Real Total Personal Consumption Expenditures Per Capita from the BEA, 1947q1–2025q2

Long-Run Risk from Innovation: Results



» Effect of R&D sustained over business cycle horizons

▸ Robustness

The Innovation Risk Premium

Innovation Risk Premium Estimation: Specification, Method and Data

Theory: Reduced-form asset pricing equation

$$E_t\left[R^i_{t+1}\right] - R^f_t = \lambda_c \beta^i_c + \lambda_x \beta^i_x \tag{9}$$

Empirical model:

$$R^i_t - R^f_{t-1} = \boldsymbol{\beta}^i \boldsymbol{\lambda} + \boldsymbol{\beta}^i \boldsymbol{v}_t + u^i_t \qquad \text{where} \qquad \varepsilon_{s,t} = \zeta_0 + \boldsymbol{\zeta}_s \boldsymbol{v}_t + w_t \quad \Rightarrow \quad \lambda_x = \boldsymbol{\zeta}_s \, \boldsymbol{\lambda} \tag{18}$$

Estimation method: 3-stage “Fama-Macbeth” procedure (PCA+OLS) — Giglio and Xiu (2021) $\Leftarrow$ omitted risks

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Data: $\mathbf{R} - R^f$ excess returns from 183 portfolios: 153 of stock anomalies from Jensen et al. (2021); 17 of industry-sorted stocks from K. French; 13 of bonds built on yields data from Gürkaynak et al. (2007) with maturities 0.5, 1, 2, 3, 4, 5, 6, 7, 10, 15, 20, 25, 30 years. Timespan: 1971q4–2024q4

Innovation Risk Premium Estimation: Results

	Baseline	S: Tot. R&D	Z: Raw TFP	Q: N.F. Empl.	s: Net
Horizon: 1 quarter					
p=6	5.63	6.26	6.97	6.12	8.65
	[0.93]	[0.90]	[1.22]	[1.03]	[1.28]
p=14	17.21	10.39	18.47	14.18	16.43
	[1.32]	[0.74]	[1.35]	[1.12]	[1.08]
p=22	−4.86	−35.53	2.26	−8.66	−14.51
	[−0.21]	[−1.30]	[0.09]	[−0.38]	[−0.55]
Horizon: 4 years					
p=6	2.07	1.76	2.17	2.04	2.66
	[1.33]	[1.11]	[1.33]	[1.36]	[0.97]
p=14	12.06***	8.48**	12.95***	11.27***	17.22***
	[3.28]	[2.50]	[3.52]	[3.11]	[2.75]
p=22	13.53***	10.71**	15.23***	11.97**	20.12**
	[2.80]	[2.23]	[3.17]	[2.52]	[2.28]
Num.Obs.	213	213	213	213	206

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

- significant premium, averaging shocks over 1 year (consistent w Eberhart et al. (2004))

"True" factors selection

Innovation Risk Premium Estimation: Results

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p=6	5.63	6.26	6.97	6.12	8.65
	[0.93]	[0.90]	[1.22]	[1.03]	[1.28]
p=14	17.21	10.39	18.47	14.18	16.43
	[1.32]	[0.74]	[1.35]	[1.12]	[1.08]
p=22	−4.86	−35.53	2.26	−8.66	−14.51
	[−0.21]	[−1.30]	[0.09]	[−0.38]	[−0.55]
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p=6	2.07	1.76	2.17	2.04	2.66
	[1.33]	[1.11]	[1.33]	[1.36]	[0.97]
p=14	12.06***	8.48**	12.95***	11.27***	17.22***
	[3.28]	[2.50]	[3.52]	[3.11]	[2.75]
p=22	13.53***	10.71**	15.23***	11.97**	20.12**
	[2.80]	[2.23]	[3.17]	[2.52]	[2.28]
Num.Obs.	213	213	213	213	206

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

- significant premium, averaging shocks over 1 year (consistent w Eberhart et al. (2004))

“True” factors selection

Innovation Risk Premium Estimation: Results

	Baseline	S: Tot. R&D	Z: Raw TFP	Q: N.F. Empl.	s: Net
			Horizon: 1 quarter		
p=6	5.63	6.26	6.97	6.12	8.65
	[0.93]	[0.90]	[1.22]	[1.03]	[1.28]
p=14	17.21	10.39	18.47	14.18	16.43
	[1.32]	[0.74]	[1.35]	[1.12]	[1.08]
p=22	−4.86	−35.53	2.26	−8.66	−14.51
	[−0.21]	[−1.30]	[0.09]	[−0.38]	[−0.55]
			Horizon: 4 years		
p=6	2.07	1.76	2.17	2.04	2.66
	[1.33]	[1.11]	[1.33]	[1.36]	[0.97]
p=14	12.06***	8.48**	12.95***	11.27***	17.22***
	[3.28]	[2.50]	[3.52]	[3.11]	[2.75]
p=22	13.53***	10.71**	15.23***	11.97**	20.12**
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Innovation Risk from cash-flows: Specification, Method and Data

Theory: risk premia in returns reflect exposure of assets cash-flows

Campbell (1996) decomposition

$$E_t\left[R^i_{t+1}\right] - R^f_t \approx \lambda_x \cdot \beta^i_{x,D}\,, \qquad (19)$$

Empirical model: Following Bansal et al. (2005)

$$\Delta \ln D^i_t = \beta^i_{0,D} + \beta^i_{x,D} \cdot \frac{1}{H}\sum_{l=1}^{H} \varepsilon_{s,t-l} + u^i_t \qquad (20)$$

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Estimation method: 2-stage "Fama-Macbeth" procedure (OLS)

Data: R, D US sorted stock portfolios returns and cash-flows from CRSP.

▸ Cash-flow details

Portfolios from a "legacy" pool (size, B/M, momentum — n: 15), an "extended" pool (funding conditions and investment opportunities — n: 51), a "wide" pool (industry — n:68); accounting data from Compustat.

▸ Portfolios construction

Final timespan: 1967q1/1975q1–2022q4.

Innovation Risk from cash-flows: Sensitivities

	Firm-R&D (Small firms)			Firm-R&D (Big firms)			Turnover (Small firms)			Tobin Q (Small firms)		
	1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
$\tilde{s}$: shock	-0.00	-0.02	1.09	-0.03	-0.07	-0.17	0.06	0.28	0.75	0.27	0.20	-0.06
$\tilde{s}$: level	-0.58	-0.73	-3.37	-0.29	-0.28	-1.20	-0.76	0.99	3.53	1.92	0.63	-0.37

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- **Higher-intangibles** firms: **negative** reaction to aggregate R&D shocks

Innovation Risk from cash-flows: the Premium

	R&D: shock	R&D: level	Adj. TFP	Raw TFP	Cons.
			Horizon: 1 quarter		
Ext. pool	2.28^{**}	0.06^{*}	-2.47^{**}	1.97^{***}	1.72^{**}
	[2.31]	[1.68]	[−2.12]	[3.14]	[2.58]
R^2 (%)	16.77	4.89	17.95	20.44	24.85
MAPE (%)	0.46	0.48	0.43	0.44	0.41
			Horizon: 2 years		
Ext. pool	0.71^{**}	0.04	1.17^{**}	0.40^{**}	0.32
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- Premium from R&D shocks significant and **consistent across horizon**

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Conclusions and Next Steps

Summary and Road Ahead

- Endogenous growth theory suggests how to measure aggregate R&D
- R&D has persistent effects on TFP growth, accumulating through system interactions
- Uncertainty on R&D levels is significantly priced risk in stock markets

Moving forward:

Big picture:

Summary and Road Ahead

- Endogenous growth theory suggests how to measure aggregate R&D
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Moving forward:

- Application to physical capital?
- Extensive margin of (ideas) capital? …interaction with financial frictions and implications for uncertainty?
- International evidence?

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- R&D has persistent effects on TFP growth, accumulating through system interactions
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- International evidence?

Big picture:

This branch: **supply** of (intangible) capital / Rest of my research: **demand** of capital

$\longrightarrow$ **Integration**: predictive power in financial markets, tests of macroeconomic theory

The Innovation Long-Run Risk Component

revision requested by the *Journal of Monetary Economics*

Fabio Franceschini

University of Bologna (IT)

January 26th, 2026

Technical Details

TFP growth rate approximation 1

Ideas growth rate from law of motion/production schedule

$$\frac{I_t}{I_{t-1}} = 1 - \phi + \chi \left(S_{t-1}^{\eta} I_{t-1}^{(-1+\psi)} Q_{t-1}^{-\omega} \right) \tag{21}$$

$$\ln \left(\frac{I_t}{I_{t-1}} \right) \approxeq -\phi + \chi \left(S_{t-1}^{\eta} I_{t-1}^{(-1+\psi)} Q_{t-1}^{-\omega} \right) \tag{22}$$

$$\Delta \ln I_t \approxeq -\phi + \chi \cdot \exp \left\{ \ln \left(S_{t-1}^{\eta} I_{t-1}^{(-1+\psi)} Q_{t-1}^{-\omega} \right) \right\} \tag{23}$$

$$= -\phi + \chi \cdot \exp \left\{ \eta \ln S_{t-1} - (1 - \psi) \ln I_{t-1} - \omega \ln Q_{t-1} \right\} \tag{24}$$

$$\approxeq -\phi + \chi + \chi\eta \left(\ln S_{t-1} - \frac{1-\psi}{\eta} \ln I_{t-1} - \frac{\omega}{\eta} \ln Q_{t-1} \right) \tag{25}$$

Productivity growth rate applying TFP definition

$$\ln Z_t = a_t + \xi \ln I_t \tag{26}$$

$$\Delta \ln Z_t = \Delta a_t + \xi \Delta \ln I_t \tag{27}$$

$$\approxeq \Delta a_t + \xi \left[-\phi + \chi + \chi\eta \left(\ln S_{t-1} - \frac{1-\psi}{\eta} \ln I_{t-1} - \frac{\omega}{\eta} \ln Q_{t-1} \right) \right] \tag{28}$$

$$= \Delta a_t + \xi(\chi - \phi) + \xi\chi\eta \left(\ln S_{t-1} - \frac{1-\psi}{\eta} \ln I_{t-1} - \frac{\omega}{\eta} \ln Q_{t-1} \right) \tag{29}$$

Back

TFP growth rate approximation 2

Assuming $Q_t = L_t^\kappa$

$$\Delta \ln Z_t \approxeq \Delta a_t + \xi(\chi - \phi) + \xi\chi\eta\left(\ln S_{t-1} - \frac{1-\psi}{\eta}\ln I_{t-1} - \frac{\omega\kappa}{\eta}\ln L_{t-1}\right) \tag{30}$$

Expressing effective R&D in term of Z

$$\Delta \ln Z_t \approxeq \Delta a_t + \xi(\chi - \phi) + \xi\chi\eta\left(\ln S_{t-1} - \frac{1-\psi}{\eta\xi}(\ln Z_{t-1} - a_{t-1}) - \frac{\omega\kappa}{\eta}\ln L_{t-1}\right) \tag{31}$$

Rearranging and assuming $a_t = \rho_a a_{t-1} + \varepsilon_t^a$

$$\Delta \ln Z_t \approxeq \xi(\chi - \phi) + \xi\chi\eta\left(\ln S_{t-1} - \frac{1-\psi}{\eta\xi}\ln Z_{t-1} - \frac{\omega\kappa}{\eta}\ln L_{t-1}\right) + (\rho_a - 1 + \chi(1-\psi))a_{t-1} + \varepsilon_t^a \tag{32}$$

Back

Effective R&D level recovery estimator

Estimator, sum of a feasible (plug-in) estimate and an observable component:

$$\hat{\tilde{s}}_t \equiv \hat{\tilde{s}}_t + \hat{\kappa_s}^t \cdot \tilde{s}_0 \qquad \text{where} \qquad \hat{\tilde{s}}_t \equiv \hat{\alpha_Z}\left(\sum_{j=0}^{t-1} \hat{\kappa_s}^j (\Delta \ln Z_{t-j} - \hat{\mu})\right) + \sum_{j=0}^{t-1} \hat{\kappa_s}^j \Delta \hat{\hat{s}}_{t-j} \tag{33}$$

Estimation Variance estimator:

$$\hat{\text{Var}}\left[\hat{\tilde{s}}_t \middle| X\right] = \hat{\text{Var}}\left(\text{E}\left[\hat{\tilde{s}}_t \middle| \hat{\theta}, X\right] \middle| X\right) + \hat{\text{E}}\left[\text{Var}\left(\hat{\tilde{s}}_t \middle| \hat{\theta}, X\right) \middle| X\right] \tag{34}$$

where

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where

$$\hat{\mathrm{Var}} \left(\mathrm{E} \left[\tilde{\hat{s}}_t | \hat{\theta}, X \right] | X \right) = \nabla \tilde{\hat{s}}_t (\hat{\alpha_Z}, \hat{\alpha_L}, \hat{b_s})^\top \begin{bmatrix} \hat{\sigma^2_{\alpha_Z}} & \hat{\sigma_{\alpha_Z, \alpha_L}} & 0 \\ \hat{\sigma_{\alpha_Z, \alpha_L}} & \hat{\sigma^2_{\alpha_L}} & 0 \\ 0 & 0 & \hat{\sigma^2_{b_s}} \end{bmatrix} \nabla \tilde{\hat{s}}_t (\hat{\alpha_Z}, \hat{\alpha_L}, \hat{b_s}) \tag{35}$$

$$\hat{\mathrm{E}} \left[\mathrm{Var} \left(\tilde{\hat{s}}_t | \hat{\theta}, X \right) | X \right] = \left(\hat{\kappa_s}^{2t} + t(2t-1) \hat{\kappa_s}^{2(t-1)} \cdot \hat{\mathrm{Var}}(\hat{\kappa}_s | X) \right) \hat{\sigma^2_{\tilde{s}}} + \nabla \kappa^{2t} (\hat{\kappa_s}) \hat{\mathrm{Var}}(\hat{\kappa}_s | X) \nabla \hat{\sigma^2_{\tilde{s}}} (\hat{\kappa_s}) \tag{36}$$

with

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with

$$\nabla \tilde{\tilde{s}}_t (\hat{\alpha_Z}, \hat{\alpha_L}, \hat{b_s}) = \begin{bmatrix} \sum_{j=0}^{t-1} -\hat{b_s} \cdot j \cdot \hat{\kappa_s}^{j-1} \left(\overline{\Delta \ln S_{t-j}} - \hat{\alpha_L} \overline{\Delta \ln L_{t-j}}\right) \\ -\sum_{j=0}^{t-1} \hat{\kappa_s}^j \overline{\Delta \ln L_{t-j}} \\ \sum_{j=0}^{t-1} -\hat{\alpha_Z} \cdot j \cdot \hat{\kappa_s}^{j-1} \left(\overline{\Delta \ln S_{t-j}} - \hat{\alpha_L} \overline{\Delta \ln L_{t-j}}\right) \end{bmatrix} \tag{37}$$

$$\nabla \kappa^{2t}(\hat{\kappa_s}) = 2t \cdot \hat{\kappa_s}^{2t-1} \qquad \text{and} \qquad \nabla \hat{\sigma}^2_{\tilde{s}}(\hat{\kappa_s}) = \frac{1}{T} \sum_{t=1}^{T} \left\{ \left(\overline{\Delta \ln S_t} - \hat{\alpha_L} \overline{\Delta \ln L_t}\right)^2 \left[\sum_{l=0}^{T-t} l \cdot \hat{\kappa_s}^{2l-1}\right] \right\} \tag{38}$$

Back

Campbell (1996) Decomposition

Campbell (1996) first established

$$\ln R^i_{t+1} - E_t\left[\ln R^i_{t+1}\right] \approx \{E_{t+1} - E_t\}\left[\sum_{j=0}^{\infty} \kappa^j \Delta \ln D_{i,t+j}\right] - \{E_{t+1} - E_t\}\left[\sum_{j=1}^{\infty} \kappa^j \ln R^i_{t+j}\right]$$

β^i can then be decomposed:

$$E_t\left[R^i_{t+1}\right] - R^f_t \approx \lambda_c\, \beta^i_c + \lambda_x(\beta^i_{x,D} - \beta^i_{x,R}) \tag{39}$$

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In Bansal et al. (2005):

$$E_t\left[R^i_{t+1}\right] - R^f_t \approx \lambda_x \beta^i_{x,D} \tag{40}$$

- Long-run risk only (β^i_x)
- Cash-flows exposure only ($\beta^i_{x,D}$)

Back

Cash-flow risk portfolios construction

- Common stocks with NYSE size $\geqslant$ 1st percentile and price $> \$2$ (removes $< 0.4\%$ of market cap)
- Minimum 12 consecutive monthly observations
- Portfolios formed end of June, value-weighted, held July–June

"Legacy" pool:
(5 portfolios per sorting variable)

- **Size**: Market capitalization relative to NYSE breakpoints
- **BM**: Book equity ($t-1$) over capitalization ($t-1$); non-financials only
- **Momentum** (Mom): Cumulative returns from month $t-12$ to $t-1$

"Extended" pool:
(3×2 portfolios per sorting variable, terciles $\times$ NYSE size split)

- "Legacy" pool portfolios
- **R&D** (RD): R&D expenditures over capitalization; non-financial/non-utility (Chan et al. 2001)
- **Turnover** (To): Sales-to-assets ratio (Haugen and Baker 1996)
- **Profitability** (Prof): Gross profits over assets; non-financial/non-utility (Novy-Marx 2013)
- **Leverage** (Lvg): Debt-to-assets ratio; non-financials only (Bhandari 1988)
- **Asset Growth** (AG): Asset first difference; non-financial/non-utility (Cooper et al. 2008)
- **Tobin's Q** (TQ): (Assets $-$ Book Equity $+$ Market Cap) $/$ Assets (Chung and Pruitt 1994)

"Wide" pool:
(1 portfolio per industry)

- "Extended" pool portfolios
- **Industry**: 17-industry definition by K. French

Back

Dividends growth rate computation

$D_{p,t+1} = y_{p,t+1} V_{p,t}$ where

- $V_{p,t+1} = h_{p,t+1} V_t$ with $V_{p,0} = 1$
- $y_{p,t} = R_{p,t} - h_{p,t}$

All relies on $h_{p,t}$, which is the weighted sum of all portfolios stocks' RETX adjusted for share repurchases as

$$h_t = \left(\frac{P_{t+1}}{P_t}\right) \cdot \min\left[\left(\frac{n_{t+1}}{n_t}\right), 1\right] \tag{41}$$

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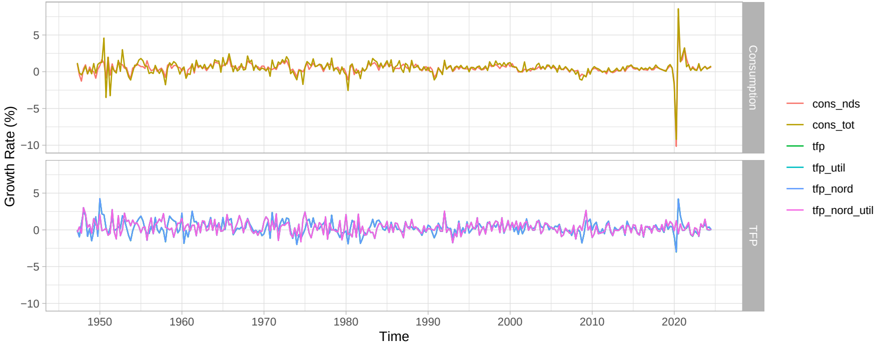
Additional Evidence

TFP stationarity

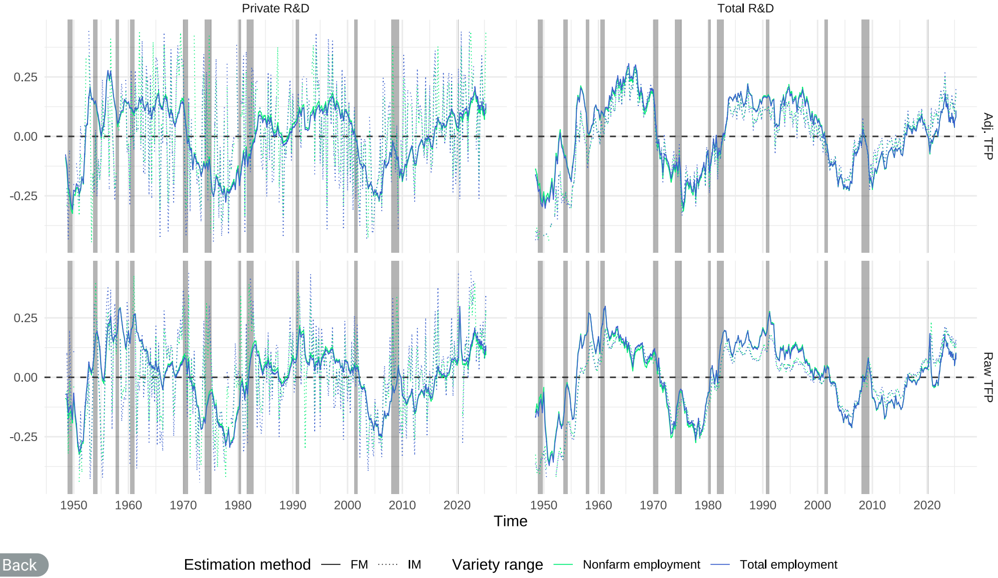
	Unadj. TFP	Adj. TFP
ADF u.r. stat	-10.81^{***}	-12.38^{***}
AC(1)	0.194^{***}	0.050
	(0.057)	(0.058)
Num. obs.	299	299

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$



◂ Back to set-up ◂ Back to results

All gross effective R&D series



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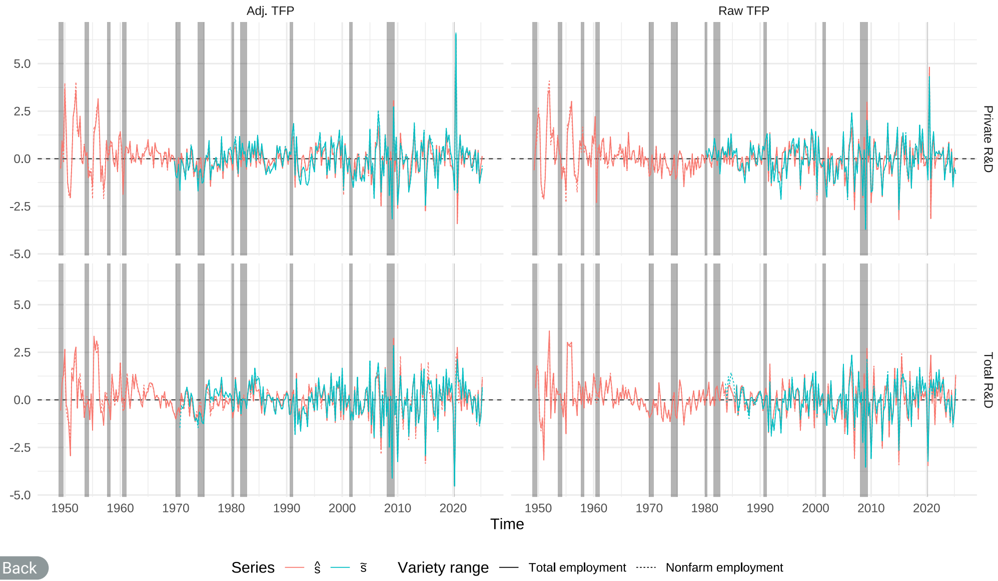
All effective R&D series

◂ Back

All effective R&D structural shocks series



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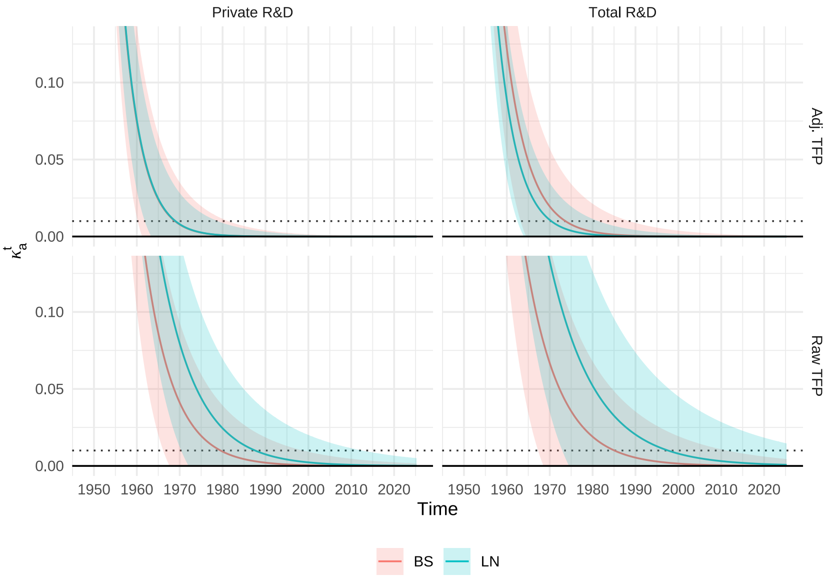
Recovery approximation accuracy



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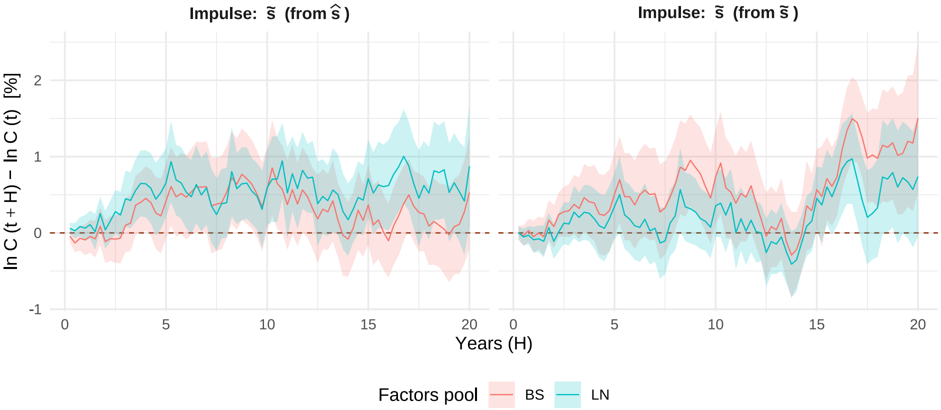
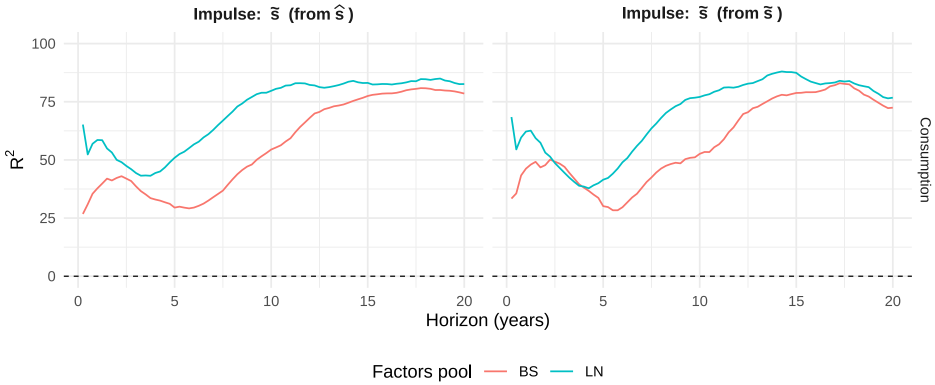
LP: Robustness



LP: Robustness



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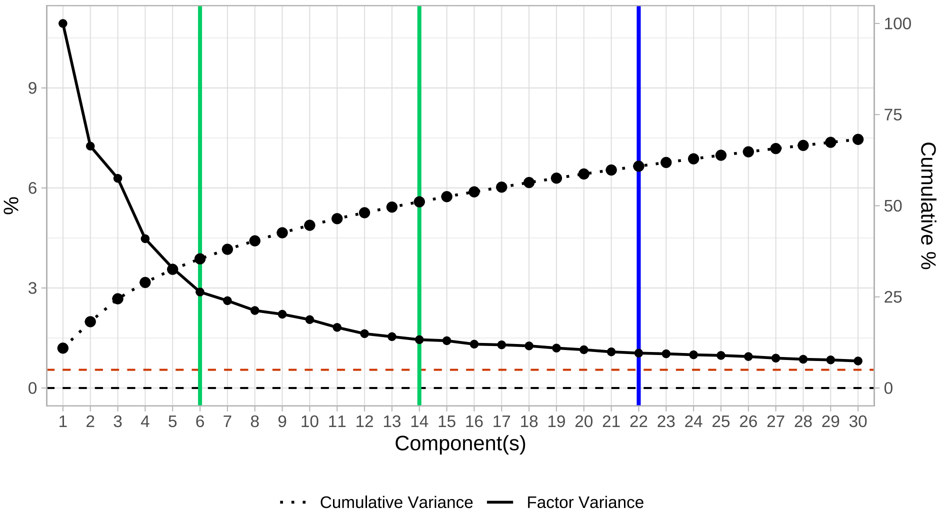
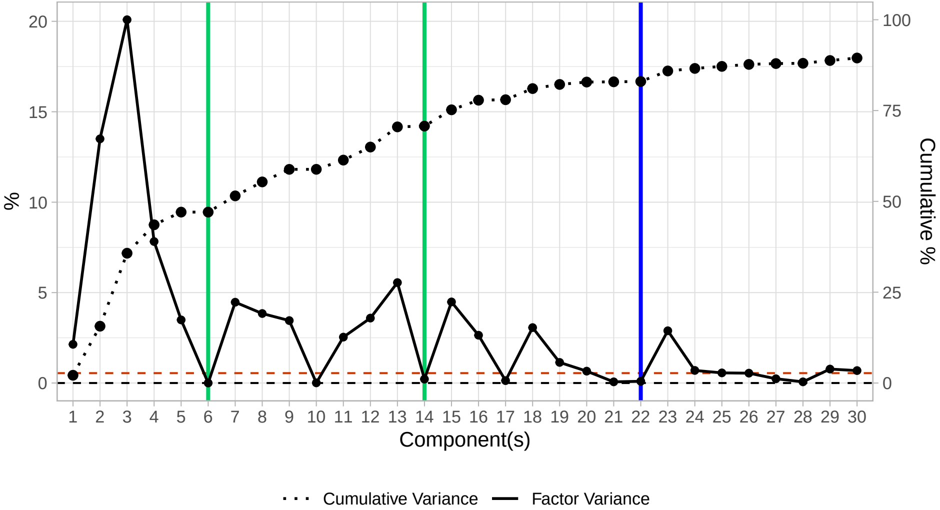
“True” Risk Factors Recovery



“True” Risk Factors Recovery



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