# The Long-run Innovation Risk Component

**Fabio Franceschini**

ffabio.econ @ gmail.com
University of Bologna

University of Milano - Bicocca
January 28th, 2025

# **Long-Run** Innovation **Risk** Component

*Worries about long-run prospects: persistence is key...*

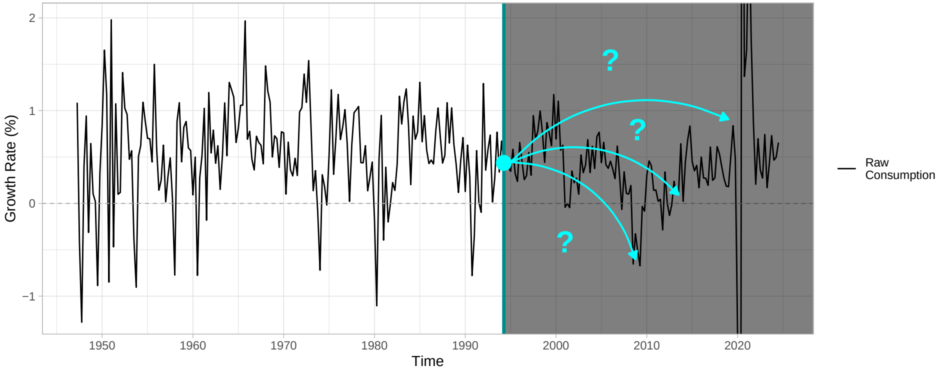



**Figure 1:** Consumption is US expenditures in services and non-durable from BEA;

# Long-Run Innovation Risk Component

*...what persistence ?*

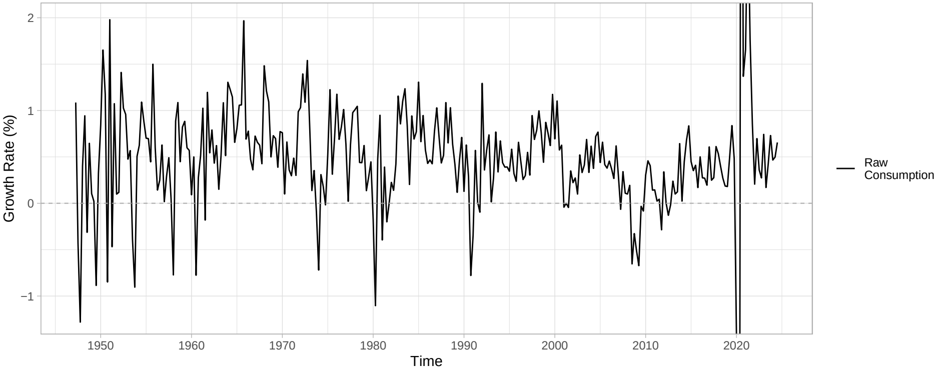



**Figure 1:** Consumption is US expenditures in services and non-durable from BEA;

# Long-Run Innovation Risk **Component**

*A persistent part, predictable at long horizons (eg ~12y)*

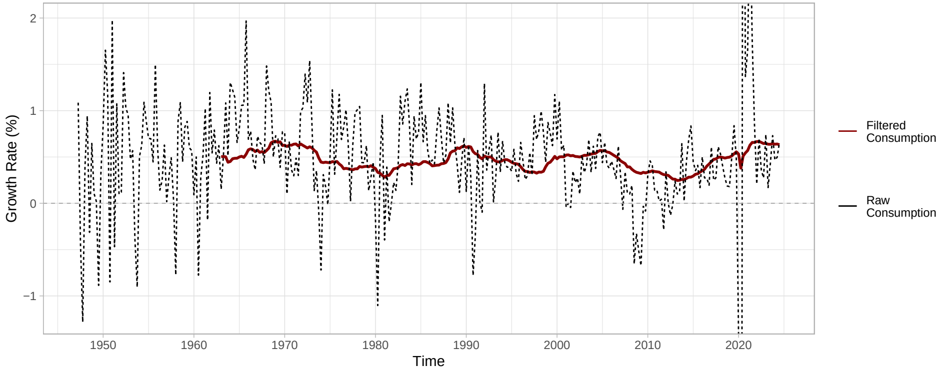



**Figure 1:** Consumption is US expenditures in services and non-durable from BEA; The filtered series are the $6^{th}$ component of Ortu et al. (2013) decomposition.

# Long-Run **Innovation** Risk Component

*Consumption tracks Total Factor Productivity (TFP) in the medium-long term*

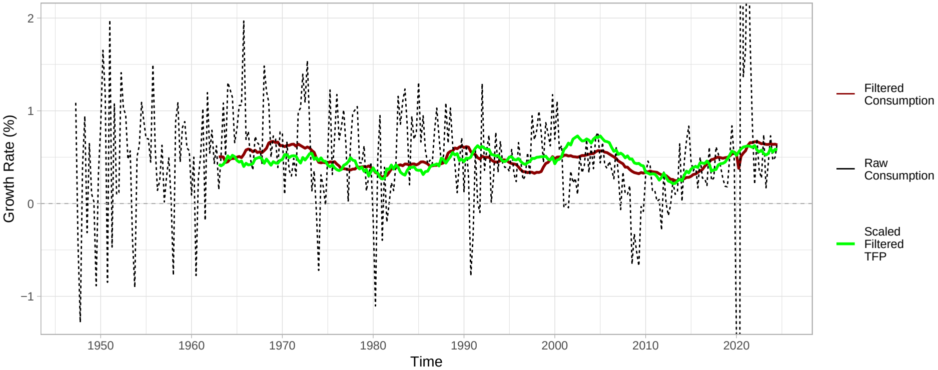



**Figure 1:** Consumption is US expenditures in services and non-durable from BEA; "TFP" is the utilization-adjusted TFP from Fernald (2012). The filtered series are the 6th component of Ortu et al. (2013) decomposition. Cross-correlation between Consumption and TFP is 0.62;

# Long-Run Innovation Risk Component

*Innovation key driver of productivity growth*

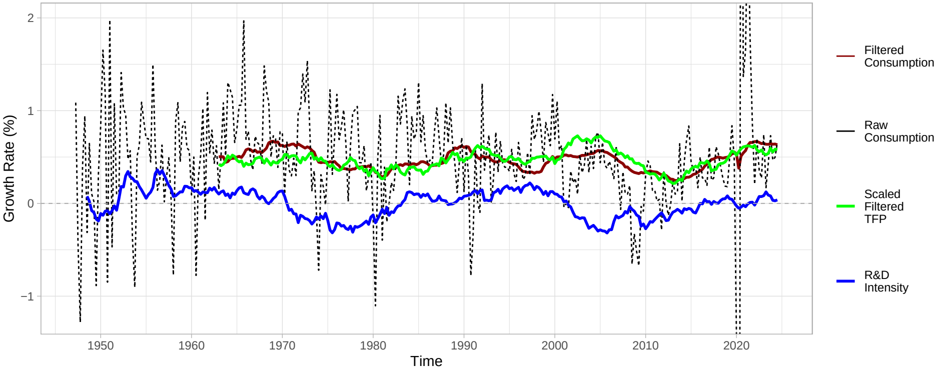



**Figure 1:** Consumption is US expenditures in services and non-durable from BEA; "TFP" is the utilization-adjusted TFP from Fernald (2012). The filtered series are the $6^{th}$ component of Ortu et al. (2013) decomposition. Cross-correlation between Consumption and TFP is 0.62; with (an arbitrary 1y lag) R&D is 0.60 and 0.53, respectively.

# This paper in a nutshell

Key element: Aggregate Research and Development (R&D) investment intensity

R&D intensity process identifies the persistent component of TFP

# This paper in a nutshell

Key element: Aggregate Research and Development (R&D) investment intensity

- *definition* relies on endogenous growth ideas' production function only
- 

R&D intensity process    identifies    the persistent component of TFP

- 
- 
- 

# This paper in a nutshell

Key element: Aggregate Research and Development (R&D) investment intensity

- *definition* relies on endogenous growth ideas' production function only
- *dynamics* mirrored in Error Correction Term of R&D and TFP level cointegration

R&D intensity process identifies the persistent component of TFP

# This paper in a nutshell

Key element: Aggregate Research and Development (R&D) investment intensity

- *definition* relies on endogenous growth ideas' production function only
- *dynamics* mirrored in Error Correction Term of R&D and TFP level cointegration

R&D intensity process identifies the persistent component of TFP

- stationary but highly persistent
-
-

# This paper in a nutshell

Key element: Aggregate Research and Development (R&D) investment intensity

- *definition* relies on endogenous growth ideas' production function only
- *dynamics* mirrored in Error Correction Term of R&D and TFP level cointegration

R&D intensity process identifies the persistent component of TFP

- stationary but highly persistent
- forecasts TFP and consumption growth
-

# This paper in a nutshell

Key element: Aggregate Research and Development (R&D) investment intensity

- *definition* relies on endogenous growth ideas' production function only
- *dynamics* mirrored in Error Correction Term of R&D and TFP level cointegration

R&D intensity process identifies the persistent component of TFP

- stationary but highly persistent
- forecasts TFP and consumption growth
- associated to a positive risk premium in cross-section of US stocks

# Relation to literature

**(Innovation) LRR framework** Bansal and Yaron (2004); Croce (2014); Kung and Schmid (2015); …

*Contribution:* supports the framework by direct empirical validation of predictions

# Relation to literature

**(Innovation) LRR framework** Bansal and Yaron (2004); Croce (2014); Kung and Schmid (2015); …

*Contribution:* supports the framework by direct empirical validation of predictions

**Empirical LRR** Ortu et al. (2013); Dew-Becker and Giglio (2016); Schorfheide et al. (2018); Liu et al. (2022); …

*Contribution:* new component, new identification strategy (relies on an economic condition)

# Relation to literature

**(Innovation) LRR framework** Bansal and Yaron (2004); Croce (2014); Kung and Schmid (2015); ...

*Contribution:* supports the framework by direct empirical validation of predictions

**Empirical LRR** Ortu et al. (2013); Dew-Becker and Giglio (2016); Schorfheide et al. (2018); Liu et al. (2022); ...

*Contribution:* new component, new identification strategy (relies on an economic condition)

**Endogenous growth** Rivera-Batiz and Romer (1991); Jones (1999); Bloom et al. (2020); Kruse-Andersen (2023); ...

*Contribution:* studies dynamics of R&D intensity and tests framework on financial markets

# Relation to literature

**(Innovation) LRR framework** Bansal and Yaron (2004); Croce (2014); Kung and Schmid (2015); ...

*Contribution:* supports the framework by direct empirical validation of predictions

**Empirical LRR** Ortu et al. (2013); Dew-Becker and Giglio (2016); Schorfheide et al. (2018); Liu et al. (2022); ...

*Contribution:* new component, new identification strategy (relies on an economic condition)

**Endogenous growth** Rivera-Batiz and Romer (1991); Jones (1999); Bloom et al. (2020); Kruse-Andersen (2023); ...

*Contribution:* studies dynamics of R&D intensity and tests framework on financial markets

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

*Contribution:* first risk factor related to aggregate R&D

# Theoretical framework

# Key ingredients to define R&D intensity

TFP driven by an exogenous process and ideas

$$Z_t = e^{a_t} \cdot I_t^{\xi} \tag{1}$$

# Key ingredients to define R&D intensity

TFP driven by an exogenous process and ideas

$$Z_t = e^{a_t} \cdot I_t^{\xi} \tag{1}$$

Ideas' dynamics embody semi- AND fully-endogenous production schedule (Jones (1999))

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

# Key ingredients to define R&D intensity

TFP driven by an exogenous process and ideas

$$Z_t = e^{a_t} \cdot I_t^{\xi} \tag{1}$$

Ideas' dynamics embody semi- AND fully-endogenous production schedule (Jones (1999))

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

» R&D key determinant of productivity growth

▸ Details ▸ $\Delta \ln Z$ stationarity

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

» Convenient definition of R&D intensity

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

# Fluctuations in TFP growth *predictions*

Assuming a stationary $s_t$

$$\tilde{s}_t = s_t - \bar{s}$$

It drives conditional expectations' fluctuations

$$E_t \left[\Delta \ln Z_{t+1}\right] \approx \mu + \gamma_1 \cdot \tilde{s}_t + \Delta a_t \tag{5}$$

# Fluctuations in TFP growth *predictions*

Assuming a stationary $s_t$

$$\tilde{s}_t = s_t - \bar{s}$$

It drives conditional expectations' fluctuations

$$E_t\left[\Delta \ln Z_{t+1}\right] \approx \mu + \gamma_1 \cdot \tilde{s}_t + \Delta a_t \tag{5}$$

Assuming a stationary $s_t$

$$\begin{aligned}\tilde{s}_t &= s_t - \bar{s} \\ &= \rho_s \tilde{s}_{t-1} + \varepsilon_t^s\end{aligned}$$

It drives conditional expectations' fluctuations

$$E_t\left[\Delta \ln Z_{t+1}\right] \approx \mu + \gamma_1 \cdot \tilde{s}_t + \Delta a_t \tag{5}$$

# Fluctuations in TFP growth *predictions*

Assuming a stationary $s_t$

$$\begin{aligned}\tilde{s}_t &= s_t - \bar{s} \\ &= \rho_s \tilde{s}_{t-1} + \varepsilon_t^s\end{aligned}$$

It drives conditional expectations' fluctuations

$$E_t\left[\Delta \ln Z_{t+1}\right] \approx \mu + \gamma_1 \cdot \tilde{s}_t + \Delta a_t \tag{5}$$

Persistence in R&D makes shocks affect economy for longer

$$\{E_{t+1} - E_t\}\left(\sum_{j=0}^{\infty} \Delta \ln Z_{t+1+j}\right) \tag{6}$$

# Fluctuations in TFP growth *predictions*

Assuming a stationary $s_t$

$$\begin{aligned}\tilde{s}_t &= s_t - \bar{s} \\ &= \rho_s \tilde{s}_{t-1} + \varepsilon_t^s\end{aligned}$$

It drives conditional expectations' fluctuations

$$E_t \left[\Delta \ln Z_{t+1}\right] \approx \mu + \gamma_1 \cdot \tilde{s}_t + \Delta a_t \tag{5}$$

Persistence in R&D makes shocks affect economy for longer

$$\{E_{t+1} - E_t\}\left(\sum_{j=0}^{\infty} \Delta \ln Z_{t+1+j}\right) = \frac{\rho_s}{1-\rho_s} \varepsilon_{t+1}^s \tag{6}$$

Competitive markets:

$$E_t\left[R^i_{t+1}\right] - R^f_t = -R^f_t \cdot \mathrm{Cov}_t\left[m_{t+1}, R^i_{t+1}\right] \tag{7}$$

Epstein and Zin (1989) preferences (EIS = 1, risk aversion set by $\theta$):

$$m_{t+1} - E_t\left[m_{t+1}\right] = -\Delta c_{t+1} - (\theta - 1) \cdot \{E_{t+1} - E_t\} \sum_{j=1}^{\infty} \Delta c_{t+j} \tag{8}$$

(9)

Competitive markets:

$$E_t\left[R^i_{t+1}\right] - R^f_t = -R^f_t \cdot \mathrm{Cov}_t\left[m_{t+1}, R^i_{t+1}\right] \tag{7}$$

Epstein and Zin (1989) preferences (EIS = 1, risk aversion set by θ):

$$m_{t+1} - E_t\left[m_{t+1}\right] = -\Delta c_{t+1} - (\theta - 1) \cdot \{E_{t+1} - E_t\} \sum_{j=1}^{\infty} \Delta c_{t+j} \tag{8}$$

$$= -b_c \varepsilon_{c,t+1} - b_x \varepsilon_{x,t+1} \tag{9}$$

Competitive markets:

$$E_t\left[R^i_{t+1}\right] - R^f_t = -R^f_t \cdot \mathrm{Cov}_t\left[m_{t+1}, R^i_{t+1}\right] \tag{7}$$

Epstein and Zin (1989) preferences (EIS = 1, risk aversion set by $\theta$):

$$m_{t+1} - E_t\left[m_{t+1}\right] = -\Delta c_{t+1} - (\theta - 1) \cdot \{E_{t+1} - E_t\} \sum_{j=1}^{\infty} \Delta c_{t+j} \tag{8}$$

$$= -b_c \varepsilon_{c,t+1} - b_x \varepsilon_{x,t+1} \tag{9}$$

Result, testable pricing equation

$$E_t\left[R^i_{t+1}\right] - R^f_t = \lambda_c\, \beta^i_c + \lambda_x \beta^i_x \tag{10}$$

Competitive markets:

$$E_t\left[R^i_{t+1}\right] - R^f_t = -R^f_t \cdot \mathrm{Cov}_t\left[m_{t+1}, R^i_{t+1}\right] \tag{7}$$

Epstein and Zin (1989) preferences (EIS = 1, risk aversion set by $\theta$):

$$m_{t+1} - E_t\left[m_{t+1}\right] = -\Delta c_{t+1} - (\theta - 1) \cdot \{E_{t+1} - E_t\} \sum_{j=1}^{\infty} \Delta c_{t+j} \tag{8}$$

$$= -b_c \varepsilon_{c,t+1} - b_x \varepsilon_{x,t+1} \tag{9}$$

Result, testable pricing equation

$$E_t\left[R^i_{t+1}\right] - R^f_t = \lambda_c \beta^i_c + \lambda_x \beta^i_x \tag{10}$$

» Does $s_t$ identify a LRR $x_t$?

# The empirical R&D intensity

# Fully-endogenous R&D intensity is non-stationary and too persistent

**Table 1:** statistics of Kung and Schmid (2015) R&D intensity measure. In the first column original data sources are used; $S$ is yearly R&D expenditure from the National Science Foundation and $I$ is the R&D stock from BLS, spanning 1963 to 2020. Data of second and third columns span 1947 Q1 to 2021 Q4, sources follow.

| | $(\ln S_t - \ln I_t)$ | $(\ln S_t - \frac{1}{\xi} \ln Z_t)$ | |
|---|---|---|---|
| | $\tilde{s}_t$ | $\hat{s}_t$ | |
| $1 - \xi$ | — | 0.35 | 0.3 |
| ADF u.r. stat | $-2.55$ | $-2.11$ | $-2.09$ |
| AC(1) | 0.989 | 0.999 | 1.000 |
| | (0.006) | (0.000) | (0.000) |
| Num. obs. | 57 | 299 | 299 |

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

- Non-stationary $\tilde{s}$ or $\hat{s}$ can produce spurious forecasting results

▸ $\Delta$TFP stationarity

- Half-life of shocks > 30 years, but innovation component in consumption < 16 years

» Previous fully-endogenous-based evidence is unreliable

# From the model to the data

$$\tilde{s}_t = \ln S_t - \frac{1-\psi}{\eta} \ln I_t - \frac{\omega}{\eta} \ln Q_t - \bar{s}$$

I follow the literature:

# From the model to the data

$$\tilde{s}_t = \ln S_t - \frac{1-\psi}{\eta} \ln I_t - \frac{\omega}{\eta} \ln Q_t - \bar{s}$$

I follow the literature:

**Goods variety range** measure is made operational by assuming

$$Q_t = L_t^{\kappa} \qquad 0 < \kappa < 1$$

# From the model to the data

$$\tilde{s}_t = \ln S_t - \frac{1-\psi}{\eta}\ln I_t - \frac{\omega\kappa}{\eta}\ln L_t - \bar{s}$$

I follow the literature:

**Goods variety range** measure is made operational by assuming

$$Q_t = L_t^{\kappa} \qquad 0 < \kappa < 1$$

$$\tilde{s}_t = \ln S_t - \frac{1-\psi}{\eta} \ln I_t - \frac{\omega\kappa}{\eta} \ln L_t - \bar{s}$$

I follow the literature:

**Goods variety range** measure is made operational by assuming

$$Q_t = L_t^{\kappa} \qquad 0 < \kappa < 1$$

**Ideas stock** is challenging to identify empirically! TFP more robust

$$\ln I_t = \frac{1}{\xi} \ln Z_t - \frac{1}{\xi} a_t$$

$$\tilde{s}_t = \ln S_t - \frac{1-\psi}{\eta\xi}(\ln Z_t - a_t) - \frac{\omega\kappa}{\eta}\ln L_t - \bar{s}$$

I follow the literature:

**Goods variety range** measure is made operational by assuming

$$Q_t = L_t^{\kappa} \qquad 0 < \kappa < 1$$

**Ideas stock** is challenging to identify empirically! TFP more robust

$$\ln I_t = \frac{1}{\xi}\ln Z_t - \frac{1}{\xi}a_t$$

# From the model to the data

$$\tilde{s}_t = \ln S_t - \frac{1-\psi}{\eta\xi}(\ln Z_t - a_t) - \frac{\omega\kappa}{\eta}\ln L_t - \bar{s}$$

I follow the literature:

**Goods variety range** measure is made operational by assuming

$$Q_t = L_t^{\kappa} \qquad 0 < \kappa < 1$$

**Ideas stock** is challenging to identify empirically! TFP more robust

$$\ln I_t = \frac{1}{\xi}\ln Z_t - \frac{1}{\xi}a_t$$

**External factor** assumed to be spanned by a set of macro factors $f$

$$a_t = b' f_t$$

# From the model to the data

$$\tilde{s}_t = \ln S_t - \frac{1-\psi}{\eta\xi}(\ln Z_t - \mathbf{b}'\mathbf{f}_t) - \frac{\omega\kappa}{\eta}\ln L_t - \bar{s}$$

I follow the literature:

**Goods variety range** measure is made operational by assuming

$$Q_t = L_t^{\kappa} \qquad 0 < \kappa < 1$$

**Ideas stock** is challenging to identify empirically! TFP more robust

$$\ln I_t = \frac{1}{\xi}\ln Z_t - \frac{1}{\xi}a_t$$

**External factor** assumed to be spanned by a set of macro factors $\mathbf{f}$

$$a_t = \mathbf{b}'\mathbf{f}_t$$

# Macroeconomic Data

*S*

- **Real US R&D expenditure from Bureau of Economic Analysis**, quarterly series, spanning 1947 Q1 to 2021 Q4. Baseline series: Y006RC, table 5.3.5, deflated by Y006RG, table 5.3.4.

# Macroeconomic Data

$S$

- **Real US R&D expenditure from Bureau of Economic Analysis**, quarterly series, spanning 1947 Q1 to 2021 Q4. Baseline series: Y006RC, table 5.3.5, deflated by Y006RG, table 5.3.4.

$Z$

- **US TFP estimated by Fernald (2012)**, quarterly series, spanning 1947 Q2 to 2021 Q4. Baseline series: utilization-adjusted series, using capital values without R&D capital.

# Macroeconomic Data

$S$

- **Real US R&D expenditure from Bureau of Economic Analysis**, quarterly series, spanning 1947 Q1 to 2021 Q4.
  Baseline series: Y006RC, table 5.3.5, deflated by Y006RG, table 5.3.4.

$Z$

- **US TFP estimated by Fernald (2012)**, quarterly series, spanning 1947 Q2 to 2021 Q4.
  Baseline series: utilization-adjusted series, using capital values without R&D capital.

$L$

- **Employment Level from Bureau of Labor Statistics**, monthly series, spanning 1948-01 to 2024-11.
  Baseline series: LNS12000000.

# Macroeconomic Data

$S$

- **Real US R&D expenditure from Bureau of Economic Analysis**, quarterly series, spanning 1947 Q1 to 2021 Q4.
  Baseline series: Y006RC, table 5.3.5, deflated by Y006RG, table 5.3.4.

$Z$

- **US TFP estimated by Fernald (2012)**, quarterly series, spanning 1947 Q2 to 2021 Q4.
  Baseline series: utilization-adjusted series, using capital values without R&D capital.

$L$

- **Employment Level from Bureau of Labor Statistics**, monthly series, spanning 1948-01 to 2024-11.
  Baseline series: LNS12000000.

$f$

- **5 factors as in Ai et al. (2018)** (US P/D, 3m/3y/5y bond yields, stock mkt integrated volatility), spanning 1947 Q1 to 2022 Q4.
- **9 factors from Ludvigson and Ng (2009)**, monthly series, spanning 1960-03 to 2024-06.

# Macroeconomic Data

$S$

- **Real US R&D expenditure from Bureau of Economic Analysis**, quarterly series, spanning 1947 Q1 to 2021 Q4.
  Baseline series: Y006RC, table 5.3.5, deflated by Y006RG, table 5.3.4.

$Z$

- **US TFP estimated by Fernald (2012)**, quarterly series, spanning 1947 Q2 to 2021 Q4.
  Baseline series: utilization-adjusted series, using capital values without R&D capital.

$L$

- **Employment Level from Bureau of Labor Statistics**, monthly series, spanning 1948-01 to 2024-11.
  Baseline series: LNS12000000.

$f$

- **5 factors as in Ai et al. (2018)** (US P/D, 3m/3y/5y bond yields, stock mkt integrated volatility), spanning 1947 Q1 to 2022 Q4.
- **9 factors from Ludvigson and Ng (2009)**, monthly series, spanning 1960-03 to 2024-06.

$C$

- **Real US Consumption from Bureau of Economic Analysis**, quarterly series, spanning 1947 Q1 to 2023 Q4.
  Baseline series: non-durable goods (A797RX) plus services (A796RX).

# Cointegration estimation details

$$\ln Z_t = \alpha_0 + \alpha_S \ln S_t + \alpha_L \ln L_t + \boldsymbol{\alpha}_f' \mathbf{f}_t + \epsilon_t^Z \quad (11)$$

**DOLS instead of VECM**

- stock-vs-flow variables timing issue

# Cointegration estimation details

$$\ln Z_t = \alpha_0 + \alpha_S \ln S_t + \alpha_L \ln L_t + \boldsymbol{\alpha}_f' \mathbf{f}_t + \epsilon_t^Z + \sum_{i \in \{S, L, \mathbf{f}_1\}} \tag{11}$$

**DOLS instead of VECM**

- stock-vs-flow variables timing issue

# Cointegration estimation details

$$\ln Z_t = \alpha_0 + \alpha_S \ln S_t + \alpha_L \ln L_t + \alpha_f' f_t + \epsilon_t^Z + \sum_{i \in \{S,L,f_1\}} \sum_{j=Lg_i}^{Ld_i} \delta_{i,j} \Delta i_{t+j} \tag{11}$$

**DOLS instead of VECM**

- stock-vs-flow variables timing issue

# Cointegration estimation details

$$\ln Z_t = \alpha_0 + \alpha_S \ln S_t + \alpha_L \ln L_t + \boldsymbol{\alpha}_f' \mathbf{f}_t + \epsilon_t^Z + \sum_{i \in \{S, L, \mathbf{f}_1\}} \sum_{j=Lg_i}^{Ld_i} \delta_{i,j} \Delta i_{t+j} \tag{11}$$

**DOLS instead of VECM**

- stock-vs-flow variables timing issue
- regressors dimensionality (and first differences' collinearity): enables estimation via AdaLASSO (Mendes (2011), Neto (2023))

More details

# Cointegration estimation details

$$\ln Z_t = \alpha_0 + \alpha_S \ln S_t + \alpha_L \ln L_t + \boldsymbol{\alpha}_f' \mathbf{f}_t + \epsilon_t^Z + \sum_{i \in \{S, L, \mathbf{f}_1\}} \sum_{j=Lg_i}^{Ld_i} \delta_{i,j} \Delta i_{t+j} \tag{11}$$

**DOLS instead of VECM**

- stock-vs-flow variables timing issue
- regressors dimensionality (and first differences' collinearity): enables estimation via AdaLASSO (Mendes (2011), Neto (2023))

More details

**Z as the dependent variable**

- use of most recent LEVELS observations $(\widehat{Lg}_i >> \widehat{Ld}_i \quad \forall i)$

# "Flexible"-scale-effects R&D intensity is stationary but persistent

**Table 2:** Standard Errors in parenthesis, computed as in Mendes (2011). AC(1) is the coefficient of an AR(1) model fit.

| | | | | |
|---|---|---|---|---|
| $\ln Z$ : | Adj TFP | Raw TFP | Adj TFP | |
| $\ln L$ : | Tot. emp. | | Nonfarm emp. | Tot. emp. |
| f : | | BS | | LN |
| $\alpha_S$ | 0.233*** | 0.269*** | 0.217*** | 0.227*** |
| | (0.022) | (0.020) | (0.021) | (0.029) |
| max lag | 20 | 32 | 20 | 10 |
| lags n. | 8 | 19 | 8 | 6 |
| max lead | 0 | 4 | 0 | 0 |
| leads n. | 0 | 1 | 0 | 0 |
| $\alpha_L$ | −0.098*** | −0.261*** | −0.046*** | −0.085*** |
| | (0.013) | (0.012) | (0.013) | (0.018) |
| max lag | 0 | 1 | 0 | 0 |
| lags n. | 0 | 1 | 0 | 0 |
| leads n. | 0 | 0 | 0 | 0 |
| $tt$ | F | F | F | F |
| $tt^2$ | F | F | F | F |
| I(1) controls | 0 | 0 | 0 | 0 |
| I(0) controls | 3 | 5 | 3 | 4 |
| Num. obs. | 262 | 262 | 262 | 245 |
| | | $\tilde{s}_t$ | | |
| SD | 0.149 | 0.128 | 0.162 | 0.139 |
| ADF u.r. stat | −2.51** | −2.66*** | −2.36** | −2.23** |
| KPSS p.v. | 0.1+ | 0.1+ | 0.09 | 0.1+ |
| AC(1) | 0.961 | 0.954 | 0.960 | 0.962 |
| | (0.015) | (0.017) | (0.015) | (0.016) |

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

▸ Cross-correlations

# "Flexible"-scale-effects R&D intensity is stationary but persistent

**Table 2:** Standard Errors in parenthesis, computed as in Mendes (2011). AC(1) is the coefficient of an AR(1) model fit.

| | | | | |
|---|---|---|---|---|
| $\ln Z$ : | Adj TFP | Raw TFP | Adj TFP | |
| $\ln L$ : | Tot. emp. | | Nonfarm emp. | Tot. emp. |
| f : | | BS | | LN |
| $\alpha_S$ | 0.233*** | 0.269*** | 0.217*** | 0.227*** |
| | (0.022) | (0.020) | (0.021) | (0.029) |
| max lag | 20 | 32 | 20 | 10 |
| lags n. | 8 | 19 | 8 | 6 |
| max lead | 0 | 4 | 0 | 0 |
| leads n. | 0 | 1 | 0 | 0 |
| $\alpha_L$ | −0.098*** | −0.261*** | −0.046*** | −0.085*** |
| | (0.013) | (0.012) | (0.013) | (0.018) |
| max lag | 0 | 1 | 0 | 0 |
| lags n. | 0 | 1 | 0 | 0 |
| leads n. | 0 | 0 | 0 | 0 |
| $tt$ | F | F | F | F |
| $tt^2$ | F | F | F | F |
| I(1) controls | 0 | 0 | 0 | 0 |
| I(0) controls | 3 | 5 | 3 | 4 |
| Num. obs. | 262 | 262 | 262 | 245 |
| | | $\tilde{s}_t$ | | |
| SD | 0.149 | 0.128 | 0.162 | 0.139 |
| ADF u.r. stat | −2.51** | −2.66*** | −2.36** | −2.23** |
| KPSS p.v. | 0.1+ | 0.1+ | 0.09 | 0.1+ |
| AC(1) | 0.961 | 0.954 | 0.960 | 0.962 |
| | (0.015) | (0.017) | (0.015) | (0.016) |

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

Cross-correlations

# “Flexible”-scale-effects R&D intensity is stationary but persistent

**Table 2:** Standard Errors in parenthesis, computed as in Mendes (2011). AC(1) is the coefficient of an AR(1) model fit.

| | | | | |
|---|---|---|---|---|
| **ln** $Z$ : | Adj TFP | Raw TFP | Adj TFP | |
| **ln** $L$ : | Tot. emp. | | Nonfarm emp. | Tot. emp. |
| **f** : | | BS | | LN |
| $\alpha_S$ | 0.233*** | 0.269*** | 0.217*** | 0.227*** |
| | (0.022) | (0.020) | (0.021) | (0.029) |
| max lag | 20 | 32 | 20 | 10 |
| lags n. | 8 | 19 | 8 | 6 |
| max lead | 0 | 4 | 0 | 0 |
| leads n. | 0 | 1 | 0 | 0 |
| $\alpha_L$ | −0.098*** | −0.261*** | −0.046*** | −0.085*** |
| | (0.013) | (0.012) | (0.013) | (0.018) |
| max lag | 0 | 1 | 0 | 0 |
| lags n. | 0 | 1 | 0 | 0 |
| leads n. | 0 | 0 | 0 | 0 |
| $tt$ | F | F | F | F |
| $tt^2$ | F | F | F | F |
| I(1) controls | 0 | 0 | 0 | 0 |
| I(0) controls | 3 | 5 | 3 | 4 |
| Num. obs. | 262 | 262 | 262 | 245 |
| | $\tilde{s}_t$ | | | |
| SD | 0.149 | 0.128 | 0.162 | 0.139 |
| ADF u.r. stat | −2.51** | −2.66*** | −2.36** | −2.23** |
| KPSS p.v. | 0.1+ | 0.1+ | 0.09 | 0.1+ |
| AC(1) | 0.961 | 0.954 | 0.960 | 0.962 |
| | (0.015) | (0.017) | (0.015) | (0.016) |

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

▸ Cross-correlations

# “Flexible”-scale-effects R&D intensity is stationary but persistent

**Table 2:** Standard Errors in parenthesis, computed as in Mendes (2011). AC(1) is the coefficient of an AR(1) model fit.

| **ln** $Z$ : | Adj TFP | Raw TFP | Adj TFP | |
|---|---|---|---|---|
| **ln** $L$ : | Tot. emp. | | Nonfarm emp. | Tot. emp. |
| **f** : | | BS | | LN |
| $\alpha_S$ | $0.233^{***}$ | $0.269^{***}$ | $0.217^{***}$ | $0.227^{***}$ |
| | (0.022) | (0.020) | (0.021) | (0.029) |
| max lag | 20 | 32 | 20 | 10 |
| lags n. | 8 | 19 | 8 | 6 |
| max lead | 0 | 4 | 0 | 0 |
| leads n. | 0 | 1 | 0 | 0 |
| $\alpha_L$ | $-0.098^{***}$ | $-0.261^{***}$ | $-0.046^{***}$ | $-0.085^{***}$ |
| | (0.013) | (0.012) | (0.013) | (0.018) |
| max lag | 0 | 1 | 0 | 0 |
| lags n. | 0 | 1 | 0 | 0 |
| leads n. | 0 | 0 | 0 | 0 |
| $tt$ | F | F | F | F |
| $tt^2$ | F | F | F | F |
| I(1) controls | 0 | 0 | 0 | 0 |
| I(0) controls | 3 | 5 | 3 | 4 |
| Num. obs. | 262 | 262 | 262 | 245 |
| | | $\tilde{s}_t$ | | |
| SD | 0.149 | 0.128 | 0.162 | 0.139 |
| ADF u.r. stat | $-2.51^{**}$ | $-2.66^{***}$ | $-2.36^{**}$ | $-2.23^{**}$ |
| KPSS p.v. | 0.1+ | 0.1+ | 0.09 | 0.1+ |
| AC(1) | 0.961 | 0.954 | 0.960 | 0.962 |
| | (0.015) | (0.017) | (0.015) | (0.016) |

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

Cross-correlations

# “Flexible”-scale-effects R&D intensity is stationary but persistent

**Table 2:** Standard Errors in parenthesis, computed as in Mendes (2011). AC(1) is the coefficient of an AR(1) model fit.

| | | | | |
|---|---|---|---|---|
| $\ln Z$ : | Adj TFP | Raw TFP | Adj TFP | |
| $\ln L$ : | Tot. emp. | | Nonfarm emp. | Tot. emp. |
| $f$ : | | BS | | LN |
| $\alpha_S$ | $0.233^{***}$ | $0.269^{***}$ | $0.217^{***}$ | $0.227^{***}$ |
| | (0.022) | (0.020) | (0.021) | (0.029) |
| max lag | 20 | 32 | 20 | 10 |
| lags n. | 8 | 19 | 8 | 6 |
| max lead | 0 | 4 | 0 | 0 |
| leads n. | 0 | 1 | 0 | 0 |
| $\alpha_L$ | $-0.098^{***}$ | $-0.261^{***}$ | $-0.046^{***}$ | $-0.085^{***}$ |
| | (0.013) | (0.012) | (0.013) | (0.018) |
| max lag | 0 | 1 | 0 | 0 |
| lags n. | 0 | 1 | 0 | 0 |
| leads n. | 0 | 0 | 0 | 0 |
| $tt$ | F | F | F | F |
| $tt^2$ | F | F | F | F |
| I(1) controls | 0 | 0 | 0 | 0 |
| I(0) controls | 3 | 5 | 3 | 4 |
| Num. obs. | 262 | 262 | 262 | 245 |
| | | $\tilde{s}_t$ | | |
| SD | 0.149 | 0.128 | 0.162 | 0.139 |
| ADF u.r. stat | $-2.51^{**}$ | $-2.66^{***}$ | $-2.36^{**}$ | $-2.23^{**}$ |
| KPSS p.v. | 0.1+ | 0.1+ | 0.09 | 0.1+ |
| AC(1) | 0.961 | 0.954 | 0.960 | 0.962 |
| | (0.015) | (0.017) | (0.015) | (0.016) |

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

Cross-correlations

# "Flexible"-scale-effects R&D intensity is stationary but persistent

**Table 2:** Standard Errors in parenthesis, computed as in Mendes (2011). AC(1) is the coefficient of an AR(1) model fit.

| | | | | |
|---|---|---|---|---|
| **ln** $Z$ : | Adj TFP | Raw TFP | Adj TFP | |
| **ln** $L$ : | Tot. emp. | | Nonfarm emp. | Tot. emp. |
| **f** : | BS | | | LN |
| $\alpha_S$ | $0.233^{***}$ | $0.269^{***}$ | $0.217^{***}$ | $0.227^{***}$ |
| | (0.022) | (0.020) | (0.021) | (0.029) |
| max lag | 20 | 32 | 20 | 10 |
| lags n. | 8 | 19 | 8 | 6 |
| max lead | 0 | 4 | 0 | 0 |
| leads n. | 0 | 1 | 0 | 0 |
| $\alpha_L$ | $-0.098^{***}$ | $-0.261^{***}$ | $-0.046^{***}$ | $-0.085^{***}$ |
| | (0.013) | (0.012) | (0.013) | (0.018) |
| max lag | 0 | 1 | 0 | 0 |
| lags n. | 0 | 1 | 0 | 0 |
| leads n. | 0 | 0 | 0 | 0 |
| $tt$ | F | F | F | F |
| $tt^2$ | F | F | F | F |
| I(1) controls | 0 | 0 | 0 | 0 |
| I(0) controls | 3 | 5 | 3 | 4 |
| Num. obs. | 262 | 262 | 262 | 245 |
| | | $\tilde{s}_t$ | | |
| SD | 0.149 | 0.128 | 0.162 | 0.139 |
| ADF u.r. stat | $-2.51^{**}$ | $-2.66^{***}$ | $-2.36^{**}$ | $-2.23^{**}$ |
| KPSS p.v. | 0.1+ | 0.1+ | 0.09 | 0.1+ |
| AC(1) | 0.961 | 0.954 | 0.960 | 0.962 |
| | (0.015) | (0.017) | (0.015) | (0.016) |

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

Cross-correlations

# “Flexible”-scale-effects R&D intensity is stationary but persistent

**Table 2:** Standard Errors in parenthesis, computed as in Mendes (2011). AC(1) is the coefficient of an AR(1) model fit.

| **ln** $Z$ : | Adj TFP | Raw TFP | Adj TFP | |
|---|---|---|---|---|
| **ln** $L$ : | Tot. emp. | | Nonfarm emp. | Tot. emp. |
| **f** : | | BS | | LN |
| $\alpha_S$ | $0.233^{***}$ | $0.269^{***}$ | $0.217^{***}$ | $0.227^{***}$ |
| | (0.022) | (0.020) | (0.021) | (0.029) |
| max lag | 20 | 32 | 20 | 10 |
| lags n. | 8 | 19 | 8 | 6 |
| max lead | 0 | 4 | 0 | 0 |
| leads n. | 0 | 1 | 0 | 0 |
| $\alpha_L$ | $-0.098^{***}$ | $-0.261^{***}$ | $-0.046^{***}$ | $-0.085^{***}$ |
| | (0.013) | (0.012) | (0.013) | (0.018) |
| max lag | 0 | 1 | 0 | 0 |
| lags n. | 0 | 1 | 0 | 0 |
| leads n. | 0 | 0 | 0 | 0 |
| $tt$ | F | F | F | F |
| $tt^2$ | F | F | F | F |
| I(1) controls | 0 | 0 | 0 | 0 |
| I(0) controls | 3 | 5 | 3 | 4 |
| Num. obs. | 262 | 262 | 262 | 245 |
| | | $\tilde{s}_t$ | | |
| SD | 0.149 | 0.128 | 0.162 | 0.139 |
| ADF u.r. stat | $-2.51^{**}$ | $-2.66^{***}$ | $-2.36^{**}$ | $-2.23^{**}$ |
| KPSS p.v. | 0.1+ | 0.1+ | 0.09 | 0.1+ |
| AC(1) | 0.961 | 0.954 | 0.960 | 0.962 |
| | (0.015) | (0.017) | (0.015) | (0.016) |

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

Cross-correlations

# The long-run innovation risk component

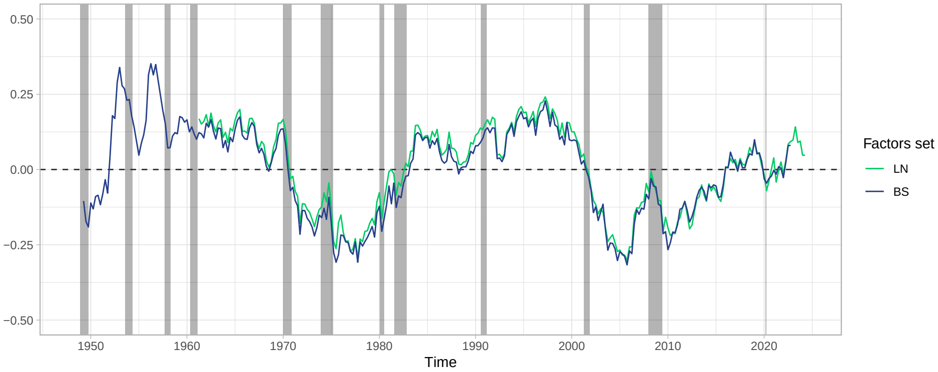



**Figure 2:** Shaded areas mark NBER recessions. Cross-correlation: 0.990.

# TFP predictability

$$E_t\left[\Delta \ln Z_{t+1}\right] = \mu + \gamma_1 \cdot \tilde{s}_t + \boldsymbol{\gamma}'_g \mathbf{g}_t \tag{12}$$

# TFP predictability

$$E_t\left[\Delta \ln Z_{t+1}\right] = \mu + \gamma_1 \cdot \tilde{s}_t + \gamma_g' g_t \quad (12)$$

**Table 3:** TFP growth forecast regression results. TFP growth is the utilization-adjusted TFP growth from Fernald (2012); controls in (BS) specification are the predictive factors used in Bansal and Shaliastovich (2013) plus market integrated volatility, as in Ai et al. (2018); controls in (LN) specification are the factors computed in Ludvigson and Ng (2009)

| $\ln Z$ : | Adj TFP | | Raw TFP | Adj TFP | |
|---|---|---|---|---|---|
| $\ln L$ : | Tot. emp. | | | Nonfarm emp. | Tot. emp. |
| $f$ : | BS | | | | LN |
| $\tilde{s}_t$ | 0.193*** | 0.171*** | 0.160** | 0.194*** | 0.158*** |
| | [4.74] | [3.91] | [2.46] | [4.80] | [3.89] |
| ARMA | (1,0) | (1,0) | (1,2) | (0,1) | (0,1) |
| Controls set | BS | LN | BS | BS | LN |
| p.v. ($F_{controls}$) | 0.00% | 0.00% | 14.46% | 0.21% | 0.00% |
| p.v. ($LR_{controls}$) | 0.00% | 0.00% | 8.36% | 0.07% | 0.00% |
| $R^2$ | 10.6% | 11.9% | 5.7% | 10.6% | 11.6% |
| Num. obs. | 294 | 251 | 294 | 294 | 252 |

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

1 SD shock to $\tilde{s}_t \approx +0.18\%$ in TFP growth, quarterly

# TFP predictability

$$E_t\left[\Delta \ln Z_{t+1}\right] = \mu + \gamma_1 \cdot \tilde{s}_t + \gamma_g' g_t \tag{12}$$

**Table 3:** TFP growth forecast regression results. TFP growth is the utilization-adjusted TFP growth from Fernald (2012); controls in (BS) specification are the predictive factors used in Bansal and Shaliastovich (2013) plus market integrated volatility, as in Ai et al. (2018); controls in (LN) specification are the factors computed in Ludvigson and Ng (2009)

| $\ln Z$ : | Adj TFP | | Raw TFP | Adj TFP | |
|---|---|---|---|---|---|
| $\ln L$ : | Tot. emp. | | | Nonfarm emp. | Tot. emp. |
| $f$ : | BS | | | | LN |
| $\tilde{s}_t$ | 0.193*** | 0.171*** | 0.160** | 0.194*** | 0.158*** |
| | [4.74] | [3.91] | [2.46] | [4.80] | [3.89] |
| ARMA | (1,0) | (1,0) | (1,2) | (0,1) | (0,1) |
| Controls set | BS | LN | BS | BS | LN |
| p.v. ($F_{controls}$) | 0.00% | 0.00% | 14.46% | 0.21% | 0.00% |
| p.v. ($LR_{controls}$) | 0.00% | 0.00% | 8.36% | 0.07% | 0.00% |
| $R^2$ | 10.6% | 11.9% | 5.7% | 10.6% | 11.6% |
| Num. obs. | 294 | 251 | 294 | 294 | 252 |

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

1 SD shock to $\tilde{s}_t \approx +0.18\%$ in TFP growth, quarterly

# Consumption predictability

$$E_t\left[\Delta \ln C_{t+j}\right] = \pi_0 + \pi_{s,j}\tilde{s}_t + \boldsymbol{\pi}'_{g,j}\mathbf{g}_t \tag{13}$$

$$E_t\left[\Delta \ln C_{t+j}\right] = \pi_0 + \pi_{s,j}\tilde{s}_t + \boldsymbol{\pi}'_{g,j}\mathbf{g}_t \tag{13}$$

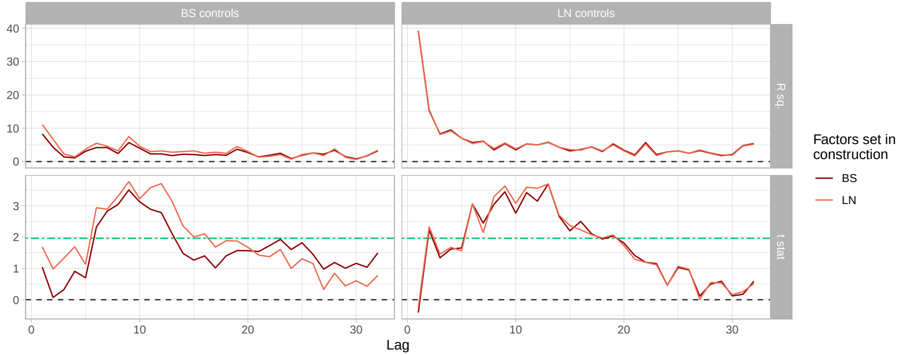



**Figure 3:** 'BS' stands for controls used in Bansal and Shaliastovich (2013), starting in 1948 Q1; 'LNG' in Ludvigson and Ng (2009), starting in 1960 Q2.

# The premium of long-run innovation risk

## Returns

- **US stocks from Center for Research in Security Prices (CRSP)**, monthly series, spanning 1926-12 to 2021-12.
  - Quarterly real returns (deflated as in Hansen et al. (2005)), monthly compounding, adjusted for delistings as in Bali et al. (2016)
  - Quarterly cash-flow growth rates, obtained following Bansal et al. (2005) and Hansen et al. (2005)

  Details
- **US stocks factors from Global Factor Data** (Jensen et al. (2021)), monthly series, 1926-01 to 2024-11. Used series: 118 out of 153, spanning 1951 Q4 to 2023 Q4.

# Financial Data

## Returns

- **US stocks from Center for Research in Security Prices (CRSP)**, monthly series, spanning 1926-12 to 2021-12.
  - Quarterly real returns (deflated as in Hansen et al. (2005)), monthly compounding, adjusted for delistings as in Bali et al. (2016)
  - Quarterly cash-flow growth rates, obtained following Bansal et al. (2005) and Hansen et al. (2005)

  ▸ Details
- **US stocks factors from Global Factor Data** (Jensen et al. (2021)), monthly series, 1926-01 to 2024-11. Used series: 118 out of 153, spanning 1951 Q4 to 2023 Q4.

## Accounting data

- **US firms accounting data from Compustat**, yearly series, spanning 1975 Q1 to 2021 Q4. Used series: book equity, R&D expenditures.

# A traditional test of the LRR price

$$E_t \left[R^i_{t+1}\right] - R^f_t = \lambda_c \; \beta^i_c + \lambda_x \; \beta^i_x \tag{14}$$

Following Bansal et al. (2005)

# A traditional test of the LRR price

$$E_t\left[R^i_{t+1}\right] - R^f_t = \lambda_c\ \beta^i_c + \lambda_x\ \beta^i_x \tag{14}$$

Following Bansal et al. (2005)

- Focus on long-run risk only $\beta^i_x$

# A traditional test of the LRR price

Exploiting Campbell (1996)

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

$\beta^i$s can be decomposed:

$$E_t\left[R^i_{t+1}\right] - R^f_t = \lambda_c\, \beta^i_c + \lambda_x(\beta^i_{x,D} - \beta^i_{x,R}) \tag{14}$$

Following Bansal et al. (2005)

- Focus on long-run risk only $\beta^i_x$

# A traditional test of the LRR price

Exploiting Campbell (1996)

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

$\beta^i$s can be decomposed:

$$E_t\left[R^i_{t+1}\right] - R^f_t = \lambda_c \beta^i_c + \lambda_x(\beta^i_{x,D} - \beta^i_{x,R}) \tag{14}$$

Following Bansal et al. (2005)

- Focus on long-run risk only $\beta^i_x$
- Focus on cash-flows exposure to long-run risk

# Test assets statistics

**Table 4:** Test asset portfolios returns and cash-flows growth: quarterly summary statistics. First series are from 1947 Q2 to 2022 Q1, the R&D portfolios start from 1975 Q1.

| Portfolio | Returns Mean | Returns SD | CF growth Mean | CF growth SD |
|---|---|---|---|---|
| size.01 | 0.06569 | 0.18418 | 0.02767 | 0.17561 |
| size.02 | 0.03768 | 0.15135 | 0.01470 | 0.15258 |
| size.09 | 0.02213 | 0.10717 | 0.00659 | 0.15094 |
| size.10 | 0.01758 | 0.09801 | 0.00241 | 0.09691 |
| bm.01 | 0.02476 | 0.10114 | 0.02050 | 0.28804 |
| bm.02 | 0.02337 | 0.09135 | 0.01872 | 0.25541 |
| bm.09 | 0.02741 | 0.11662 | 0.00933 | 0.20893 |
| bm.10 | 0.03312 | 0.12231 | 0.01144 | 0.19516 |
| mom.01 | 0.01498 | 0.21583 | -0.01330 | 0.22345 |
| mom.02 | 0.01176 | 0.12973 | -0.00812 | 0.16180 |
| mom.09 | 0.02605 | 0.10352 | 0.00245 | 0.26211 |
| mom.10 | 0.03639 | 0.12087 | -0.00819 | 0.29443 |
| rd.01 | 0.02895 | 0.10367 | 0.00954 | 0.15829 |
| rd.02 | 0.02464 | 0.08621 | 0.00528 | 0.12731 |
| rd.04 | 0.03991 | 0.11387 | 0.01552 | 0.16616 |
| rd.05 | 0.06591 | 0.19221 | 0.03406 | 0.20777 |

# Test assets statistics

**Table 4:** Test asset portfolios returns and cash-flows growth: quarterly summary statistics. First series are from 1947 Q2 to 2022 Q1, the R&D portfolios start from 1975 Q1.

| Portfolio | Returns Mean | Returns SD | CF growth Mean | CF growth SD |
|---|---|---|---|---|
| size.01 | 0.06569 | 0.18418 | 0.02767 | 0.17561 |
| size.02 | 0.03768 | 0.15135 | 0.01470 | 0.15258 |
| size.09 | 0.02213 | 0.10717 | 0.00659 | 0.15094 |
| size.10 | 0.01758 | 0.09801 | 0.00241 | 0.09691 |
| bm.01 | 0.02476 | 0.10114 | 0.02050 | 0.28804 |
| bm.02 | 0.02337 | 0.09135 | 0.01872 | 0.25541 |
| bm.09 | 0.02741 | 0.11662 | 0.00933 | 0.20893 |
| bm.10 | 0.03312 | 0.12231 | 0.01144 | 0.19516 |
| mom.01 | 0.01498 | 0.21583 | -0.01330 | 0.22345 |
| mom.02 | 0.01176 | 0.12973 | -0.00812 | 0.16180 |
| mom.09 | 0.02605 | 0.10352 | 0.00245 | 0.26211 |
| mom.10 | 0.03639 | 0.12087 | -0.00819 | 0.29443 |
| rd.01 | 0.02895 | 0.10367 | 0.00954 | 0.15829 |
| rd.02 | 0.02464 | 0.08621 | 0.00528 | 0.12731 |
| rd.04 | 0.03991 | 0.11387 | 0.01552 | 0.16616 |
| rd.05 | 0.06591 | 0.19221 | 0.03406 | 0.20777 |

# Test assets statistics

**Table 4:** Test asset portfolios returns and cash-flows growth: quarterly summary statistics. First series are from 1947 Q2 to 2022 Q1, the R&D portfolios start from 1975 Q1.

| Portfolio | Returns Mean | Returns SD | CF growth Mean | CF growth SD |
|---|---|---|---|---|
| size.01 | 0.06569 | 0.18418 | 0.02767 | 0.17561 |
| size.02 | 0.03768 | 0.15135 | 0.01470 | 0.15258 |
| size.09 | 0.02213 | 0.10717 | 0.00659 | 0.15094 |
| size.10 | 0.01758 | 0.09801 | 0.00241 | 0.09691 |
| bm.01 | 0.02476 | 0.10114 | 0.02050 | 0.28804 |
| bm.02 | 0.02337 | 0.09135 | 0.01872 | 0.25541 |
| bm.09 | 0.02741 | 0.11662 | 0.00933 | 0.20893 |
| bm.10 | 0.03312 | 0.12231 | 0.01144 | 0.19516 |
| mom.01 | 0.01498 | 0.21583 | -0.01330 | 0.22345 |
| mom.02 | 0.01176 | 0.12973 | -0.00812 | 0.16180 |
| mom.09 | 0.02605 | 0.10352 | 0.00245 | 0.26211 |
| mom.10 | 0.03639 | 0.12087 | -0.00819 | 0.29443 |
| rd.01 | 0.02895 | 0.10367 | 0.00954 | 0.15829 |
| rd.02 | 0.02464 | 0.08621 | 0.00528 | 0.12731 |
| rd.04 | 0.03991 | 0.11387 | 0.01552 | 0.16616 |
| rd.05 | 0.06591 | 0.19221 | 0.03406 | 0.20777 |

# Test assets statistics

**Table 4:** Test asset portfolios returns and cash-flows growth: quarterly summary statistics. First series are from 1947 Q2 to 2022 Q1, the R&D portfolios start from 1975 Q1.

| Portfolio | Returns Mean | Returns SD | CF growth Mean | CF growth SD |
|---|---|---|---|---|
| size.01 | 0.06569 | 0.18418 | 0.02767 | 0.17561 |
| size.02 | 0.03768 | 0.15135 | 0.01470 | 0.15258 |
| size.09 | 0.02213 | 0.10717 | 0.00659 | 0.15094 |
| size.10 | 0.01758 | 0.09801 | 0.00241 | 0.09691 |
| bm.01 | 0.02476 | 0.10114 | 0.02050 | 0.28804 |
| bm.02 | 0.02337 | 0.09135 | 0.01872 | 0.25541 |
| bm.09 | 0.02741 | 0.11662 | 0.00933 | 0.20893 |
| bm.10 | 0.03312 | 0.12231 | 0.01144 | 0.19516 |
| mom.01 | 0.01498 | 0.21583 | -0.01330 | 0.22345 |
| mom.02 | 0.01176 | 0.12973 | -0.00812 | 0.16180 |
| mom.09 | 0.02605 | 0.10352 | 0.00245 | 0.26211 |
| mom.10 | 0.03639 | 0.12087 | -0.00819 | 0.29443 |
| rd.01 | 0.02895 | 0.10367 | 0.00954 | 0.15829 |
| rd.02 | 0.02464 | 0.08621 | 0.00528 | 0.12731 |
| rd.04 | 0.03991 | 0.11387 | 0.01552 | 0.16616 |
| rd.05 | 0.06591 | 0.19221 | 0.03406 | 0.20777 |

# Cash-flows sensitivity to long-run risks

$$\Delta \ln D_{i,t} = \beta^{i}_{x,D} \left( \frac{1}{L} \sum_{l=1}^{L} x_{t-l} \right) + \nu_{i,t} \qquad (15)$$

# Cash-flows sensitivity to long-run risks

$$\Delta \ln D_{i,t} = \beta^{i}_{x,D} \left( \frac{1}{L} \sum_{l=1}^{L} x_{t-l} \right) + \nu_{i,t} \tag{15}$$

**Table 5:** Test assets cash-flows sensitivity to long-run risk components. L=16. From 1975 Q1 to 2022 Q1.

| Portfolio | $\beta_C$ | $\beta_{Z\text{-raw}}$ | $\beta_{Z\text{-adj}}$ | $\beta_{\tilde{s}\text{-BS}}$ | $\beta_{\tilde{s}\text{-LN}}$ |
|---|---|---|---|---|---|
| size.01 | 1.245 | 4.624 | 8.145 | 16.042 | 18.977 |
| size.02 | 0.238 | 7.076 | 9.422 | 12.454 | 13.968 |
| size.09 | 1.432 | 7.282 | 1.317 | -3.427 | -4.200 |
| size.10 | -0.415 | 4.014 | -2.535 | -0.894 | -0.934 |
| bm.01 | -2.126 | 12.756 | 6.596 | 2.437 | 2.456 |
| bm.02 | -1.861 | 8.248 | 2.371 | 4.085 | 4.683 |
| bm.09 | 3.041 | 9.280 | 5.844 | 1.936 | 1.713 |
| bm.10 | -0.276 | 4.359 | -5.128 | 2.698 | 3.078 |
| mom.01 | -5.273 | -1.836 | -1.620 | -3.097 | -3.641 |
| mom.02 | 3.279 | 5.482 | -4.846 | -1.532 | -1.791 |
| mom.09 | 9.293 | 12.116 | 3.322 | 1.253 | 1.023 |
| mom.10 | 6.509 | 15.769 | -1.913 | -2.662 | -5.490 |
| rd.01 | 0.794 | 4.354 | 1.465 | -3.177 | -2.795 |
| rd.02 | -1.902 | 13.573 | 8.317 | 4.332 | 2.802 |
| rd.04 | 0.125 | 15.837 | 12.275 | 7.127 | 5.621 |
| rd.05 | -1.294 | 20.648 | 11.143 | 15.662 | 14.056 |

# Cash-flows sensitivity to long-run risks

$$\Delta \ln D_{i,t} = \beta^{i}_{x,D} \left( \frac{1}{L} \sum_{l=1}^{L} x_{t-l} \right) + \nu_{i,t} \tag{15}$$

**Table 5:** Test assets cash-flows sensitivity to long-run risk components. L=16. From 1975 Q1 to 2022 Q1.

| Portfolio | $\beta_C$ | $\beta_{Z\text{-raw}}$ | $\beta_{Z\text{-adj}}$ | $\beta_{\tilde{s}\text{-BS}}$ | $\beta_{\tilde{s}\text{-LN}}$ |
|---|---|---|---|---|---|
| size.01 | 1.245 | 4.624 | 8.145 | 16.042 | 18.977 |
| size.02 | 0.238 | 7.076 | 9.422 | 12.454 | 13.968 |
| size.09 | 1.432 | 7.282 | 1.317 | -3.427 | -4.200 |
| size.10 | -0.415 | 4.014 | -2.535 | -0.894 | -0.934 |
| bm.01 | -2.126 | 12.756 | 6.596 | 2.437 | 2.456 |
| bm.02 | -1.861 | 8.248 | 2.371 | 4.085 | 4.683 |
| bm.09 | 3.041 | 9.280 | 5.844 | 1.936 | 1.713 |
| bm.10 | -0.276 | 4.359 | -5.128 | 2.698 | 3.078 |
| mom.01 | -5.273 | -1.836 | -1.620 | -3.097 | -3.641 |
| mom.02 | 3.279 | 5.482 | -4.846 | -1.532 | -1.791 |
| mom.09 | 9.293 | 12.116 | 3.322 | 1.253 | 1.023 |
| mom.10 | 6.509 | 15.769 | -1.913 | -2.662 | -5.490 |
| rd.01 | 0.794 | 4.354 | 1.465 | -3.177 | -2.795 |
| rd.02 | -1.902 | 13.573 | 8.317 | 4.332 | 2.802 |
| rd.04 | 0.125 | 15.837 | 12.275 | 7.127 | 5.621 |
| rd.05 | -1.294 | 20.648 | 11.143 | 15.662 | 14.056 |

Innovative firms' cash-flows grow more when all the economy innovates more: spillovers?

# Cross-sectional risk premium

$$\mathrm{E}\left[R^i\right] = \lambda_0 + \lambda_x \cdot \beta^i_{x,D} \tag{16}$$

**Table 6:** cross-sectional risk premia estimated following Fama and Macbeth (1973). t-statistics are HAC, computed as advised by Lazarus et al. (2018). From 1975 Q1 to 2022 Q1.

| | Cons. | Raw TFP | Util+R&D-adj. TFP | $\tilde{s}$ (BS) | $\tilde{s}$ (LN) |
|---|---|---|---|---|---|
| *Horizon: 1 year* | | | | | |
| $\lambda_0$ (%) | 6.06*** | 5.76*** | 7.05*** | 7.71*** | 7.59*** |
| t-stat | [3.11] | [2.89] | [3.89] | [4.18] | [4.13] |
| $\lambda_x$ (%) | 0.08 | 0.12 | 0.24*** | 0.56*** | 0.51*** |
| t-stat | [1.49] | [1.61] | [2.60] | [3.88] | [3.67] |
| MAPE (%) | 0.83 | 0.84 | 0.86 | 0.81 | 0.82 |
| $R^2$ (%) | 1.5 | 2.5 | 4.6 | 31.5 | 27.8 |
| *Horizon: 8 year* | | | | | |
| $\lambda_0$ (%) | 6.59*** | 5.70*** | 7.18*** | 4.40** | 4.62** |
| t-stat | [3.68] | [3.17] | [4.02] | [2.41] | [2.54] |
| $\lambda_x$ (%) | 0.05 | 0.39*** | 0.46*** | 0.72*** | 0.64*** |
| t-stat | [0.21] | [4.24] | [4.44] | [4.15] | [3.94] |
| MAPE (%) | 0.85 | 0.72 | 0.69 | 0.54 | 0.57 |
| $R^2$ (%) | −1.2 | 14.5 | 13.3 | 70.1 | 66.8 |

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

# Cross-sectional risk premium

$$E\left[R^i\right] = \lambda_0 + \lambda_x \cdot \beta^i_{x,D} \tag{16}$$

**Table 6:** cross-sectional risk premia estimated following Fama and Macbeth (1973). t-statistics are HAC, computed as advised by Lazarus et al. (2018). From 1975 Q1 to 2022 Q1.

| | Cons. | Raw TFP | Util+R&D-adj. TFP | $\tilde{s}$ (BS) | $\tilde{s}$ (LN) |
|---|---|---|---|---|---|
| | | | *Horizon: 1 year* | | |
| $\lambda_0$ (%) | 6.06*** | 5.76*** | 7.05*** | 7.71*** | 7.59*** |
| t-stat | [3.11] | [2.89] | [3.89] | [4.18] | [4.13] |
| $\lambda_x$ (%) | 0.08 | 0.12 | 0.24*** | 0.56*** | 0.51*** |
| t-stat | [1.49] | [1.61] | [2.60] | [3.88] | [3.67] |
| MAPE (%) | 0.83 | 0.84 | 0.86 | 0.81 | 0.82 |
| $R^2$ (%) | 1.5 | 2.5 | 4.6 | 31.5 | 27.8 |
| | | | *Horizon: 8 year* | | |
| $\lambda_0$ (%) | 6.59*** | 5.70*** | 7.18*** | 4.40** | 4.62** |
| t-stat | [3.68] | [3.17] | [4.02] | [2.41] | [2.54] |
| $\lambda_x$ (%) | 0.05 | 0.39*** | 0.46*** | 0.72*** | 0.64*** |
| t-stat | [0.21] | [4.24] | [4.44] | [4.15] | [3.94] |
| MAPE (%) | 0.85 | 0.72 | 0.69 | 0.54 | 0.57 |
| $R^2$ (%) | −1.2 | 14.5 | 13.3 | 70.1 | 66.8 |

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

# Cross-sectional risk premium

$$E\left[R^i\right] = \lambda_0 + \lambda_x \cdot \beta^i_{x,D} \tag{16}$$

**Table 6:** cross-sectional risk premia estimated following Fama and Macbeth (1973). t-statistics are HAC, computed as advised by Lazarus et al. (2018). From 1975 Q1 to 2022 Q1.

| | Cons. | Raw TFP | Util+R&D-adj. TFP | $\tilde{s}$ (BS) | $\tilde{s}$ (LN) |
|---|---|---|---|---|---|
| | | | *Horizon: 1 year* | | |
| $\lambda_0$ (%) | $6.06^{***}$ | $5.76^{***}$ | $7.05^{***}$ | $7.71^{***}$ | $7.59^{***}$ |
| t-stat | [3.11] | [2.89] | [3.89] | [4.18] | [4.13] |
| $\lambda_x$ (%) | 0.08 | 0.12 | $0.24^{***}$ | $0.56^{***}$ | $0.51^{***}$ |
| t-stat | [1.49] | [1.61] | [2.60] | [3.88] | [3.67] |
| MAPE (%) | 0.83 | 0.84 | 0.86 | 0.81 | 0.82 |
| $R^2$ (%) | 1.5 | 2.5 | 4.6 | 31.5 | 27.8 |
| | | | *Horizon: 8 year* | | |
| $\lambda_0$ (%) | $6.59^{***}$ | $5.70^{***}$ | $7.18^{***}$ | $4.40^{**}$ | $4.62^{**}$ |
| t-stat | [3.68] | [3.17] | [4.02] | [2.41] | [2.54] |
| $\lambda_x$ (%) | 0.05 | $0.39^{***}$ | $0.46^{***}$ | $0.72^{***}$ | $0.64^{***}$ |
| t-stat | [0.21] | [4.24] | [4.44] | [4.15] | [3.94] |
| MAPE (%) | 0.85 | 0.72 | 0.69 | 0.54 | 0.57 |
| $R^2$ (%) | $-1.2$ | 14.5 | 13.3 | 70.1 | 66.8 |

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

# Omitted-factors robust premium

Giglio and Xiu (2021) provides a 3-pass procedure to better control for omitted factors.

It relies on Principal Components of a wide cross-section of test assets.

**Table 7:** risk premia estimation. Optimal number of components $p*$ estimated as in Alessi et al. (2010).

| | $p*$ | $p$ | $T$ |
|---|---|---|---|
| PCs n. | 9 | 13 | |
| Test assets $R^2$ | 62.0% | 83.4% | 289 |
| $\lambda_{\tilde{s}\text{-BS}}$ | 3.63 | 6.09* | 285 |
| | [1.48] | [1.82] | |
| $\lambda_{\tilde{s}\text{-LN}}$ | 7.14*** | 10.25*** | 251 |
| | [2.94] | [3.18] | |

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

# Omitted-factors robust premium

Giglio and Xiu (2021) provides a 3-pass procedure to better control for omitted factors.

It relies on Principal Components of a wide cross-section of test assets.

**Table 7:** risk premia estimation. Optimal number of components $p*$ estimated as in Alessi et al. (2010).

| | $p*$ | $p$ | $T$ |
|---|---|---|---|
| PCs n. | 9 | 13 | |
| Test assets $R^2$ | 62.0% | 83.4% | 289 |
| $\lambda_{\tilde{s}\text{-BS}}$ | 3.63 | 6.09* | 285 |
| | [1.48] | [1.82] | |
| $\lambda_{\tilde{s}\text{-LN}}$ | 7.14*** | 10.25*** | 251 |
| | [2.94] | [3.18] | |

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

# Delving deeper

# On R&D fluctuations' origins

A step towards identification of R&D intensity structural shocks and stricter test of theory

A step towards identification of R&D intensity structural shocks and stricter test of theory

- Markup and funding liquidity often assumed as drivers (Kung and Schmid (2015), Li (2011)):

**Table 8:** estimates of the $\tilde{s}$ regression from the VAR. In brackets, estimates' t statistics; "$\mathbf{max}\,|\text{roots}|$" is the maximum eigenvalue of the companion matrix estimated. $\Delta$ mark-up is the 1st principal component of markup differenced series, while Intermediary Capital Ratio (ICR) is from He et al. (2017), sample from 1970 Q2 to 2017 Q4. Lags selected by AIC.

| | $\tilde{s}$ | $\Delta$Mark-Up | I.C.R. |
|---|---|---|---|
| Lag: 1 | $0.961^{***}$ [47.25] | $-0.054^{**}$ [$-2.75$] | $-0.022$ [$-1.07$] |
| T | $R^2$ | $p(F)$ | $\mathbf{max}\,|\text{roots}|$ |
| 191 | 92.9% | 0 | 0.946 |

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

A step towards identification of R&D intensity structural shocks and stricter test of theory

- Markup and funding liquidity often assumed as drivers (Kung and Schmid (2015), Li (2011)):

**Table 8:** estimates of the $\tilde{s}$ regression from the VAR. In brackets, estimates' t statistics; "$\mathbf{max}\,|\text{roots}|$" is the maximum eigenvalue of the companion matrix estimated. $\Delta$ mark-up is the 1$^{st}$ principal component of markup differenced series, while Intermediary Capital Ratio (ICR) is from He et al. (2017), sample from 1970 Q2 to 2017 Q4. Lags selected by AIC.

| | $\tilde{s}$ | $\Delta$Mark-Up | I.C.R. |
|---|---|---|---|
| Lag: 1 | $0.961^{***}$ <br> $[47.25]$ | $-0.054^{**}$ <br> $[-2.75]$ | $-0.022$ <br> $[-1.07]$ |
| T | $R^2$ | $p(F)$ | $\mathbf{max}\,|\text{roots}|$ |
| 191 | 92.9% | 0 | 0.946 |

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

» more work needed

# Further extensions

- Intra- and inter-sectorial R&D sensitivities
- R&D intensity and aggregate uncertainty:
  - possible strong non-linearities
  - possible significant role of funding conditions

# Conclusion

- Evidence in support of Long-Run Risk framework
- R&D matters for investors and exposure to it is a significant risk measure

# Conclusion

- Evidence in support of Long-Run Risk framework
- R&D matters for investors and exposure to it is a significant risk measure
- R&D fluctuations from 2$^{nd}$-gen endogenous growth models easier to study
- R&D intensity is highly persistent and forecasts TFP and consumption growth
- R&D intensity is associated to a positive risk premium in financial markets

# The Long-run Innovation Risk Component

**Fabio Franceschini**

ffabio.econ @ gmail.com
University of Bologna

University of Milano - Bicocca
January 28th, 2025

# References 1


Ai, Hengjie et al. (2018). **“News Shocks and the Production-Based Term Structure of Equity Returns”.** In: The Review of Financial Studies 31 (7), pp. 2423–2467.

Alessi, Lucia, Matteo Barigozzi, and Marco Capasso (2010). **“Improved penalization for determining the number of factors in approximate factor models”.** In: Statistics & Probability Letters 80.23, pp. 1806–1813.

Bali, Turan G., R. F. (Robert F. ) Engle, and Scott Murray (2016). **Empirical asset pricing: the cross section of stock returns.** Hoboken, New Jersey: Wiley. 494 pp. ISBN: 978-1-118-09504-1.

Bansal, Ravi, Robert F. Dittmar, and Christian T. Lundblad (2005). **“Consumption, Dividends, and the Cross Section of Equity Returns”.** In: The Journal of Finance 60 (4), pp. 1639–1672.

Bansal, Ravi and Ivan Shaliastovich (2013). **“A Long-Run Risks Explanation of Predictability Puzzles in Bond and Currency Markets”.** In: Review of Financial Studies 26 (1), pp. 1–33.

Bansal, Ravi and Amir Yaron (2004). **“Risks for the Long Run: A Potential Resolution of Asset Pricing Puzzles”.** In: The Journal of Finance 59 (4), pp. 1481–1509.

Bloom, Nicholas et al. (2020). **“Are Ideas Getting Harder to Find?”** In: American Economic Review 110 (4), pp. 1104–1144.

# References 2


- Campbell, John Y. (1996). **"Understanding Risk and Return".** In: Journal of Political Economy 104 (2), pp. 298–345.
- Choi, In and Eiji Kurozumi (2012). **"Model selection criteria for the leads-and-lags cointegrating regression".** In: Journal of Econometrics 169 (2), pp. 224–238.
- Croce, Mariano Massimiliano (2014). **"Long-run productivity risk: A new hope for production-based asset pricing?"** In: Journal of Monetary Economics 66, pp. 13–31.
- Dew-Becker, Ian and Stefano Giglio (2016). **"Asset Pricing in the Frequency Domain: Theory and Empirics".** In: Review of Financial Studies 29.8, pp. 2029–2068.
- Epstein, Larry G. and Stanley E. Zin (1989). **"Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: A Theoretical Framework".** In: Econometrica 57 (4), p. 937.
- Fama, Eugene F. and James D. Macbeth (1973). **"Risk, Return, and Equilibrium: Empirical Tests".** In: Journal of Political Economy 81 (3), pp. 607–636.
- Fernald, John G. (2012). **"A Quarterly, Utilization-Adjusted Series on Total Factor Productivity".** In: Federal Reserve Bank of San Francisco, Working Paper Series, pp. 01–28.
- Giglio, Stefano and Dacheng Xiu (2021). **"Asset Pricing with Omitted Factors".** In: Journal of Political Economy 129.7, pp. 1947–1990.

# References 3


- Hansen, Lars Peter, John C. Heaton, and Nan Li (2005). **Intangible Risk.**
- He, Zhiguo, Bryan Kelly, and Asaf Manela (2017). **"Intermediary asset pricing: New evidence from many asset classes".** In: Journal of Financial Economics 126 (1), pp. 1–35.
- Jensen, Theis Ingerslev, Bryan T. Kelly, and Lasse Heje Pedersen (2021). **"Is There a Replication Crisis in Finance?"** In: SSRN Electronic Journal.
- Jones, Charles I. (1999). **"Growth: With or Without Scale Effects?"** In: American Economic Review 89.2, pp. 139–144.
- Kruse-Andersen, Peter K. (2023). **"Testing R&D-Based Endogenous Growth Models*".** In: Oxford Bulletin of Economics and Statistics n/a (n/a).
- Kung, Howard and Lukas Schmid (2015). **"Innovation, Growth, and Asset Prices".** In: The Journal of Finance 70 (3), pp. 1001–1037.
- Lazarus, Eben et al. (2018). **"HAR Inference: Recommendations for Practice".** In: Journal of Business and Economic Statistics 36 (4), pp. 541–559.
- Lettau, Martin and Sydney C. Ludvigson (2001). **"Consumption, Aggregate Wealth, and Expected Stock Returns".** In: The Journal of Finance 56 (3), pp. 815–849.
- Li, Dongmei (2011). **"Financial Constraints, R&D Investment, and Stock Returns".** In: Review of Financial Studies 24.9, pp. 2974–3007.

# References 4


- Liu, Yukun et al. (2022). **“Long-Run Risk: Is It There?”** In: The Journal of Finance 77.3, pp. 1587–1633.
- Ludvigson, Sydney C. and Serena Ng (2009). **“Macro Factors in Bond Risk Premia”.** In: Review of Financial Studies 22 (12), pp. 5027–5067.
- Melone, Alessandro (2021). **“Consumption Disconnect Redux”.** In: SSRN Electronic Journal.
- Mendes, Eduardo F. (2011). **Model Selection Consistency for Cointegrating Regressions.** arXiv: `1104.5667[stat]`.
- Neto, David (2023). **“Penalized leads-and-lags cointegrating regression: a simulation study and two empirical applications”.** In: Empirical Economics 65.2, pp. 949–971.
- Ortu, Fulvio, Andrea Tamoni, and Claudio Tebaldi (2013). **“Long-Run Risk and the Persistence of Consumption Shocks”.** In: Review of Financial Studies 26 (11), pp. 2876–2915.
- Rivera-Batiz, Luis A and Paul M Romer (1991). **“Economic Integration and Endogenous Growth”.** In: pp. 531–555.
- Schorfheide, Frank, Dongho Song, and Amir Yaron (2018). **“Identifying Long-Run Risks: A Bayesian Mixed-Frequency Approach”.** In: Econometrica 86.2, pp. 617–654.

# Appendix

# TFP growth rate approximation 1

Ideas growth rate from law of motion/production schedule

$$\frac{I_t}{I_{t-1}} = 1 - \phi + \chi\left(S_{t-1}^{\eta} I_{t-1}^{(-1+\psi)} Q_{t-1}^{-\omega}\right) \tag{17}$$

$$\ln\left(\frac{I_t}{I_{t-1}}\right) \approxeq -\phi + \chi\left(S_{t-1}^{\eta} I_{t-1}^{(-1+\psi)} Q_{t-1}^{-\omega}\right) \tag{18}$$

$$\Delta \ln I_t \approx -\phi + \chi \cdot \exp\left\{\ln\left(S_{t-1}^{\eta} I_{t-1}^{(-1+\psi)} Q_{t-1}^{-\omega}\right)\right\} \tag{19}$$

$$= -\phi + \chi \cdot \exp\{\eta \ln S_{t-1} - (1-\psi)\ln I_{t-1} - \omega \ln Q_{t-1}\} \tag{20}$$

$$\approxeq -\phi + \chi + \chi\left(\eta \ln S_{t-1} - (1-\psi)\ln I_{t-1} - \omega \ln Q_{t-1}\right) \tag{21}$$

Productivity growth rate applying TFP definition

$$\ln Z_t = a_t + \xi \ln I_t \tag{22}$$

$$\Delta \ln Z_t = \Delta a_t + \xi \Delta \ln I_t \tag{23}$$

$$\approxeq \Delta a_t + \xi\left[-\phi + \chi + \chi\left(\eta \ln S_{t-1} - (1-\psi)\ln I_{t-1} - \omega \ln Q_{t-1}\right)\right] \tag{24}$$

$$= \Delta a_t + \xi(\chi - \phi) + \xi\chi\left(\eta \ln S_{t-1} - (1-\psi)\ln I_{t-1} - \omega \ln Q_{t-1}\right) \tag{25}$$

# TFP growth rate approximation 2

Assuming $Q_t = L_t^{\kappa}$

$$\Delta \ln Z_t \approxeq \Delta a_t + \xi(\chi - \phi) + \xi\chi\left(\eta \ln S_{t-1} - (1-\psi)\ln I_{t-1} - \omega\kappa \ln L_{t-1}\right) \tag{26}$$

Expressing in term of $Z$

$$\Delta \ln Z_t \approxeq \Delta a_t + \xi(\chi - \phi) + \xi\chi\left(\eta \ln S_{t-1} - \frac{1-\psi}{\xi}(\ln Z_{t-1} - a_{t-1}) - \omega\kappa \ln L_{t-1}\right) \tag{27}$$

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

$$\Delta \ln Z_t \approxeq \xi(\chi - \phi) + \xi\chi\left(\eta \ln S_{t-1} - \frac{1-\psi}{\xi}\ln Z_{t-1} - \omega\kappa \ln L_{t-1}\right) + (\rho_a - 1 + \chi(1-\psi))a_{t-1} + \varepsilon_t^a \tag{28}$$

Assuming $(\ln S_t - \frac{1-\psi}{\eta}\ln I_t - \frac{\omega}{\eta}\ln Q_t) = \bar{s} + \tilde{s}_t \sim I(0)$

$$\bar{s} + \tilde{s}_t = \eta \ln S_t - \frac{1-\psi}{\xi}\ln Z_t + \frac{1-\psi}{\xi}a_t - \omega\kappa \ln L_t \tag{29}$$

$$\ln Z_t = \frac{-\bar{s}\xi}{1-\psi} + \frac{\eta\xi}{1-\psi}\ln S_t - \frac{\omega\kappa\xi}{1-\psi}\ln L_t + a_t + \frac{-\xi}{1-\psi}\tilde{s}_t \tag{30}$$

$$\Delta \ln Z_{t+1} = \Delta a_t + \xi(\chi - \phi) + \xi\chi\eta\left(\bar{s} + \tilde{s}_t\right) \tag{31}$$

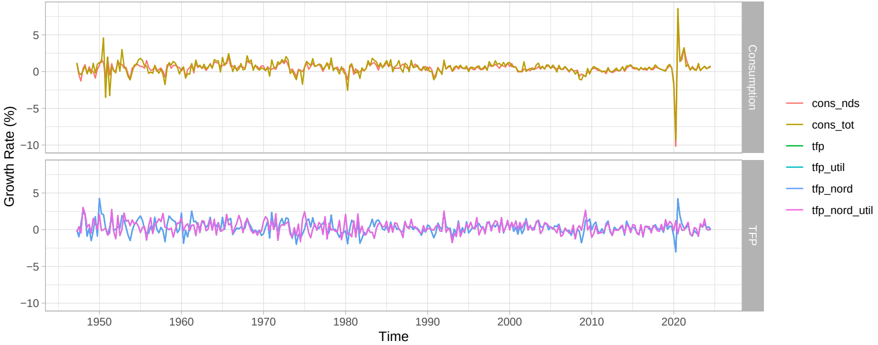
$$= (\xi(\chi - \phi) + \xi\chi\eta\bar{s}) + \xi\chi\eta\tilde{s}_t + \Delta a_t \tag{32}$$

# TFP stationarity

**Table 9:** data from Fernald (2012).

| | 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 previous results

**Figure 4:** first differences of the macroeconomic series forecasted.

# AdaLASSO DOLS

1. Start by setting standard maximum number of lags and leads (see Choi and Kurozumi (2012)):

$$Lg = Ld = 12 \times (T/100)^{1/4}$$

2. Perform 10-fold cross-validation to select optimal regularization parameter $\lambda$ in

$$\min_{\begin{pmatrix}\alpha\\ \alpha_f\\ \delta\end{pmatrix}} \sum_{t=1}^{T} \left\{ \ln Z_t - \begin{bmatrix}\alpha\\ \alpha_f\end{bmatrix}' \begin{bmatrix}1\\ \ln S_t\\ \ln L_t\\ f_t\end{bmatrix} + \delta' \begin{bmatrix}\Delta S_{t-Lg}\\ \dots\\ \Delta S_{t+Ld}\\ \Delta L_{t-Lg}\\ \dots\\ \Delta L_{t+Ld}\\ \Delta(f_1)_{t-Lg}\\ \dots\\ \Delta(f_1)_{t+Ld}\end{bmatrix} \right\}^2 + \lambda \left( \sum_i w_i \cdot |\delta_i| + \sum_j w_j \cdot |(\alpha_f)_i| \right)$$

3. Set $w_i = |\delta_i|^{-0.9}$ and $w_j = |(\alpha_f)_j|^{-0.9}$ (initial values set by a preliminary OLS or Ridge Regression)
4. Repeat steps 2 and 3 until convergence
5. Replicate steps 2, 3 and 4, 999 times; select median model (i.e. the one associated to the median value of $\lambda$)
6. Repeat steps 2, 3, 4 and 5 by increasing/decreasing lags/leads by 4 (a year) if boundaries are hit/slack

Back

# Cross-correlations across specifications

**Table 10:** correlation among specifications of the ECTs. Naming format: Z-variable, S-variable, Q-variable, factors set.

| | nord_util.tot.bs | raw.tot.bs | nord_util.nonfarm.bs | nord_util.tot.ln |
|---|---|---|---|---|
| raw.tot.bs | 0.829 | - | - | - |
| nord_util.nonfarm.bs | 0.993 | 0.798 | - | - |
| nord_util.tot.ln | 0.990 | 0.876 | 0.99 | - |

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

$$h_t = \left(\frac{P_{t+1}}{P_t}\right) \cdot \mathbf{min}\left[\left(\frac{n_{t+1}}{n_t}\right), 1\right] \tag{33}$$

Back