Creative Destruction Cycles:

Schumpeterian Growth In An Estimated DSGE Model

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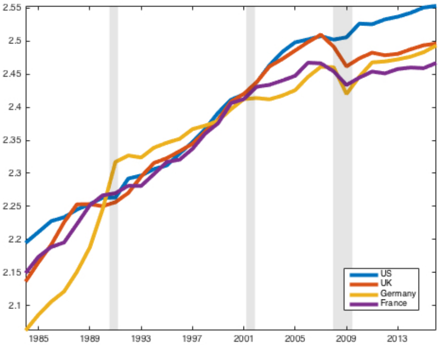
The Productivity Slowdown



Log of TFP in major developed countries (in USD 2010 ppp based)
in blue: US, in red: UK, in purple: France, in yellow: Germany

Source: Bergeaud, Cette and Lecat (2016)

TFP in Macro Models

- During the last decade TFP has significantly deviated from the Great Moderation trend in many developed countries
- Yet standard macro models (e.g. Christiano, Eichenbaum and Evans (2005) or Smets and Wouters (2007)) are silent about the interpretation of the TFP slowdown
- In this paper we introduce an endogenous TFP engine in Smets and Wouters (2007) in order to evaluate the dynamic properties of DSGE models in which TFP is endogenously determined and to shed light on the TFP slowdown

From the Puzzle to the Model

- The idea of the paper: building a fully-fledged DSGE model à la Smets and Wouters (2007) in which TFP is determined by a sector of Schumpeterian innnovators

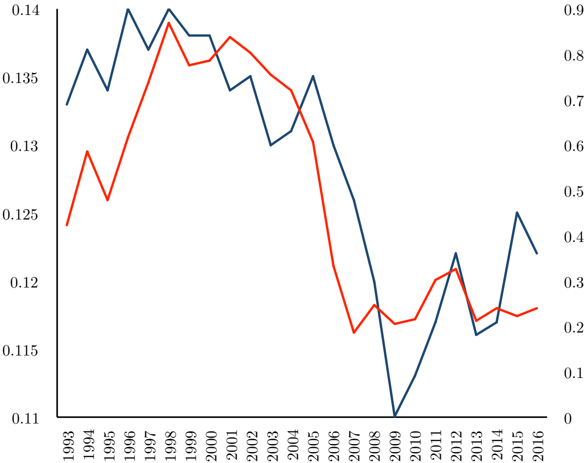
- TFP in the model will thus be affected by the entire set of stochastic shocks used in standard macro models (risk premium, investment specific technology, prices and wages mark-up, govt spending and monetary policy shocks)

- **In standard models:** exogenous TFP shocks drive the business cycle
  In this model: business cycle affects TFP, and TFP in turn drives the business cycle (feedback loop)

Creative Destruction and TFP Dynamics: some empirical evidence

- Liu (1993) shows firms' entry and exit to be amongst the major drivers of productivity growth for Chilean firms
- Campbell (1998) shows that firms' entry rates covary with output and TFP fluctuations in the US
- Brandt et al. (2011) show that creative destruction is the main source of productivity improvements in Chinese establishments

Schumpeter and the TFP Slowdown



In blue: New Firm Birth Rates in the US (BLS)
In red: TFP gains, centered 5-years moving average
(Bergeaud, Cette and Lecat 2016)

Previous Contributions

- Guerron-Quintana and Jinnai (2017) $\rightarrow$ TFP slowdown driven by asset liquidity shocks
- Bianchi, Kung and Morales (2017) $\rightarrow$ TFP slowdown driven by decreased technology utilization
- Anzoategui et al. (2017) $\rightarrow$ TFP slowdown driven by liquidity demand shocks

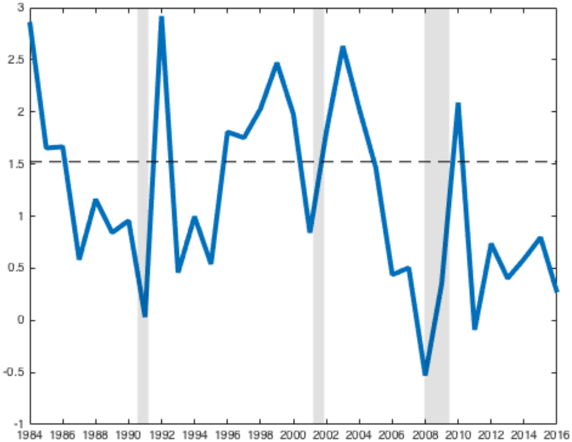
All these stories are inconsistent with one of the key facts in the empirical literature (see Fernald, 2014): the TFP contraction started already in 2004-2005, when the economy was booming and liquidity was abundant

An Alternative View

- In this paper I propose a different narrative: the TFP slowdown was driven by supply-side innovation drivers
- Namely I identify a strong contribution of R&D efficiency shocks to the TFP dynamics, i.e. less innovation for the same amount of R&D
- I argue that, differently from the previous contribution, this interpretation is consistent with key facts in the TFP slowdown and related contributions in the empirical literature: think of Fernald (2014), Gordon (2015) or Bloom et al. (2017)

The predictions and the policy implications of this paper are radically different: the TFP slowdown **may be here to stay**

The financial crisis ended up, the TFP slowdown did not



TFP in the US 1984-2016, annual data
The dashed line is the pre 2005 sample mean.
Source: Bergeaud, Cette and Lecat (2016)

Contributions of the Paper:

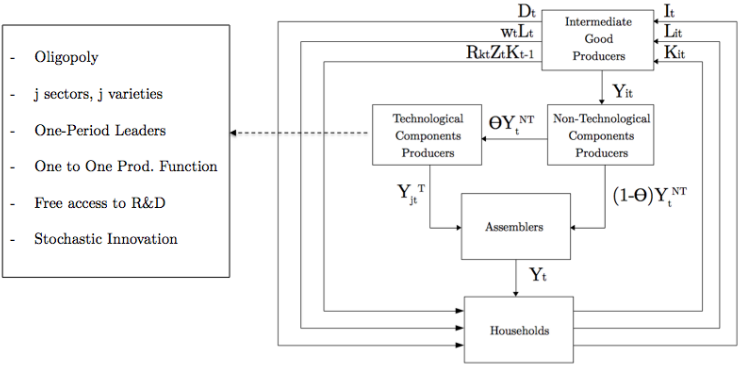
(i) On the theoretical side: incorporation of a Schumpeterian growth engine in a fully-fledged estimated DSGE model

(ii) On the empirical side: the paper proposes a different interpretation of the TFP slowdown, arguing that the latter is driven by supply-side innovation factors

(iii) Furthermore: the model is able to generate a positive comovements in output, consumption, investment TFP, and hours worked. This allows to overcome important anomalies in news shocks literature without relying on non-standard preferences (see Jaimovich and Rebelo, 2009 and Bouakez, 2018)

The Structure of the Model

I augment a standard DSGE à la Smets and Wouters (2007) with a sector of Schumpeterian innovators à la Benigno and Fornaro (2016)



The Innovation Sector (1/5)

- The technological component is produced via a linear production function with a unit of the non-tech component, i.e. ${Y_{j,t}}^{T} = {Y_t}^{NT}$

- Several oligopolists compete in each of the j sectors in the technological component production, but only one player in each of the j sectors will be able to produce it: the one who will innovate. Hence, the market structure will result in a monopolistical competition

- Finally, the tech component will be resold to the assembler with a mark-up ζ on the price of the non-tech component, so that: $p_{j,t}^{T} = \zeta p_t^{NT}$

The Innovation Sector (2/5)

- In every period, in each sector j, one player innovates and becomes the monopolist with a certain probability μ_{jt}

  - The probability of becoming a leader non-linearly depends on the amount of invested R&D, and it is subject to convex adjustment costs. ϵ_t^J is an AR(1) R&D specific technology shock.

$$\mu_{jt} = \frac{J_{j,t}}{A_{j,t}}(1 - Z(\frac{J_{j,t}}{J_{j,t-1}}))\epsilon_t^{RD}$$

- Convex adjustment costs produce realistic innovation lag
- The player that innovates takes the leadership position and exploits the monopoly rent for one period. After one period, the monopoly position is randomly assigned to another player

The Innovation Sector (3/5)

- Given the production function fashion, the leader's profit will be: $\Pi_{j,t} = (p_{j,t}^{T} - p_t^{NT})y_{j,t}^{T} = \theta_{j,T}(\zeta - 1)p_t y_t$
- Hence, the innovator maximizes her potential profits in t+1 at the net of the R&D investment:

$$max \sum_{s=0}^{\infty} \mathbb{E}_t \frac{\Xi_{t+s} P_t}{\Xi_t P_{t+s}} \mu_{jt} \Pi_{j,t+1} - q_t^j J_t$$

$$s.t. q_t^j J_t \leq T_t^j$$

where T_t^j is a lump-sum transfer from the households to the innovation sector

- Outcome: the incentive to innovate depends on the level of economic activity

The Innovation Sector (4/5)

- This optimality conditions, which states that the marginal profit investing one extra unit of R&D should equal its marginal cost, allow us to determine the amount of R&D investment in the economy:

$$\theta_T\left(\Gamma-1\right)\frac{Y_t}{A_t}\left(1-\left(1+\varrho\right)\left(\frac{J_t}{J_{t-1}}\right)^{\varrho}\right)\right)\epsilon_t^j - E_t\frac{\beta^s\Xi_t P_t}{\Xi_{t+1}P_{t+1}}\frac{Y_{t+1}}{A_{t+1}}\left(\frac{J_t}{J_{t+1}}^{1+\varrho}\right)\epsilon_{t+1}^j = q_t^J$$

- By selecting the symmetric equilibrium, it is possible to determine the probability of innovation in every sector, which for the law of large numbers will become the share of sectors that will innovate:

$$\mu_t = \frac{J_t}{A_t}(1-Z(\frac{J_t}{J_{t-1}}))\epsilon_t^{RD}$$

The Innovation Sector (5/5)

- Hence, aggregate productivity will result in:

$$A_t = (1 - \mu_t)A_{t-1} + \mu_t(1 + \gamma + \epsilon_t^a)A_{t-1}$$

- Thus, the productivity growth rate will be defined as:

$$\frac{A_t}{A_{t-1}} = 1 + (\gamma + \epsilon_t^a)\mu_t$$

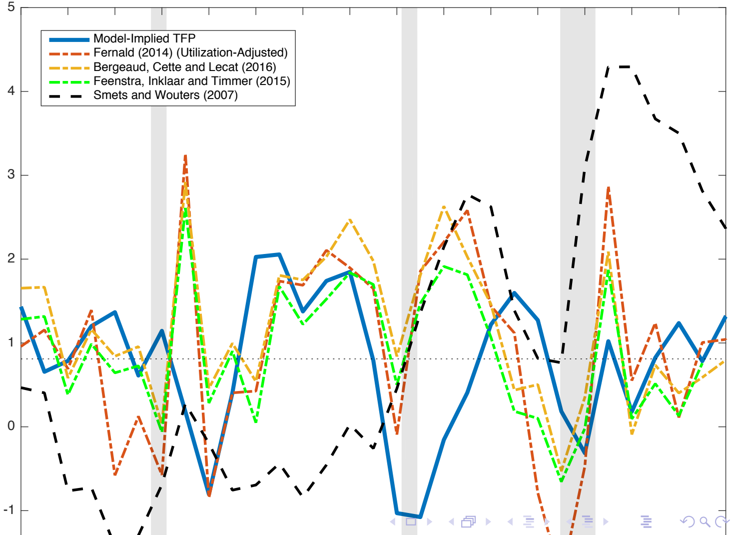
where ϵ_t^a is an AR(1) shock to the innovation step, i.e. to the productivity gap between two consecutive vintages of technology

Solution and Estimation

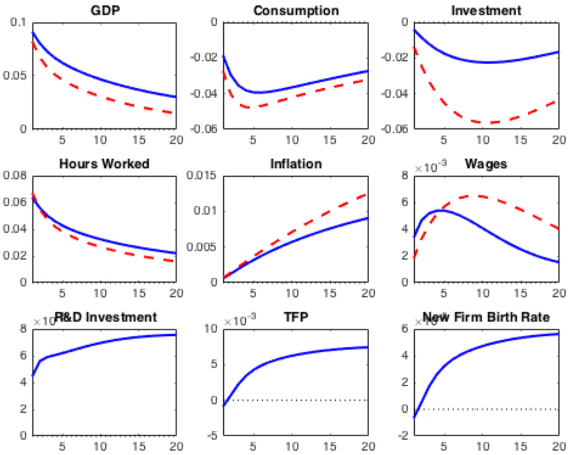
- I solve the system of equations just described with a first-order Taylor approximation around its deterministic steady state
- I select 10 observables: Output, Consumption, Net Investment, Wages, Worked Hours, Inflation, R&D Investment, R&D Relative Price, New Firm Birth Rate, and the Wu-Xia Federal Funds Rate
- With the Wu-Xia Federal Funds Rate, the model abstracts from the Zero Lower Bound. Hence, the model features a unique steady-state (differently from Benigno and Fornaro, 2016)
- Trending variables (in logs) are de-normalized in measurement equations i.e. $dX_{t,obs} = \frac{X_t}{A_t} - \frac{X_{t-1}}{A_{t-1}} + \frac{A_t}{A_{t-1}}$
- Parameters estimated via Bayesian methods on 1984q2 - 2016q4

Empirical Validation

The TFP estimates implied by the model are comparable to those obtained in several empirical works

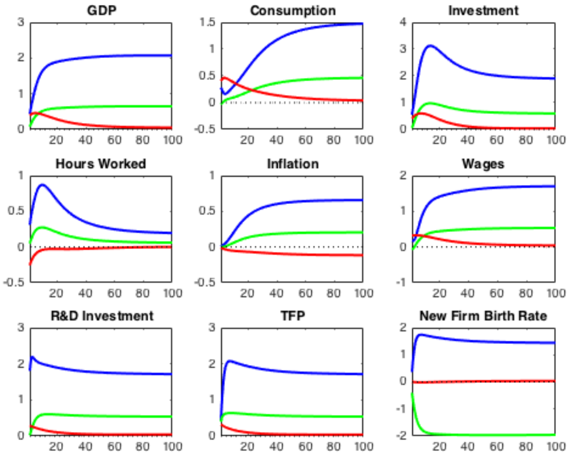


Endogenous TFP as a Source of Persistence



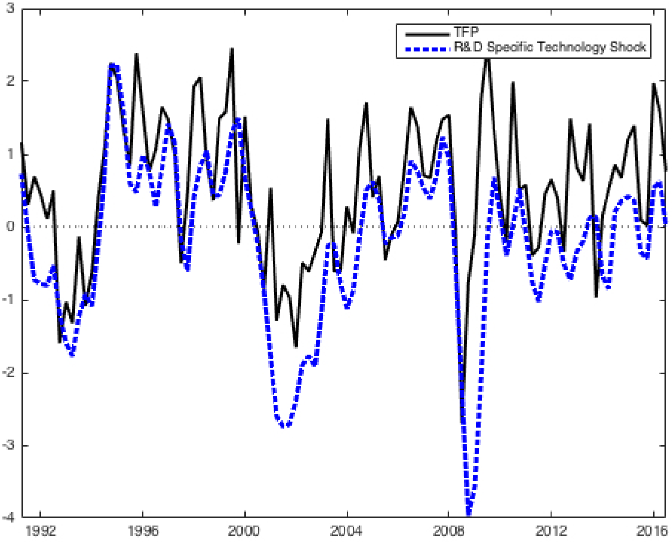
Solid Black Line: Endogenous Productivity Model
Dashed Blue Line: Smets and Wouters (2007)

The Jaimovich and Rebelo (2009) Puzzle

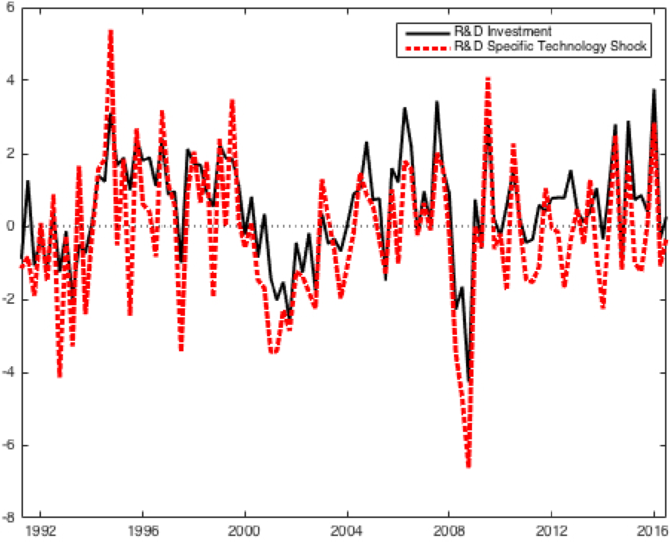


In blue: dynamic response to a R&D Tech Shock
In red: dynamic response to an Exogenous TFP Shock
In green: dynamic response to an Innovation Step Shock

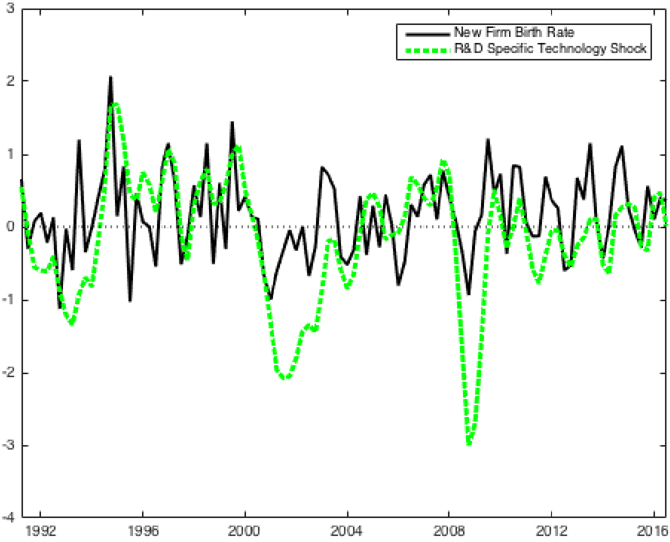
R&D Tech Shock Contribution on TFP



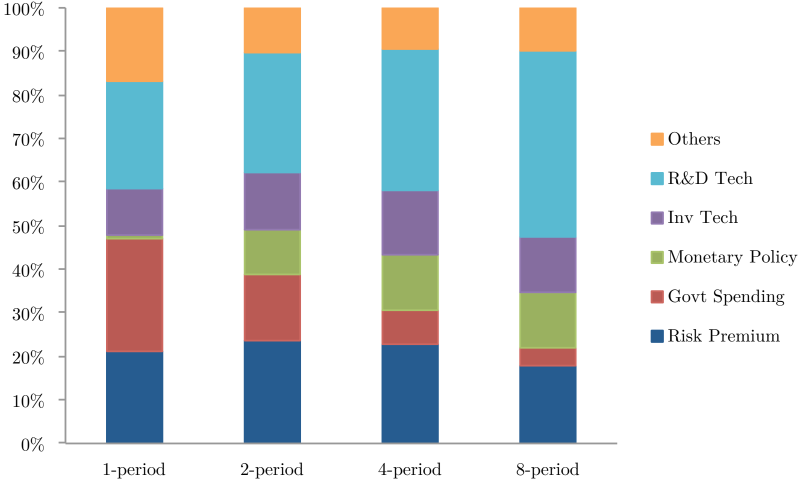
R&D Tech Shock Contribution on R&D



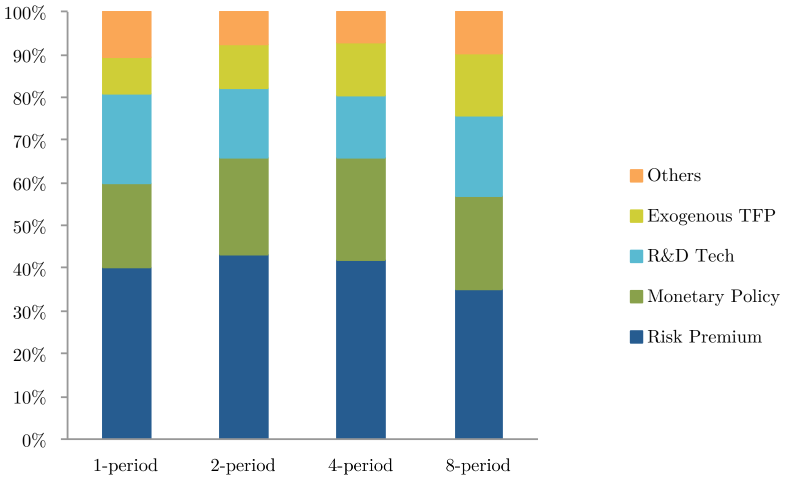
R&D Tech Shock Contribution on Entry Rate



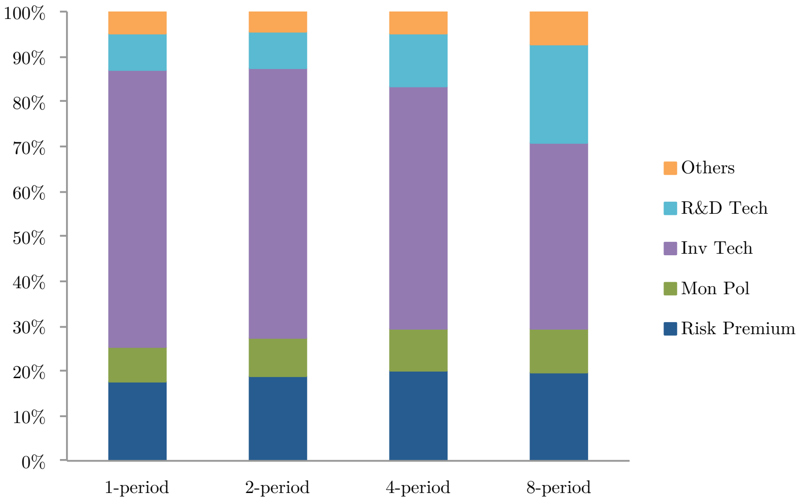
Variance Decomposition - GDP



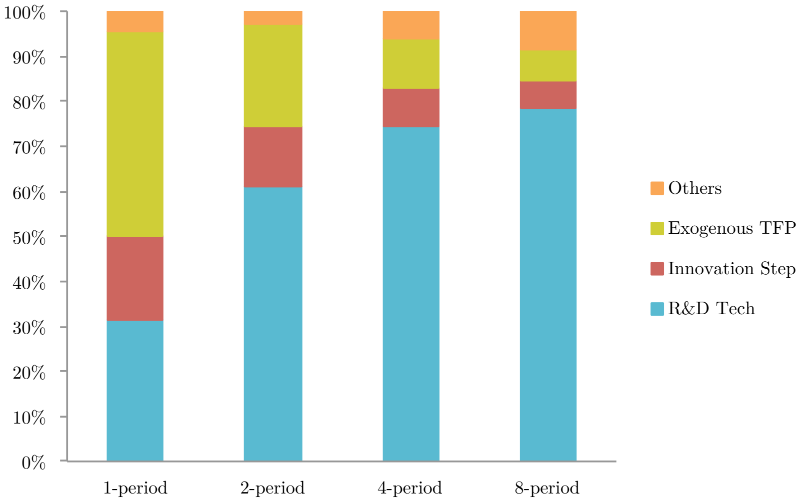
Variance Decomposition - Consumption



Variance Decomposition - Investment



Variance Decomposition - TFP



Conclusions

- I embedded a Schumpeterian growth engine in a fully-fledged standard DSGE model
- The model is able to produce TFP estimates comparable to those generated by non-structural models
- The paper sheds light on the sources of the TFP slowdown: the variance and the historical decomposition suggest that the major drivers of TFP fluctuations are shocks to R&D efficiency
- The TFP slowdown began prior and did not end up with the recovery from the Great Recession. This delivers an unpleasant message: the TFP slowdown might be more persistent than what most endogenous TFP models predict

Thank you!