Creative Destruction Cycles:
Schumpeterian Growth in an Estimated DSGE Model

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Abstract

In this paper I incorporate a Schumpeterian mechanism of creative destruction in a standard DSGE framework. In the model, a sector of forward-looking profit maximizing innovators determines the economy's TFP growth rate. I estimate the model with Bayesian methods, and show that models featuring an endogenous TFP channel can empirically outperform models that exhibit standard, exogenous productivity dynamics. The paper provides a comprehensive comparative assessment of the impact of the endogenous TFP channel in an estimated fully-fledged DSGE model. The variance decomposition analysis shows that endogenous TFP is a powerful channel of transmission of adverse shocks throughout the business cycle. The estimates suggest that the 35% of the productivity growth rate fluctuations had endogenous origins during the Great Recession.

Keywords: DSGE model, Endogenous TFP, Schumpeterian Growth, Post-Crisis Slump

JEL No: E5, E24, E32, O47

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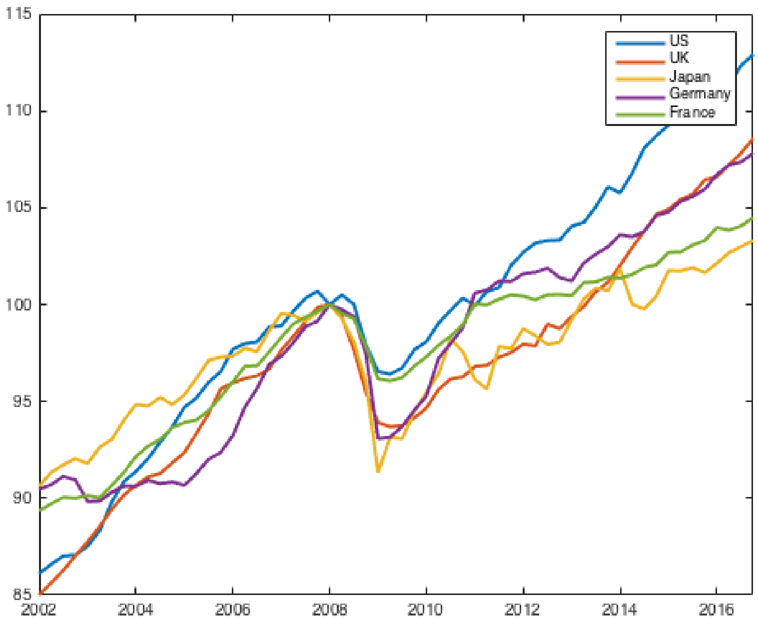
> "Are there circumstances in which changes in aggregate demand can have an appreciable, persistent effect on aggregate supply? Prior to the Great Recession, most economists would probably have answered this question with a qualified "no". [...] This conclusion deserves to be reconsidered in light of the failure of the level of economic activity to return to its pre-recession trend in most advanced economies."
>
> *Janet Yellen, October 2016*

In contrast with standard models predictions, in most of the developed economies GDP did not recover to its pre-crisis growth trend after the Great Recession. Hall (2014) shows that in 2013 output in the U.S. was still 13 percent below its trend path from 1990 through 2007, with large drops in physical capital stock, labour force participation, and total factor productivity. Reinhart and Rogoff (2014) document that in 2014 output was still highly depressed in several OECD countries. As I show in Fig. 1, in 2017 - 10 years after the beginning of the crisis - the GDP growth path exhibits no sign of reversion to its pre-crisis trend in many of the developed economies. While in standard macroeconomic models as Christiano, Eichenbaum and Evans (2005) or Smets and Wouters (2007), GDP trend is assumed to be linear and unaffectable by temporary demand shocks, these evidences suggest that the 2008-2011 financial turmoil induced a permanent shift from the potential GDP growth path in many countries. A considerable number of empirical works supports this hypothesis. Haltmaier (2012) shows the Great Recession drove on average to a total permanent loss of 3% in terms of output growth amongst developed economies. Ball (2014) finds that potential output averagely fell by 8.4% amongst OECD economies during the Great Recession.

In this paper I explore the idea that the stochastic forces which in standard models drive the business cycle, affect effective and potential output at once. In the model I generate persistent potential output fluctuations by introducing a Schumpeterian Growth engine in a standard DSGE model. The endogenous growth mechanism generates a transmission channel from stochastic shocks hitting the economy to the TFP growth path, which is therefore affected by creative destruction cycles. In the model, standard DSGE theory is thus reconciled with the traditional endogenous growth literature. The model is based on Smets and Wouters (2007) workhorse, and embeds a simple and highly tractable endogenous TFP growth mechanism based on Benigno and Fornaro (2016) forward-looking expectations channel, that connects productivity gains to expected future innovators' profits. The model exhibits the following features: (i) productivity is driven by research and development investment; (ii) research and development investment level is determined by the optimizing behaviour of a sector of innovators; (iii) price and wages dynamics are affected by nominal and real rigidities; (iv) stochastic shocks to fundamentals stochastically hit the economy.

FIG.1 REAL GDP BEFORE AND AFTER THE GREAT RECESSION (2008=100)



Sources: BEA, UK Cabinet Office, Eurostat, JP Statistics Bureau

The model is estimated on the US data using Bayesian techniques. For tractability purposes, I do not explicitly model financial frictions, although the presence of a risk premium shock de facto provides a direct channel of transmission of adverse financial shock to productivity dynamics, and accordingly, to the whole economy. When adverse risk premium shocks hit the economy, two different channels are at work. First, agents discount future consumption at a higher rate, so that innovation profits are less attractive, R&D investment decreases, and TFP growth rate drops. Second, persistent output slumps decrease agents' expectations about future profits, so that, R&D investment decreases and accordingly the TFP growth rate drops.

The modern endogenous TFP literature derives from Comin and Gertler (2006) seminal contribution. This literature borrows endogenous productivity growth mechanisms from the theoretical endogenous growth literature of the early 1990s and introduce them into DSGE models. In particular, two contributions are relevant to understand the current development of the modern endogenous TFP literature: Romer (1990), who introduces the idea of growth via increase of varieties, and Aghion and Howitt (1992), who develops modern Schumpeterian Growth theoretical framework in the spirit of the Schumpeterian idea of creative destruction. The core mechanism of this paper is inspired by Benigno and Fornaro (2016), who develop a hybrid toy model featuring elements from both the Zero Lower Bound and the Schumpeterian Growth literature. The Benigno-Fornaro mechanism stresses the role of innovators future profits expectations in determining the current economic outcome. Positive expectations about future growth lead to high R&D investment and sustained economic growth, while adverse expectations lead to a stagnation steady state, characterized by high level of unemployment and anaemic growth.

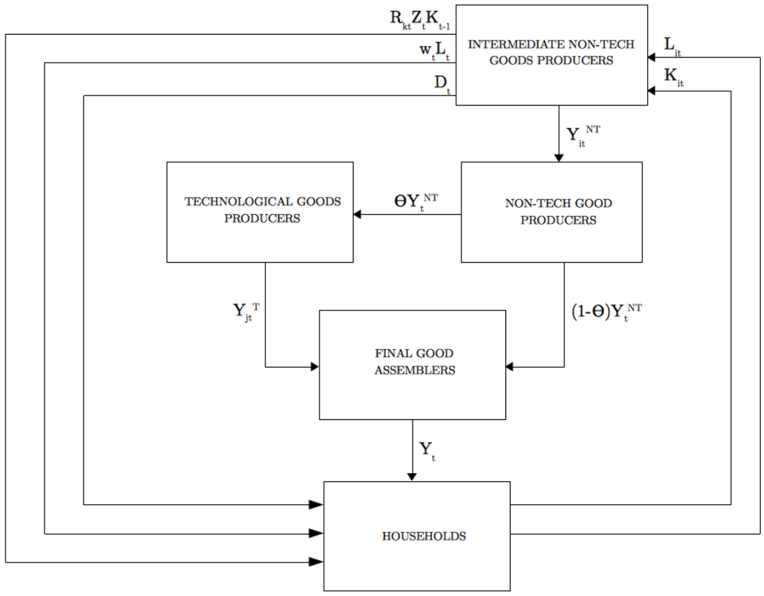
After Comin and Gertler (2006), who combines endogenous mark-ups and the Romer (1990) expanding variety mechanism into a RBC model, several authors have focused on the integration of endogenous growth mechanisms in DSGE frameworks. Bianchi and Kung (2014) develop and estimate a DSGE featuring an endogenous TFP channel that relies on a human capital accumulation mechanism. Queraltó (2015) introduces financial frictions in an endogenous TFP augmented DSGE model which borrows from Romer (1990) the idea of growth via firms creation. Guerron-Quintana and Jinnai (2015) propose an endogenous growth DSGE model featuring a credit channel à la Kiyotaki and Moore (2012). In both Queraltó (2015) and Guerron-Quintana and Jinnai (2015) adverse shocks on the financial markets can thus result in productivity drops. Anzoategui et al. (2016) estimate a New Keynesian DSGE model featuring the ZLB and a knowledge diffusion mechanism à la Comin and Gertler (2006). Finally, this work relates to Ikeda and Kurozomi (2016), who analyse the implications for optimal monetary policy in an endogenous TFP setup. With Cozzi et al. (2017), this paper represents the first example of incorporation of a creative destruction mechanism in a DSGE model à la Aghion and Howitt (1992). This paper contributes to the literature by providing a comprehensive comparative assessment of the impact of the endogenous TFP channel's introduction in a fully-fledged DSGE model featuring a rich set of frictions and stochastic shocks.

2. Introducing an Endogenous TFP in a Standard DSGE

In this section, I describe a medium-sized DSGE model whose core structure is to a large extent based on Smets and Wouters (2007, henceforth SW). I extend the SW structure to allow for endogenous productivity dynamics, throughout the introduction of a sector of innovators à la Benigno and Fornaro (2016)[1]. The rest of the building blocks are preserved in their original fashion, so that the model here presented nests and enhance the SW economy. This approach allows for a straightforward comparison with the baseline SW during empirical exercises. The economy features four different kinds of producers. A final assembler combines a non-technological good and a continuum of varieties of a technological good to obtain the final good. The non-technological good is obtained via the aggregation of a continuum of non-technological intermediate goods. Non-technological intermediate goods are produced out of labour and capital via a Cobb-Douglas technology. Technological goods are obtained from the non-technological good via a one-to-one production function. On the non-technological good producers side, I implement a production sector à la SW, while the technological good producers side is inspired to Benigno and Fornaro (2016). The structure of the economy is illustrated in Figure 2.

[1] Differently from Benigno and Fornaro (2016), the model here presented abstracts from the ZLB.

FIG.2 – STRUCTURE OF THE ECONOMY



2.1 Households

Households maximize an intertemporal utility function with habit formation in consumption $C_{j,t}$ hours worked $L_{j,t}$ bonds $B_{j,t}$ investment $I_{j,t}$ and capital utilization $U_{j,t}$. As standard in medium scale DSGE exhibiting wage rigidities, each household is a monopolistically competitive supplier of a differentiated type of labour. I define h as the habit parameter, R_t as the rate of return of capital, P_t as the price level, T_t as a lump sum tax, W_t^h as the hourly wage, K_t as the stock of physical capital, u_t as the capital stock utilization rate (with $K_{j,t}^s = u_{j,t+s}K_{j,t-1}$), a_t as the capital stock rental rate, D_t^f and D_t^j as the amount of dividend distributed by the firms and the innovators, δ as the depreciation rate and S as the investment convex adjustment cost function, where S(1)=1 and S">0. The households' intertemporal decision problem can be formulated as:

$$maxE_t\sum_{s=0}^{\infty}\beta\left[\frac{1}{1-\sigma_c}\left(C_{j,t+s}-hC_{t+s-1}\right)^{1-\sigma_c}\right]\exp\left(\frac{\sigma_c-1}{1+\sigma_l}L_{t+s}^{1+\sigma_l}\right)$$

s.t.

$$C_{j,t+s}+I_{j,t+s}+\frac{B_{j,t+s}}{\epsilon_t^bR_{t+s}P_{t+s}}-T_{t+s}\leq\frac{B_{j,t+s-1}}{P_{t+s}}+\frac{W_{j,t+s}^hL_{j,t+s}}{P_{t+s}}+\frac{R_{j,t+s}^kZ_{j,t+s}K_{j,t+s-1}}{P_{t+s}}-a\left(u_{j,t+s}\right)K_{j,t+s-1}+\frac{D_{t+s}^f}{P_{t+s}}+\frac{D_{t+s}^j}{P_{t+s}}$$

$$\text{and } K_{j,t}=\left(1-\delta\right)K_{j,t-1}+\epsilon_t^i\left[1-S\left(\frac{I_{t,j}}{I_{t-1,j}}\right)\right]I_{t,j}$$

ϵ_t^b is a shock on bonds' risk premia that might reflect inefficiencies in credit supply or temporary fluctuations in agents' risk aversion. ϵ_t^i is an investment specific technology shock, which leads to fluctuations in physical capital investment adjustment cost. Both ϵ_t^b and ϵ_t^i follow an AR(1) process in logs such that $\ln\epsilon_t^b=\rho_b\ln\epsilon_{t-1}^b+\eta_t^b$ and $\ln\epsilon_t^i=\rho_i\ln\epsilon_{t-1}^i+\eta_t^i$ where $\eta_t^b\sim N\left(0,\sigma_b\right)$ and $\eta_t^i\sim N\left(0,\sigma_i\right)$.

2.2 Final Good Assemblers

A perfectly competitive sector of final good assemblers combines the non-technological good and a continuum of varieties of the technological good throughout a Cobb-Douglas production function. Technological goods can be interpreted as patents. By assembling the technological good with a continuum of non-technological goods, the assembler acquires the right to sell to the final consumers one unit of the non-technological good produced with the latest vintage of technology. The amount of final good produced in the economy is equal to:

$$Y_t = \left(\int_0^1 Y_{jt}^{T\,\frac{\varepsilon_T - 1}{\varepsilon_T}} \, dj \right)^{\frac{\alpha_T \varepsilon_T}{\varepsilon_T - 1}} \left(Y_t^{NT} \right)^{1-\alpha_T} \quad (1)$$

To simplify the exposition I define a composite technological good as: $Y_t^T = \left(\int_0^1 Y_{jt}^{T\,\frac{\varepsilon_T - 1}{\varepsilon_T}} \, dj \right)^{\frac{\varepsilon_T}{\varepsilon_T - 1}}$. Similarly, the price of the composite technological good can be thus be computed as: $P_t^T = \left(\int_0^1 P_{jt}^{T\,1-\varepsilon_T} \, dj \right)^{\frac{1}{1-\varepsilon_T}}$ Since every variety of the technological good is priced with a markup upon the non-technological good the latter equation boils down to $P_t^T = \xi P_t^{NT}$, so that $Y_t^T = \alpha_T / \xi (1 - \alpha_T) Y_t^{NT}$. It is now possible to express aggregate output as a linear function of the non-technological good production so that:

$$Y_t = \frac{\alpha_T^{\alpha_T} (\xi - \xi\alpha_T - \alpha_T)^{1-\alpha_T}}{\xi (1 - \alpha_T)} Y_t^{NT} \quad (2)$$

Accordingly, it is possible to express the aggregate price level as a function of the non technological intermediate good price level so that:

$$P_t = \frac{\xi - \alpha_T}{\alpha_T^{\alpha_T} (\xi - \xi\alpha_T - \alpha_T)^{1-\alpha_T}} P_t^{NT} \quad (3)$$

The latter expression implies that, after log-linearization, the inflation rate $\widehat{\pi}_t^{NT}$ in the non-technological goods sector will equal the inflation rate in the final goods sector $\widehat{\pi}_t$, and the aggregate output $\widehat{y}_t^{NT}$ will equal the non technological good output $\widehat{y}_t$.

2.3 Non-Technological Good Producers

Final good producers produce a unit of the non-technological good Y_t using a continuum of i intermediate goods. They maximize profits according to the following objective function:

$$max P_t^{NT} Y_t^{NT} - \int_0^1 P_{it}^{NT} Y_{it}^{NT} \, di$$

$$\text{s.t. } \int_0^1 G \left(\frac{Y_{it}^{NT}}{Y_t^{NT}} ; \epsilon_t^p \right) di = 1$$

In the constraint of the optimization problem, G represents is the Kimball (1995) aggregation function, which guarantees that the demand for the non-technological intermediate good Y_t^{NT} is decreasing in its relative price, while the elasticity of demand is a positive function of the relative price. G has the properties of being strictly increasing and concave, with G(1)=1. The stochastic process ϵ_t^p captures changes in the elasticity of demand which result in a markup shock and follow an AR(1) process such that $\ln \epsilon_t^b = \rho_b \ln \epsilon_{t-1}^b + \eta_t^b$ where $\eta_t^b \sim N(0, \sigma_b)$.

2.4 Non-Technological Goods Intermediate Producers

The non-technological intermediate good is produced by a sector of firms using labour and capital. Since the price of the technological good is homogenous amongst the technological good producers, it is always optimal to adopt the latest vintage of technology, so that all the non-technological goods producers use the same technology A_t:

$$Y_{it}^{NT} = \epsilon_t^u K_t^{\alpha_{NT}} \left(A_t L_t\right)^{1-\alpha_{NT}} \quad (4)$$

The stochastic shock ϵ_t^u captures changes in production efficiency due to changes in capital utilization, which represents the TFP static component. The shock follows an exogenous process such that $\ln \epsilon_t^u = \rho_z \ln \epsilon_{t-1}^u + \eta_t^u$ where $\eta_t^u \sim N\left(0, \sigma_u\right)$. As standard in literature, the intermediate good producers fix prices according to Calvo pricing with partial indexation. Let $\widetilde{P_{it}^{NT}}$ be the newly set price, and $X_{t,s}^p$ a state variable that assumes value 1 when $s = 0$ and value $\Pi_{l=1}^s \pi_{t+l-1}^{\iota_p} \pi_*^{1-\iota_p}$ when $s > 0$, firms optimize prices according to the following objective function:

$$maxE_t \sum_{s=0}^{\infty} \xi_p^s \frac{\beta^s \Xi_t P_t^{NT}}{\Xi_{t+1} P_{t+s}^{NT}} \left[\widetilde{P_{it}^{NT}} \left(\Pi_{l=1}^s \pi_{t+l-1}^{\iota_p}\right) - MC_{t+s}\right] Y_{t+s}^{NT}$$

$$s.t. Y_{i,t+s}^{NT} = Y_{t+s}^{NT} G^{-1} \left(\frac{P_{it}^{NT} X_{t,s}^p}{P_{t+s}^{NT}} \tau_{t+s} \right)$$

Let ξ_p be the probability of being allowed to reoptimize prices, ι_p the price indexation coefficient and $\tau_t = \int_0^1 G' \left(\frac{Y_{it}^{NT}}{Y_t^{NT}}\right) \frac{Y_{it}^{NT}}{Y_t^{NT}} di$, the Calvo pricing scheme implies the following equation for the aggregate price index:

$$P_t^{NT} = \left(1 - \xi_p\right) P_{it}^{NT} G'^{-1} \left[\frac{P_{it}^{NT} \tau_t}{P_t^{NT}}\right] + \xi_p \pi_{t-1}^{\iota_p} \pi^{*1-\iota_p} P_{t-1}^{NT} G'^{-1} \left[\frac{\pi_{t-1}^{\iota_p} \pi^{*1-\iota_p} P_{t-1}^{NT} \tau_t}{P_t^{NT}}\right] \quad (5)$$

2.5 Technological Goods Intermediate Producers

Each of the innovators produces patents by employing one unit of the non-technological good. The assumption of constant elasticity of substitution between technological and non-technological goods implies that each innovator j employs a fixed share $\theta_{NT,j}$ of the non-technological good production in the production of the technological good. The aggregation of the individual shares $\theta_{T,j}$ of the non technological good employed by each innovator j on a continuum from 0 to 1 yields the share of non technological goods output θ_T devoted to the production of the technological good, i.e.:

$$\theta_T = \int_o^1 \theta_{T,j} dj \quad (6)$$

The oligopolistic market structure à la Benigno and Fornaro (2016), in which one innovator emerges as leader in every period for each sector j, implies that each patent will be priced with a markup $\xi > 1$ upon the cost of the final good: $P_{jt}^T = \xi P_t^{NT}$. The innovators' profit thus results to be:

$$\Pi_{jt} = P_{j,t}^T Y_{j,t}^T - \theta_{T,j} P_t^{NT} Y_t^{NT} = \theta_{T,j} \left(\xi - 1\right) P_t^{NT} Y_t^{NT} \quad (7)$$

The innovation probability depends on the amount of R&D expenditure invested by the innovator j normalized by the value of the intermediate good i. When innovating, each innovators develops a new vintage of productive technology $A_{j,t}$. I assume constant returns to the R&D on output ratio and I define Z as the convex R&D investment adjustment cost function, where Z(1)=0 and Z">0:

$$\mu_{jt} = \epsilon_t^j \left(1 - Z\left(\frac{J_{j,t}}{J_{j,t-1}}\right)\right) \frac{J_{j,t}}{Y_{j,t}^T} \quad (8)$$

By normalizing R&D investment by output in the innovation probability function, I rule out the R&D scale effect[2]. Furthermore, I introduce a shock to R&D investment adjustment cost ϵ_t^j, which follows an AR(1) process such that $\ln \epsilon_t^u = \rho_z \ln \epsilon_{t-1}^u + \eta_t^u$. Free access to research and development implies that the marginal cost of an investment in research and development is equal to the expected return of becoming a leader in period t+1:

$$J_{jt} = \mu_{jt} \frac{\Xi_{t+1}}{\Xi_t} E_t V_{t+1} \left(\Pi_{j,t+1}\right) \quad (9)$$

With some algebra, the no-arbitrage condition yields the optimal amount of R&D investments for the innovator j:

$$1 = \theta_{T,j} \left(\xi - 1\right) E_t \left(\frac{\Xi_{t+1}}{\Xi_t}\right) \frac{E_t Y_{t+1}^{NT}}{Y_{j,t}^T} \epsilon_t^j \left(1 - Z\left(\frac{J_{j,t}}{J_{j,t-1}}\right)\right) \qquad (10)$$

Being the firms symmetric, every firm will invest the same amount in R&D. This allows us to determine the aggregate level of R&D investment, where ϱ is a parameter that captures the degree of non-linearity of the R&D investment adjustment cost function:

$$\frac{J_t}{J_{t-1}} = \left(1 - \frac{1}{\theta_T(\xi-1)} \frac{Y_t}{\epsilon_t^j (E_t \Xi_{t+1}/\Xi_t) E_t Y_{t+1}}\right)^{1/\varrho} \quad (11)$$

By the law of large numbers, a fraction μ_t of innovators innovates at every period. This implies that a share μ_t of intermediate producers will achieve a gain of productivity γ_a and ϵ_t^a is a shock to the innovation step - while the non-innovating sectors will maintain the productivity level of the previous period. The technological component of TFP will thus evolve according to the following law:

$$A_{t+1} = (1 - \mu_t) A_t + \mu_t \left(1 + \gamma_a \epsilon_t^a\right) A_t \quad (12)$$

The shock the innovation step ϵ_t^a is a random shock that captures fluctuations in the difference between the productivity level in t and t+1 and can be represented by an AR(1) process in logs so that $\ln \epsilon_t^a = \rho_z \ln \epsilon_{t-1}^a + \eta_t^a$. The growth path of TFP's structural component will thus by defined by this simple rule:

$$\frac{A_{t+1}}{A_t} = 1 + \gamma_a \epsilon_t^a \mu_t \quad (13)$$

2.6 Labour Unions and the Labour Packer

As standard in literature a labour union sets wages and sells labour to the labour packer. The labour packer acquires the differentiated labour services from the workers' union and supplies labour to the non-technological intermediate good producers by maximizing the following objective function:

$$max W_t L_t - \int_o^1 W_{it} L_{it} \, di$$

$$s.t. \left[\int_0^1 H\left(\frac{L_{it}}{L_t}; \epsilon_t^w\right) di\right] = 1$$

W_t and W_{it} are the prices of the composite and the intermediate labour, and H is the Kimball aggregator, strictly increasing and concave with H(1)=1. The stochastic process ϵ_t^w captures changes in the elasticity of

[2] *For a discussion of R&D scale effect in endogenous growth models literature, see Jones* (1995)

demand for labour which result in a wage markup shock and follows an exogenous process such that $\ln \epsilon_t^w = (1-\rho_w)\ln \epsilon^b + \rho_w \ln \epsilon_{t-1}^b + \theta_w \eta_{t-1}^b + \eta_t^b$ where $\eta_t^w \sim N(0,\sigma_b)$. Let $\widetilde{W_{it}^{NT}}$ be the newly set price, and $X_{t,s}^w$ a state variable that assumes value 1 when $s=0$ and value $\Pi_t^s = \pi_{t+l-1}^{\iota_w}\pi * w_t^{1-\iota}$ when $s>0$, the labour unions optimization problem under Calvo prices with partial indexation assume the following formulation:

$$maxE_t \sum_{s=0}^{\infty} \xi_w^s \frac{\beta^s \Xi_t W_t}{\Xi_{t+1} W_{t+s}} \left[\widetilde{W_{it}} \left(\Pi_{l=1}^s \gamma \pi_{t+l-1}^{\iota_w}\right) - W_{t+s}^h\right] L_{t+s}$$

$$s.t. L_{t+s,i} = L_{t+s} H'^{-1} \left(\frac{W_{it} X_{t,s}^w}{W_{t+s}} \tau_{t+s}^w\right)$$

Let ξ_p be the probability of being allowed to reoptimize wages, ι_w the indexation coefficient the resulting aggregate wage index is:

$$W_t = (1-\xi_w)\widetilde{W}_t H'^{-1}\left[\frac{W_{it}\tau_t^w}{W_t}\right] + \xi_w \gamma \pi_{t-1}^{\iota_w} \pi *^{1-\iota_p} W_{t-1} H'^{-1}\left[\frac{\gamma \pi_{t-1}^{\iota_w} \pi^{1-\iota_w} * W_{t-1}\tau_t^w}{W_t}\right] \quad (14)$$

2.7 Government Policies

As standard in literature, the central bank follows a nominal interest rate rule in order to stabilize output and inflation, such that:

$$\frac{R_t}{R^*} = \left(\frac{R_{t-1}}{R^*}\right)^{\rho_R} \left[\left(\frac{\pi_t}{\pi^*}\right)\left(\frac{Y_t}{Y_t^*}\right)\right]^{1-\rho_R} \left(\frac{Y_t/Y_{t-1}}{Y_t^*/Y_{t-1}^*}\right)^{\psi} \epsilon_t^r \quad (15)$$

The stochastic process ϵ_t^r captures the monetary policy shock and follows an exogenous process such that $\ln \epsilon_t^r = \rho_r \ln \epsilon_{t-1}^r + \eta_t^r$ where $\eta_t^b \sim N(0,\sigma_b)$. The government budget constraint is expressed as:

$$P_t G_t + B_{t-1} = T_t + \frac{B_t}{R_t} \quad (16)$$

Government spending as a ratio of the steady-state output $\epsilon_t^g = \frac{G_T}{Y\gamma^t}$ is a random shock which captures the impact of fiscal policy shock and can be described with $\ln \epsilon_t^g = \rho_g \ln \epsilon_{t-1}^g + \rho_{ga} \ln \epsilon_t^a + \eta_t^g$ where $\eta_t^g \sim N(0,\sigma_g)$.

2.8 Aggregate Resource Constraints

Finally, the aggregate resource constraint assures that the amount of resources produced in the economy equals the total amount of resources demanded by the agents:

$$Y_t = C_t + I_t + J_t + G_t + a(u_t)\bar{K}_{t-1} \quad (17)$$

3. Econometric Approach

I detrend the model by stationarizing all the nominal variables by the structural component of total factor productivity A_t, I solve the model by computing a first-order approximate solution around its deterministic steady state, and finally I estimate the model using Bayesian methods. To decompose the static and the structural component of TFP growth, I compute the Solow Residuals in log differences as follows:

$$\frac{TFP_t}{TFP_{t-1}} = \frac{\epsilon_t^u}{\epsilon_{t-1}^u}\left(\frac{A_t}{A_{t-1}}\right)^{1-\alpha} \quad (18)$$

The first term, $\frac{\epsilon_t^u}{\epsilon_{t-1}^u}$ represents the component of TFP fluctuations due to changes in the efficiency of the utilization of physical capital, while $\frac{A_t}{A_{t-1}}$ represents the component of TFP gains determined by the process of technological advancement. I will refer to the first component as the static component of TFP, and to the second one as the structural component of TFP. The model is estimated using quarterly data from the US economy from 1984q2 to 2007q2. Further analysis, i.e. shock decomposition and forecasting power comparison is conducted on the sample 2007q3 - 2016q4 using previously estimated parameters. This expedient allows us to circumvent the limitations implied by the Zero Lower Bound during the period 2007q3 – 2016q4. The database is composed by 9 time series from 1984q2 to 2016q4: real GDP, consumption, investment, hours worked, real wages, prices, interest rate and investment in R&D and TFP. The database is constructed following the approach of Smets and Wouters (2007), with the exception of R&D, TFP and interest rates data. GDP, consumption, physical capital investment, and R&D are extracted from the Bureau of Economic Analysis database. Consumption and investment are normalized by the GDP deflator. Inflation is computed as the first difference of the log of the GDP deflator. Hours worked and real wages are extracted from the Bureau of Labour Statistics database for the Non-Farm Business Sectors. Hours worked are normalized for the civilian employment. Real wages are obtained by deflating nominal wages by the GDP price deflator. Aggregate variables are normalized by the working age population over 16. Total Factor Productivity is measured throughout the utilization adjusted TFP series from the database of the Federal Reserve of San Francisco. Instead of using the standard Federal Funds Rate, I estimate the model by using the Wu-Xia (2015) Shadow Rate, that takes into account unconventional monetary policy measures and has the advantage of not being constrained at the ZLB with respect to the Federal Funds rate. Since I estimate the model on 1984q2 - 2007q2 data, during the Great Recession the central bank operates with the pre-crisis Taylor Rule. The use of the Wu-Xia Shadow Rate does not imply any modification for the parameter estimates, theoretical moments and contemporaneous cross-correlations, since in absence of unconventional monetary policies its value coincides with that of the Federal Funds Rate. By contrast the Wu-Xia Shadow Rate it is more informative with respect to the credit market conditions at the ZLB during the forecasting exercise and allows for a more realistic historical decomposition analysis. In particular, I show that by decomposing shock contributions on the ZLB period with previously estimated parameters, the ‘missing deflation’ puzzle[3] disappears. The historical decomposition shows that a strong monetary policy shock - i.e. the Federal Reserve Quantitative Easing program - is sustaining the price level during the crisis period[4]. As standard in the literature, I calibrate one subset of parameters and I estimate the remainder. Concerning the choice of the subsets of calibrated and estimated parameters, and the prior distribution of the parameters, my approach does not significantly differ from Smets and Wouters (2007). The only extra estimated parameter I introduce is ϱ, i.e. the degree of non-linearity of the R&D adjustment cost function, which I set as quadratic in the priors. The vast majority of the parameters is estimated. The only calibrated parameters are the physical capital stock quarterly depreciation rate δ=0.025, the steady-state government spending to GDP ratio (G/Y)*=0.18, the steady-state R&D investment to GDP ratio (J/Y)*=0.038, the steady-state wage mark-up of the labour union h_{w}=1.5, and the curvature of the Kimball aggregator for the non-intermediate goods and the

[3]For a detailed discussion of the missing deflation puzzle, see Lindé, Smets and Wouters (2016)

[4]This finding is not strictly related to the introduction of the endogenous TFP channel as it also holds in absence of an endogenous TFP mechanism

labour market, which are both set to 10. Prior distributions are standard and wide, in order to let the data have the biggest say. In Table 1, I present the estimates for the structural parameters. The estimates are generally consistent with the literature. Furthermore, I obtain that R&D investment adjustment costs are approximately quadratic. In Table 2, I present the estimates for the shock processes parameters. Static and structural TFP shocks, government spending shocks, price and wages mark-up shocks results being highly persistent, while the risk premium, physical capiral and R&D investment specific technology shock, and the monetary policy shock are less persistent. Most volatile shocks are the R&D investment specific technology shock and the structural TFP shock. The price mark-up and monetary policy shock are the least volatile shocks. All the parameters estimates present a high degree of significance.

TAB. 1 - ESTIMATES OF THE STRUCTURAL PARAMETERS

Parameter	Prior Mean	Prior StDev	Distribution	Posterior Mode	Pst StDev
ψ	4.00	1.50	NORMAL	5.93	0.96
ϱ	2.00	1.00	NORMAL	2.08	0.34
σ	1.50	0.375	NORMAL	1.34	0.12
h	0.70	0.10	NORMAL	0.69	0.05
ξ_p	0.50	0.10	BETA	0.66	0.06
ξ_w	0.50	0.10	BETA	0.53	0.07
σ_l	2.00	0.75	NORMAL	1.87	0.49
ι_w	0.50	0.15	BETA	0.48	0.17
ι_p	0.50	0.15	BETA	0.36	0.15
α	0.30	0.05	NORMAL	0.27	0.02
z	0.50	0.05	BETA	0.91	0.04
Φ	1.25	0.15	NORMAL	1.77	0.08
$\rho_{r\pi}$	1.50	0.125	NORMAL	2.16	0.19
ρ_{rr}	0.75	0.25	BETA	0.82	0.03
ρ_{ry}	0.125	0.10	NORMAL	0.03	0.02
ρ_{rdy}	0.125	0.05	NORMAL	0.10	0.03
g	0.50	0.10	NORMAL	0.54	0.11

TAB. 2 - ESTIMATES OF SHOCK PROCESSES PARAMETERS

Parameter	Prior Mean	Prior Stdev	Distribution	Posterior Mode	Pst StDev
ρ_{u}	0.50	0.20	BETA	0.95	0.02
ρ_{b}	0.50	0.20	BETA	0.40	0.11
ρ_{g}	0.50	0.20	BETA	0.90	0.02
ρ_{qs}	0.50	0.20	BETA	0.55	0.10
ρ_{m}	0.50	0.20	BETA	0.50	0.08
ρ_{π}	0.50	0.20	BETA	0.88	0.05
ρ_{w}	0.50	0.20	BETA	0.92	0.03
ρ_{x}	0.50	0.20	BETA	0.47	0.06
ρ_{a}	0.50	0.20	BETA	0.95	0.01
σ_{u}	0.10	2.00	INV GAMMA	0.38	0.04
σ_{b}	0.10	2.00	INV GAMMA	0.22	0.02
σ_{g}	0.10	2.00	INV GAMMA	0.42	0.03
σ_{inv}	0.10	2.00	INV GAMMA	0.41	0.05
σ_{m}	0.10	2.00	INV GAMMA	0.10	0.02
σ_{π}	0.10	2.00	INV GAMMA	0.09	0.01
σ_{w}	0.10	2.00	INV GAMMA	0.28	0.04
σ_{x}	0.10	2.00	INV GAMMA	1.15	0.25
σ_{a}	0.10	2.00	INV GAMMA	1.17	0.09

4. Assessing the Impact of the Endogenous TFP Mechanism

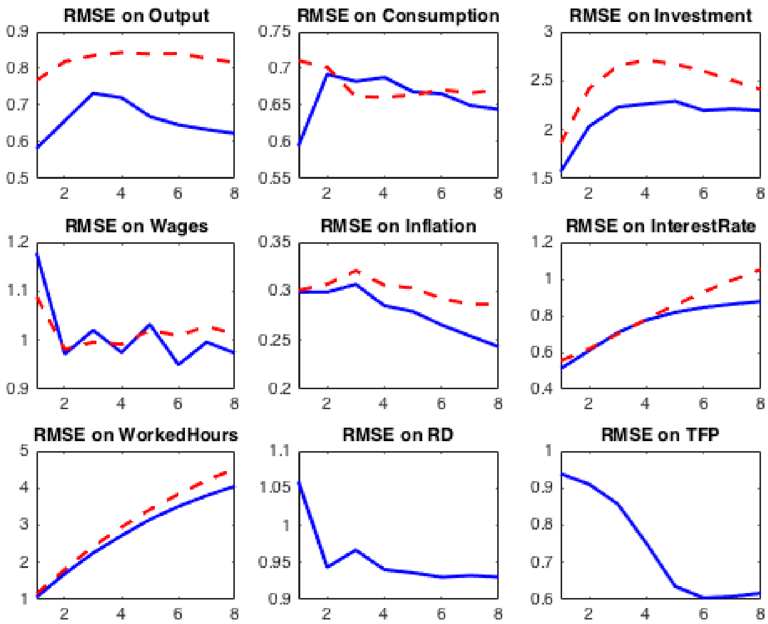
In Table 3 I report the theoretical business cycle moments implied by the model described in Section 2. I compare the implied theoretical models with the theoretical models implied by a benchmark exogenous TFP model and the empirical models implied by the data from the pre-crisis period (1984q2 - 2007q2) and from the complete sample (1984q2 - 2016q4). Endogenous TFP increases the volatility, but decreases the mean of all the considered variables. Overall, the theoretical moments implied by the model are fairly consistent with those implied by the data. Additionally, I show that, while the exogenous TFP model better approximates the empirical moments implied by the pre-crisis sample, the endogenous TFP model better approximates the empirical moments implied by the full sample. Nevertheless, the model tends to attribute an excessive volatility to TFP with respect to the data. In Figure 2 I report the Root Mean Squared Error (RMSE) for the forecasts computed on the Great Recession and its Aftermath (2007q2-2016q4) sample using previously estimated parameters. The choice of using previously estimated parameters allows us to avoid the ZLB estimation bias and allows for a greater parameters' stability. The endogenous TFP model's RMSE is represented by the blue solid line, while the exogenous TFP model's RMSE is represented by the red dashed line. On the horizontal axis I represent the forecasting horizon, expressed in quarters. I test the forecasting power of the model from 1 to 8 periods. The endogenous TFP model is shown to better predict output, inflation, interest rate and hours worked at every forecast horizons, while there is no clear winner for consumption and wages. Additionally, the model is able to predict R&D Expenditure and Total Factor Productivity series with good approximation. The results of the forecasting exercise suggest that the additional information brought by the R&D and the TFP series in the endogenous TFP model estimation allows to improve the forecasting power of standard models on the Great Recession.

In the Appendix, I show the impact of the introduction of the endogenous TFP mechanism for the impulse response functions of the model. The solid blue line represents the dynamic response for the endogenous TFP model, while the dashed red line represents the exogenous TFP benchmark model. For each observable, both impulse response functions are computed for 0.1 standard deviations wide shocks. From the comparison of the two dynamic responses, it is possible to infer the impact of the endogenous TFP channel on the impulse response functions. Some non-trivial results emerge. The response in terms of TFP is not always procyclical. This result is mostly due to the denominator effect in the R&D on output ratio, which determines the innovation probability. When the economy is affected by a random shock, both output and R&D respond. Importantly, the contraction of R&D does not always imply a contraction in TFP. Since TFP is determined by the R&D on output ratio throughout the innovation probability, if both output and R&D contract, but output shrinks more than R&D, R&D on output ratio will increase, hence TFP will rise. R&D adjustment cost in this sense plays a very important role, by constituting the major source of R&D inertia. When TFP response is procyclical, the endogenous TFP channel will thus amplify the fluctuations driven by stochastic shocks, viceversa when TFP reaction is anticyclical, endogenous TFP is smoothing the economy's fluctuations. Namely, I obtain that the static TFP shock, the structural TFP shock, the prices and wages mark-up shocks, the monetary policy shock, and the R&D investment technology shock boost TFP growth, while the risk premium shock and the investment specific technology shock contract TFP.

TAB.3 - THEORETICAL VS. EMPIRICAL MOMENTS

	Endogenous TFP		Exogenous TFP		Data (1984q2-2007q2)		Data (1984q2-2016q2)	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Output	0,29	0,90	0,42	0,73	0,52	0,54	0,38	0,61
Consumption	0,29	0,72	0,42	0,51	0,60	0,51	0,45	0,60
Investment	0,29	1,75	0,42	1,69	0,55	1,46	0,27	1,84
Hours Worked	0,10	2,35	0,93	2,02	1,40	2,08	-0,85	4,10
Inflation	0,55	0,38	0,59	0,30	0,61	0,23	0,55	0,24
Wages	0,29	0,95	0,42	0,74	0,39	0,68	0,33	0,83
Interest Rate	1,12	0,41	1,32	0,37	1,32	0,60	0,98	0,75
R&D	0,29	0,85	/	/	0,37	0,83	0,36	0,90
TFP	0,29	1,31	/	/	0,29	0,58	0,23	0,61

FIG.2 - FORECASTING POWER COMPARISON (2007Q2-2016Q4)



On the y-axis: Root Mean Square Forecast Error for output (at the top left), consumption, investment, wages, inflation, interest rate, hours worked and R&D (on the bottom right). On the x-axis: forecasting horizon. Solid line represents RMSE for forecasts computed on 2007q3-2016q4 with the baseline SW (2007) model, dashed line represents RMSE on the same sample for forecasts computed with the model described in Section 2. Forecasts for both models are computed using previous parameters estimates (on 1984q2-2007q2).

5. The Sources of Fluctuations in Endogenous TFP Models

The introduction of endogenous TFP also allows to shed light on the sources of the TFP slowdown during the Great Recession and its Aftermath (2007q3-2016q4). In Tab.4 I show the Unconditional Variance Decomposition analysis for the 9 observed variables. As in standard models, risk premium and investment specific technology shocks are key drivers of the economic fluctuations. Additionally, structural TFP, government spending and R&D investment technology shocks are amongst the most important driver of the business cycle. Monetary policy shocks have a modest effect, but they have a powerful effect on inflation. This result is in large part due to the effect of the Quantitative Easing program in sustain of the price level during the Great Recession, as I will show during the Historical Decomposition. In Tab. 5 I show the Conditional Variance Decomposition analysis for TFP. The shocks in the first two columns of the table represent TFP's exogenous component. Overall, by aggregating the static and the structural TFP components contributions, exogenous TFP shocks account for the 65% of the productivity fluctuations. This suggests that data do not reject the endogenous TFP hypothesis, since the 35% of TFP fluctuations are generated by the endogenous TFP mechanism. Furthermore, although I do not show it in the paper, if one allows for a non-linear innovation probability with wide priors, the estimated coefficient is close to 1. In other words, the data suggest the presence of a linear relationship in terms of R&D/output to TFP, despite the Bayesian estimation setup leaves the data free to suppress the endogenous TFP channel by setting the posterior equal to 0. Finally, in the Appendix I show the results of the Historical Decomposition of the observed variables. Several findings emerge. First, the R&D efficiency shock is identified as the main driver of the TFP slowdown during the Great Recession and its Aftermath. Throughout the effect of the endogenous TFP transmission channel, the R&D efficiency shock propagates to all the other variables. Hours worked and interest rates are severely affected by the endogenous TFP channel. As in standard models, the risk premium shock is the main responsible of the sharp 2008-2009 output and consumption contraction, while the investment efficiency shock is the main responsible of the investment contraction. Finally, the introduction of the Wu-Xia (2016) Shadow Rate allows us to solve the missing deflation puzzle. In standard DSGE as Smets and Wouters (2007) unrealistic price mark-up shocks sustaining the price level are typically identified by the models to justify the absence of a sharp deflation during the Great Recession. By making use of the Wu-Xia (2016) Shadow Rate this anomaly disappears. As I show in the inflation historical decomposition, the estimates indicate that a strong monetary policy shock is sustaining the price level during the Great Recession. These results suggest that the Quantitative Easing Program of the Federal Reserve was highly effective in sustaining the price level during the ZLB binding period.

TAB.4 - UNCONDITIONAL VARIANCE DECOMPOSITION

	Struct TFP	Static TFP	Risk Pr	Govt Spend	Inv Tech	Mon Pol	Price Markup	Wage Markup	R&D Tech
GDP	23.82	4.73	18.12	17.88	12.07	3.07	2.54	1.15	16.62
Cons	9.79	2.10	43.19	2.39	1.30	10.87	5.62	6.65	18.08
Inv	23.82	0.24	5.83	3.61	51.91	1.35	3.07	0.48	9.71
Labour	20.83	9.83	6.07	2.86	9.23	4.65	9.07	15.79	21.66
Inflation	9.47	2.30	1.91	1.54	5.02	27.54	28.23	17.47	6.51
Wages	13.46	0.88	3.20	1.13	1.95	5.35	11.87	45.54	16.61
IntRate	17.93	5.97	5.51	3.03	12.21	8.35	12.34	12.51	22.15
R&D	5.73	0.91	5.72	1.52	1.88	5.04	2.27	1.34	75.59
TFP	52.65	12.30	3.85	2.66	4.00	3.60	2.87	2.16	15.91

6. Concluding Remarks

In this paper I develop a New Keynesian Dynamic Stochastic General Equilibrium model featuring a creative destruction based mechanism of endogenous TFP growth. I estimate the model with U.S. data (1984q2-2007q2) using Bayesian methods, and I use the estimated parameters to perform several empirical exercises on the Great Recession and its Aftermath (2007q2-2016q2). I show the model to empirically outperform a benchmark version of the model that does not feature an endogenous TFP channel in a forecasting exercise with previously estimated parameters during the Great Recession. Additionally, the theoretical moments implied by the estimates of the model are fairly consistent with the empirical moments. The variance decomposition analysis suggests that the 35% of the productivity fluctuations of the economy are endogenous. Consistently with Bianchi and Kung (2014), the analysis highlights the role of R&D investment efficiency shocks in driving the endogenous component of TFP fluctuations during the Great Recession and its Aftermath. Finally, I show that the introduction of the creative destruction mechanism has non-trivial effect on the impulse response functions and can exacerbate or smooth the dynamic responses to adverse shocks according to TFP behaviour. The analysis raises a number of considerably relevant questions concerning the optimal policies to adopt under endogenous TFP determination assumptions. In particular, further research is needed to understand how monetary policy should react to counter adverse shocks affecting the productivity level and the implication of the presence of an endogenous TFP channel on the optimal inflation target. I hope that this paper contributed to highlight the salience of incorporating endogenous productivity dynamics in General Equilibrium models and provided tools for a better understanding of the causes of the post-crisis productivity slowdown.

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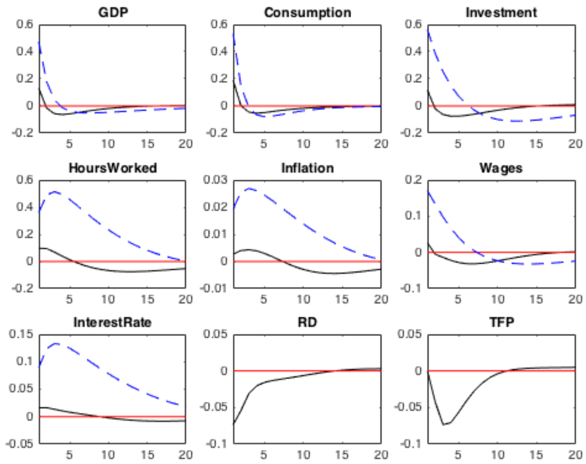
Appendix

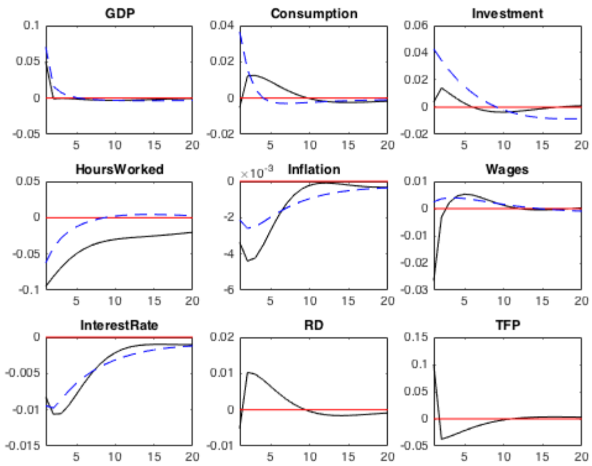
A. Impulse Response Functions

Solid Black line = Endogenous TFP, Dashed Blue Line = Exogenous TFP

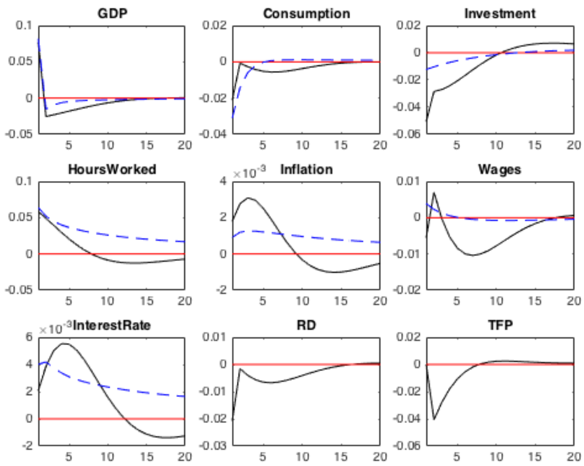
DYNAMIC RESPONSE TO A RISK PREMIUM SHOCK



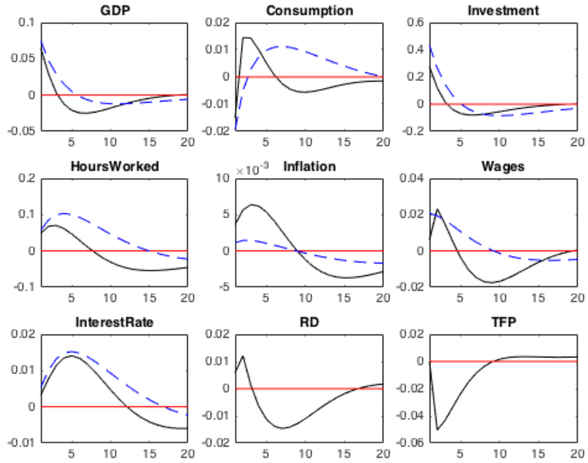
DYNAMIC RESPONSE TO A STATIC TFP SHOCK



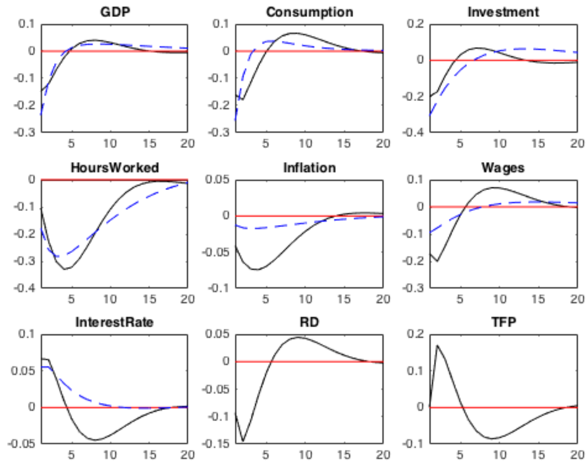
DYNAMIC RESPONSE TO A GOVERNMENT SPENDING SHOCK



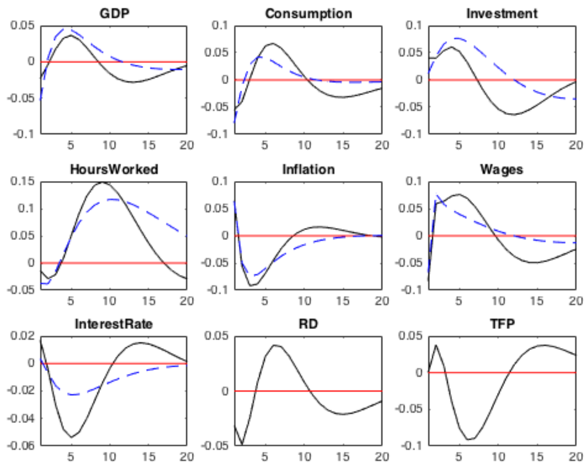
DYNAMIC RESPONSE TO AN INVESTMENT SPECIFIC TECHNOLOGY SHOCK



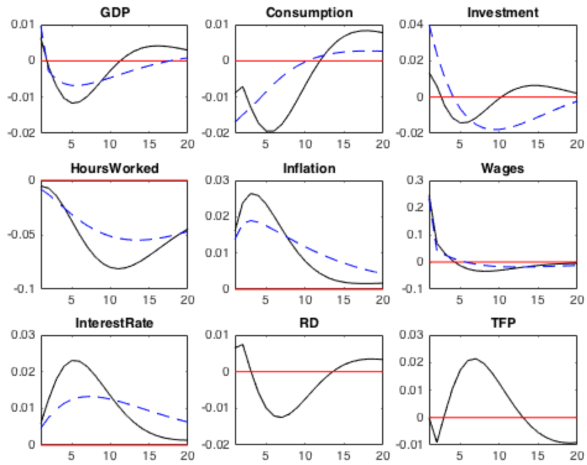
DYNAMIC RESPONSE TO A MONETARY POLICY SHOCK



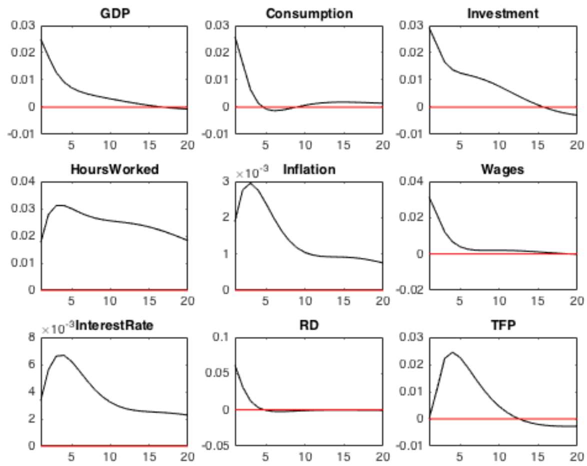
DYNAMIC RESPONSE TO A PRICE MARK-UP SHOCK



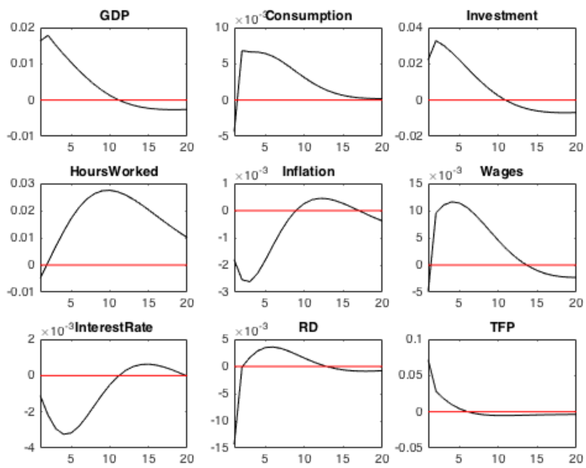
DYNAMIC RESPONSE TO A WAGE MARK-UP SHOCK



DYNAMIC RESPONSE TO A R&D INVESTMENT TECHNOLOGY SHOCK



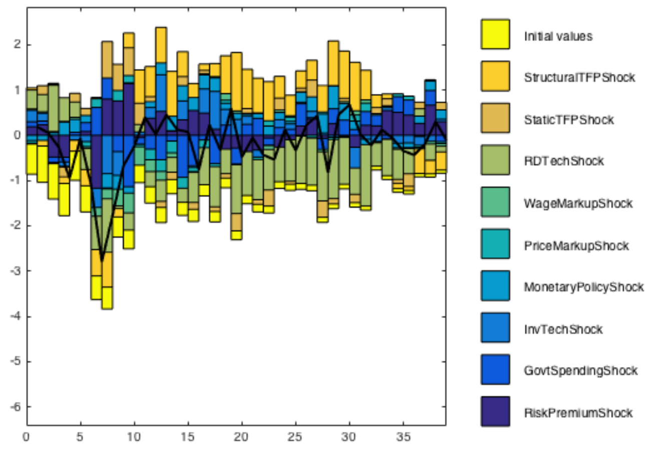
DYNAMIC RESPONSE TO A STRUCTURAL TFP SHOCK



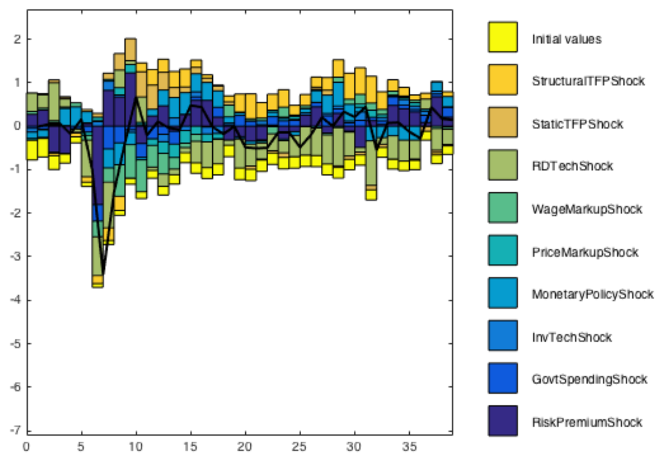
B. Historical Decomposition of the Observed Variables

during the Great Recession and its Aftermath (2007q3 – 2016q4)

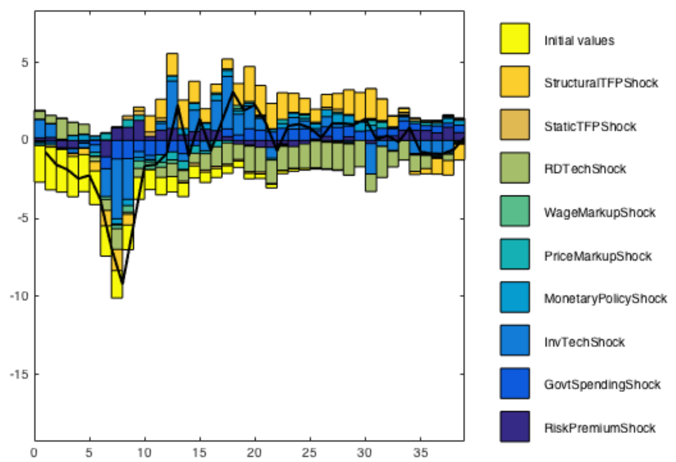
OUTPUT HISTORICAL DECOMPOSITION (1=2007Q3 - 38=2016Q4)



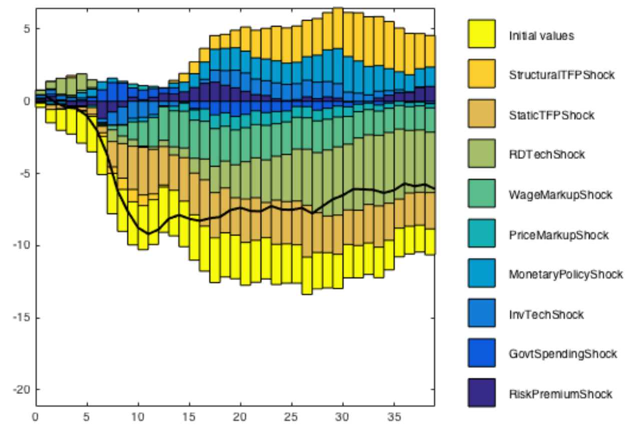
CONSUMPTION HISTORICAL DECOMPOSITION (1=2007Q3 - 38=2016Q4)



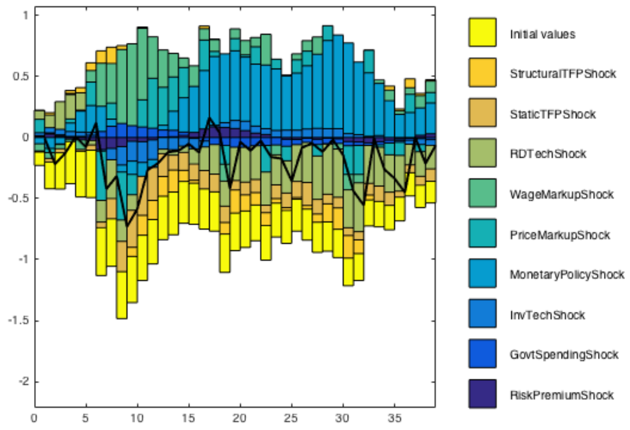
INVESTMENT HISTORICAL DECOMPOSITION (1=2007Q3 - 38=2016Q4)



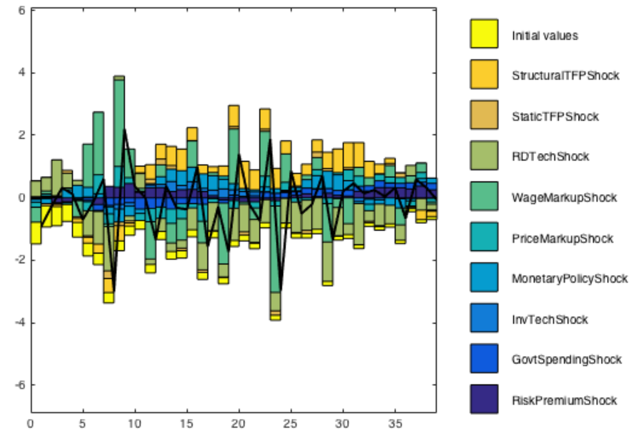
HOURS WORKED HISTORICAL DECOMPOSITION (1=2007Q3 - 38=2016Q4)



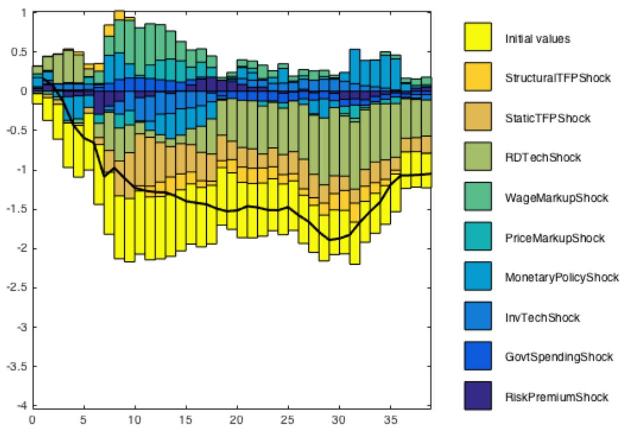
INFLATION HISTORICAL DECOMPOSITION (1=2007Q3 - 38=2016Q4)



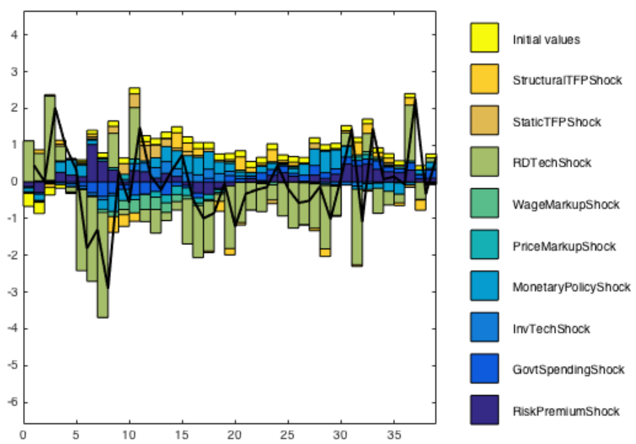
WAGES HISTORICAL DECOMPOSITION (1=2007Q3 - 38=2016Q4)



INTEREST RATES HISTORICAL DECOMPOSITION (1=2007Q3 - 38=2016Q4)



R&D HISTORICAL DECOMPOSITION (1=2007Q3 - 38=2016Q4)



TFP HISTORICAL DECOMPOSITION (1=2007Q3 - 38=2016Q4)