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Endogenous TFP, business cycle persistence and the productivity slowdown in the euro area

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Abstract

This paper analyses the endogeneity of euro area total factor productivity and its role in business cycle amplification by estimating a medium-scale DSGE model with endogenous productivity mechanism on euro area data. In this framework, total factor productivity evolves endogenously as a consequence of costly investment in R&D and adoption of new technologies. We find that the endogeneity of TFP induces a high degree of persistence in the euro area business cycle via a feedback mechanism between overall economic conditions and investment in productivity-enhancing technologies. As to the sources of the euro area productivity slowdown, we conclude that a decrease in the efficiency of R&D investment is among the key factors generating the pre-crisis productivity slowdown, while starting from the Great Recession a shock to liquidity demand is identified as the most important driving force. The endogenous technology mechanism further exerts a dampening effect on the inflation response following a recessionary shock and hence has important implications for both the negligible fall in inflation during the Great Recession, as well as the sluggish increase of inflation in the subsequent recovery.

JEL Classification: E24, E32, O31

Keywords: Endogenous Productivity, Euro Area Business Cycles, Weak Growth, Low Inflation

Non-technical summary

The pre-crisis macroeconomic paradigm focused on short-term fluctuations around a given, predetermined trend in which technological progress is not explicitly modelled but instead evolves purely exogenously in the form of a technology shock. However, the experience of advanced economies starting from the financial crisis, characterized by a deep and highly persistent recession, slowing productivity growth and sluggish inflation, challenged existing modelling approaches. This experience highlighted, among others, the need for macroeconomic frameworks capable of making statements about the drivers of technological progress and productivity growth in a macroeconomic general equilibrium setting. This paper follows this approach by estimating a medium-scale DSGE model with an endogenous total factor productivity mechanism, as initially proposed by Anzoategui, Comin, Gertler and Martinez (2018) on euro area data to investigate the causes of the persistence of the Great Recession in the euro area and the drivers of the euro area productivity slowdown.

We show that accounting for endogenous total factor productivity dynamics through productivity-enhancing investments in R&D and technology adoption considerably increases the persistence of the euro area business cycle relative to standard macroeconomic frameworks in which TFP evolves purely exogenously. Moreover, we demonstrate that the endogenous part of total factor productivity is empirically of substantial magnitude and accounts for a large share of overall TFP in the euro area. Our findings point out that euro area TFP evolves clearly procyclically as it tends to increase in upswings and to fall in downturns.

As to the development of euro area TFP over time, we show that the productivity slowdown has commenced already before the Great Recession. Starting from the Great Recession, we document a pronounced further deceleration of productivity growth. Regarding the central factors driving the euro area productivity slowdown, we demonstrate that in the pre-crisis phase, a drop in R&D efficiency constitutes a main driving force. Since the Great Recession, the liquidity demand shock, which depresses consumption relative to safe asset holdings and the resulting fall in firms' technology adoption represents the most important influencing factor. In sharp contrast to standard macroeconomic models in which the supply-side evolves strictly distinct from demand-side fluctuations, this result underlines the relevancy of demand shocks in explaining the evolution of the supply-side in the euro area. We observe starting from 2015 a gradual improvement in the endogenous part of total factor productivity as a consequence of generally improving economic conditions. The observed reduced efficiency of R&D investment in producing new innovations, however, constitutes a drag on euro area TFP going forward.

Lastly, accounting for endogenous productivity dynamics features important inflation implications as the endogenous TFP mechanism dampens the inflation response over the business cycle and thus helps in explaining both the negligible drop in euro area inflation during the Great Recession vis-à-vis a marked fall in output and the rather slow pickup during the post-crisis expansion.

1 Introduction

The recent recessions in the euro area were characterized by a severe and highly persistent output drop. Figure 1 demonstrates the marked fall in euro area real GDP starting from 2008. The persistence of the fall in output is striking as euro area GDP returned to pre-crisis levels only in 2015. In addition to the depth and severity of the recessions and the corresponding extent of business cycle persistence, the euro area experienced simultaneously a substantial slowdown in productivity. Figure 2 illustrates the evolution of hourly labor productivity in the euro area and shows that, while productivity growth had started to stagnate already in the pre-crisis phase, labor productivity fell drastically during the Great Recession. In the subsequent recovery, in turn, labor productivity has started to improve again, in line with general improving economic conditions. That given, the observed drop in labor productivity has been highly persistent and remains at this stage still below its pre-crisis trend.

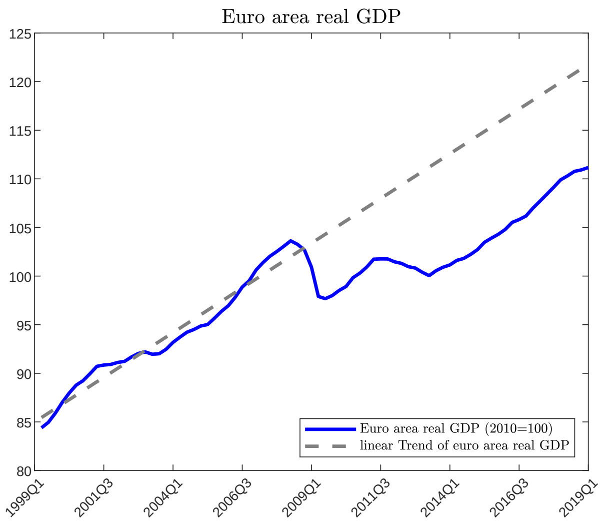

Figure 1: Real GDP in the euro area; index (2010=100); source: Eurostat

This observed depth and persistence of the Great Recession and the prevalent slowdown in productivity in the euro area as well as other advanced economies have spurred theoretical studies, which explicitly model the evolution of productivity dynamics in macroeconomic models. More specifically, these frameworks take into account that, in contrast to the standard assumption in macroeconomic models, total factor productivity may not evolve purely exogenously driven only by standard technology shocks, but is instead subject to procyclical fluctuations and can thus constitute an important source of business cycle amplification. The procyclical nature of TFP has gained further attention in the context of the sluggish inflation response in the recent expansion, which has raised, among others, discussions on the appropriate assessment of the output gap following a deep recession (see Coibion, Gorodnichenko and Ulate (2017)), as well as potential driving forces counteracting inflationary pressures.

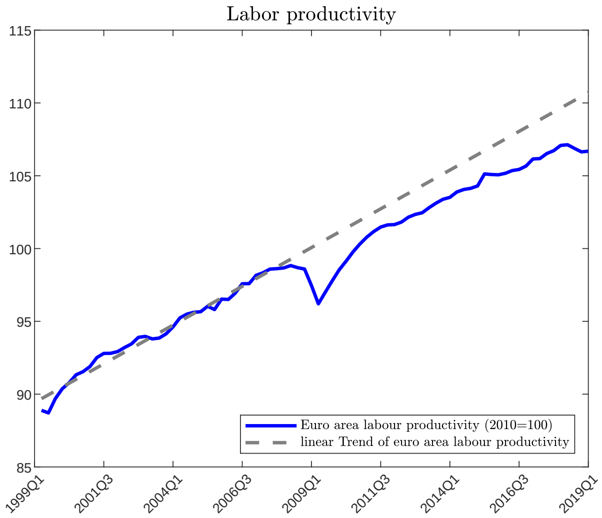

Figure 2: Hourly labor productivity in the euro area; index: 2010=100; source: Eurostat

Anzoategui, Comin, Gertler and Martinez (2018) provide a central contribution in the analysis of the procyclicality of total factor productivity and its role in business cycle amplification in the US economy. The underlying model framework constitutes the theoretical backbone of our model-based analysis of the depth of the recent recessions and the key drivers of the productivity slowdown observed in the euro area. The key insights by Anzoategui et al. (2018) can be summarized as follows. The study provides empirical evidence on the procyclical evolution of total factor productivity and its key driving forces research and development and technology adoption. Moreover, drawing on this evidence, they propose a medium-scale estimated DSGE model in the spirit of Smets and Wouters (2007), which features an endogenous total factor productivity mechanism. Hence, as opposed to standard macroeconomic models, total factor productivity is not limited to evolve purely exogenously in the form of a technology shock only, but instead evolves endogenously as the result of costly R&D investment and technology adoption. Anzoategui et al. (2018) show that taking into account the procyclicality of total factor productivity gives rise to a powerful mechanism of business cycle amplification capable of explaining the depth and persistence of the Great Recession in the US. Furthermore, the richness of the theoretical model permits the analysis of the central driving forces behind the US productivity slowdown, where the diminished efficiency of R&D investment is identified as the key source of slowdown in US productivity in the pre-crisis phase. In the period following the Great Recession, by contrast, the shock to liquidity demand, which favors safe asset holdings at the expense of consumption, emerges as the most important driver of the slowdown in US total factor productivity growth.

While the existing literature on the endogeneity of total factor productivity in macroeconomic models focuses on the US, evidence on the euro area is scarce. To shed light on the degree of procyclicality of euro area total factor productivity, its role in generating business cycle persistence and deep recessions, as well as the key drivers of the observed productivity slowdown, we estimate a medium-scale DSGE model with endogenous TFP mechanism as proposed by Anzoategui et al. (2018) on euro data. In doing so we provide insights in particular on the following central questions. Firstly, we investigate the nature of the euro area productivity slowdown as well as its key driving forces. We further provide empirical insights on the question to what degree total factor productivity in the euro area fluctuates procyclically over the business cycle. A crucial question addressed by our research centers around the feedback mechanism between the evolution of TFP on the one hand and overall economic conditions on the other hand and the role it accrues in explaining the severity and persistence of the recent euro area recessions. Lastly, based on our findings, we provide an outlook on the future revolution of euro area total factor productivity and its implications for the future dynamics of euro area GDP.

The central findings of this paper can be summarized as follows. Firstly, our results suggest that the endogenous modeling of total factor productivity substantially increases the persistence of the euro area business cycle relative to standard macroeconomic models with purely exogenous TFP. Crucially, we find that euro area total factor productivity exhibits a strong degree of procyclicality and that the corresponding resulting feedback mechanism between overall economic conditions on the one side and the evolution of total factor productivity on the other side constitutes a powerful channel capable of generating a high degree of business cycle persistence, providing important insights on both the depth and severity of the euro area recessions as well as on the drivers of the euro area productivity slowdown. More specifically, we find that the endogenous TFP component explains a high share of overall euro area total factor productivity. Regarding the evolution of the endogenous TFP component, our results show that it has exhibited a slowdown in growth discernible already in the early 2000s. During the Great Recession, however, this decline accelerated markedly and total factor productivity fell substantially. Concerning the main driving forces of the euro area productivity slowdown, we identify a decline in the efficiency of R&D investment in generating new technology innovations as the most important driver in the pre-crisis period. Starting from the Great Recession, in turn, we find that the liquidity demand shock, which raises savings at the expense of consumption and triggers typical business cycle dynamics in key economic variables, constitutes the most important endogenous source of the euro area productivity slowdown. Importantly, this result emphasizes the importance of demand-side shocks in explaining the evolution of euro area supply-side developments, while at the same time challenging the exogeneity of total factor productivity in standard macroeconomic frameworks in this context. As to the future outlook on the euro area productivity slowdown, we can deduct from our empirical analysis that towards the end of the sample, starting from approximately 2015 onward, that a recovery in the endogenous component of total factor productivity is discernible, fostered by the generally improving overall economic condition in the euro area, which support firms' activity in the field of R&D and technology adoption. A decline of the efficiency of R&D investment in triggering new innovations, as well as exogenous TFP shocks, however, remain drags on euro area productivity. Lastly, the analysis the euro area economy through the lens of a macroeconomic model in which total factor productivity evolves endogenously also holds important implications regarding the dynamics of euro area inflation in store as factoring in the spillover to productivity developments from overall economic conditions and vice versa mutes the response of inflation over the business cycle. In the event of a recessionary shock, the drop in TFP raises firms' production costs, which counteracts the standard inflationary tendencies and in sum dampens the fall in inflation. This property is thus in line with the empirically negligible downward adjustment of euro inflation during the Great Recession despite a major output drop. In an upswing, in turn, TFP increases in our euro area model as improving economic conditions support firms' investment in R&D and technology adoption, thus reducing inflationary pressures given reduced production costs as a result of the productivity gains. Thus, the endogenous TFP channel also contributes to explaining the sluggish response of inflation in the recent euro area upswing.

This paper is closely linked to studies which analyze the role of productivity dynamics in macroeconomic models and the corresponding feedback effects to and from overall economic conditions in this context. Bianchi, Kung and Morales (2019) represents a central study related to our analysis since their paper also investigates the relationship between cyclical fluctuations and productivity growth by means of an estimated DSGE model with endogenous productivity mechanism. In their framework productivity growth results from both knowledge accumulation in the form of vertical innovation (Aghion and Howitt (1992); Grossman and Helpman (1991)) through R&D and the degree of technology utilization. Their results also highlight the role of procyclical productivity movements in explaining business cycle persistence. Further analyses close to this paper studying the relationship between business cycle fluctuations and long-run growth are Comin, Gertler and Santacreu (2019) as well as Kung and Schmid (2015). Lastly, this paper relates to the literature on secular stagnation (Eggertsson, Mehrotra and Robbins (2019); Eggertsson, Mehrotra and Sing (2016); Gordon (2016)). Among these studies on secular stagnation, Benigno and Fornaro (2017) is particularly closely related as their analysis can be understood as a synthesis of the hysteresis view and the secular stagnation perspective as they demonstrate how at first temporary shortfalls in aggregate demand can translate into secular stagnation in a Keynesian growth model with nominal rigidities and technological innovation through research and development.

The outline of the paper can be summarized as follows. Firstly, we present the model framework we base our analysis on (section 2). Section 3 describes our estimation approach and shows the corresponding estimation results. We proceed to analyze the model dynamics and the key drivers of economic fluctuations in this framework (section 4). Section 5 presents the evolution of endogenous total factor productivity, the decomposition into its main components as well as its key underlying drivign shocks. Section 6 discusses the implications for euro area macroeconomic policy and section 7 concludes.

2 The model

Our analysis of the euro area business cycle and evolution of total factor productivity is based on the model proposed by Anzoategui, Comin, Gertler and Martinez (2018). The main model structure is a medium-scale New Keynesian DSGE model in the spirit of Christiano et al. (2005) and Smets and Wouters (2007) with the corresponding standard model features. The model entails price and wage rigidities of the Calvo type, monetary policy is modeled in the form of a Taylor rule and investment is subject to flow adjustment costs. As a central difference as opposed to standard DSGE frameworks in which TFP evolves purely exogenously, total factor productivity in this model is endogenous and the result of the creation of new technologies through R&D investment and technology adoption of these inventions in the production process. The model features two types of labor: Skilled labor employed in the R&D sector and in the technology adoption process, as well as unskilled labor used in production. While financial frictions are not explicitly modeled, the framework includes a liquidity demand shock, which exhibits transmission properties of a financial shock and induces typical business cycle comovement in key economic variables.

2.1 Empirical evidence on the procyclicality of R&D and technology adoption

The theoretical model underlying our analysis is subject to procyclical productivity dynamics as a result of procyclical movements in R&D and technology adoption activity. This section shows empirical evidence on the procyclical evolution of both margins generating productivity advances in the theoretical model. We first address the procyclicality of R&D activities. Figure 3 presents the evolution of business R&D expenditure in the euro area and demonstrates that the observed pattern in R&D activity is clearly procyclical: Investment in R&D increases in upswings and declines in recessions. Importantly, we observe a pronounced fall in R&D investments during the Great Recession as well as the subsequent euro area debt crisis. Likewise, during the downturn in the early 2000s, R&D expenditures dropped markedly.

Let us now turn to the procyclicality of technological diffusion. Data on technology adoption are general scarce given the lack of series on the aggregate level. Anzoategui et al. (2018) use survey data on the speed of technology diffusion covering the fraction of companies which have adopted a certain technology for 26 production technologies over the time period 1947 to 2003 in the US and the UK. Based on these data, they estimate the cyclical effect on the speed of diffusion, controlling for variables governing the general process of technology diffusion and document a robust and positive effect of the cyclical position on the speed of technology adoption. Further, Anzoategui et al. (2018) demonstrate based on UK data for three internet-related technologies provided by Eurostat that the diffusion of these technologies substantially fell during the Great Recession and increased in the subsequent recovery. In addition to the pronounced procyclicality of technology diffusion, this study also emphasizes the high magnitude of fluctuations of technology adoption over the business cycle. Additionally, Anzoategui et al. (2018)

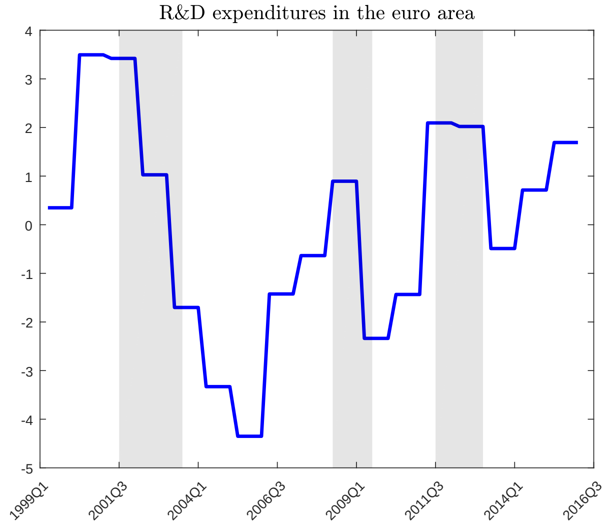

Figure 3: R&D expenditures in the euro area (12 countries, fixed composition; log-linearly detrended data; source: Eurostat; data are deflated by the GDP deflator and population adjusted; see appendix A.1 for data sources). Shaded areas indicate OECD recession dates.

approximate adoption activity by means of firms' expenditure on technology adoption. More specifically, they use a data set compiled by the Association of University Technology Managers on firms' expenditures to acquire licenses for the use of technologies generated by universities as well as research hospitals. They show that adoption expenditures are subject to a high degree of comovement with cyclical GDP. Moreover, adoption expenditures fell substantially during recessions and, most notably so, during the Great Recession. Having discussed the empirical evidence on the procyclicality of both research and development and adoption activities, we proceed to outline the main model structure underlying our analysis.

2.2 Production and endogenous TFP

This section presents the production structure of the model and demonstrates how total factor productivity and its endogenous component enter aggregate production in this framework. The model economy features two types of firms - intermediate goods and final goods producers. There are a continuum of measure one final goods producers, which are monopolistically competitive. Each final goods firm i produces differentiated output Y_t^i. The corresponding final good composite Y_t is a CES aggregate of the differentiated final goods Y_t^i:

$$Y_t = \left(\int_0^1 \left(Y_t^i\right)^{\frac{1}{\mu_t}} di \right)^{\mu_t}, \tag{1}$$

where $\mu_t > 1$ evolves exogenously. Final good firm i produces using X_t^i units of intermediate good composite, which constitutes the only production input, following the linear production function:

$$Y_t^i = X_t^i. \tag{2}$$

Final goods firms set its respective nominal price P_t^i on a staggered basis (see section (2.5.3)). Each intermediate goods firm produces a differentiated product and there exists a continuum of measure A_t of monopolistically competitive intermediate goods producers. A_t denotes the stock of adopted technologies, that is the stock of types of intermediate goods, which have been adopted for use in production. Each intermediate goods firm produces output X_t^j. The intermediate goods composite is a CES aggregate of the respective intermediate goods:

$$X_t = \left(\int_0^{A_t} \left(X_t^j \right)^{\frac{1}{\vartheta}} dj \right)^{\vartheta}, \tag{3}$$

where $\vartheta > 1$. L_t^j denotes unskilled labor, K_t^j the stock of capital and U_t^j capital utilization, used by firm j respectively. Firm j produces output using unskilled labor L_t^j and utilization-adjusted capital services $U_t^j K_t^j$ according to the Cobb-Douglas technology

$$X_t^j = \theta_t \left(U_t^j K_t^j \right)^{\alpha} \left(L_t^j \right)^{1-\alpha}. \tag{4}$$

We assume that intermediate goods firms can adjust their price in each period. Consequently, as opposed to final goods prices, intermediate goods prices are perfectly flexible. In a symmetric equilibrium for intermediate goods, we can derive the aggregate production function for the final good composite Y_t using equation (3) and (4) to a first order as:[1]

$$Y_t = \left[(A_t)^{\vartheta-1} \theta_t \right] (U_t K_t)^{\alpha} (L_t)^{1-\alpha}. \tag{5}$$

As equation (5) demonstrates, total factor productivity consists of both an exogenous component, i.e. the standard TFP shock, θ_t and an endogenous component $(A_t)^{\vartheta-1}$. Hence, the model is in addition to exogenous productivity variation also subject to endogenous productivity movements, generated by the expansion in the variety of adopted intermediate goods as measured by A_t. The model-inherent endogenous TFP mechanisms governing the creation of new goods and their adoption in the production process are described in the following section.

2.3 The endogenous TFP mechanism: Technological progress through R&D and technology adoption

The endogenous total factor productivity mechanism inherent to this model follows Comin and Gertler (2006). Hence, technological progress and thus productivity advances in this model are governed by a two-stage process, in the form of R&D on the one side and technology adoption on the other side. In the first stage, new technologies are invented through research and development, adding to the total stock of technologies Z_t. In the subsequent stage of technology adoption, firms incorporate these technologies into production. Importantly, the creation of new technologies in itself does not improve productivity, as productivity improvements are only

[1] See Anzoategui et al. (2018) for a detailed derivation of the aggregate production function.

realized once firms adopt these technologies in their production processes. Hence, the model features a realistic distinction between innovation and technological adoption, which also empirically display different degrees of procyclicality. Concerning notion, we denote the stock of adopted technologies by A_t, which constitutes a subset of the total stock of technologies Z_t. Thus, $Z_t - A_t$ denotes the stock of unadopted technologies. Innovators in the R&D sector create new technologies Z_t, while the adoption sector turns these technologies usable in production. This distinction between creation and adoption of technologies also enables to generate a realistic time lag between the invention of new goods and their adoption in production observed empirically. The stock of adopted technologies A_t corresponds to the endogenous component of TFP, as described in the previous section and increases in A_t generate endogenous productivity growth in the model.

2.3.1 R&D sector: Creation of new technologies

As previously outlined, innovation, i.e. the creation of new technologies, in the R&D sector constitutes the first stage generating endogenous productivity growth in this framework. The R&D sector features a continuum of measure one of innovators. Innovators employ skilled labor to create new intermediate goods. L_{srt}^p refers to skilled labor used by innovator p. Each unit of skilled labor employed in the R&D sector at time t can create φ_t new technologies in the subsequent period $t+1$. φ_t evolves according to the process

$$\varphi_t = \chi_t Z_t L_{srt}^{\rho_z - 1}, \tag{6}$$

where χ_t denotes an exogenous shock to R&D technology and L_{srt} is the aggregate level of skilled labor working in research and development. More specifically, χ_t denotes a R&D efficiency shock and hence captures exogenous variations in the efficiency of investment in R&D in creating new technologies. The presence of Z_t, which innovators take as given, incorporates public learning-by-doing in the R&D process (Romer (1990)). The R&D process is subject to a congestion externality: Increases in aggregate R&D activity reduce R&D efficiency for each individual innovator as we assume $\rho_z < 1$.[2]

Innovator p's decision problem consists of choosing L_{srt}^p to maximize

$$\max_{L_{srt}^p} E_t \left\{ \Lambda_{t,t+1} J_{t+1} \varphi_t L_{srt}^p \right\} - w_{st} L_{srt}^p, \tag{7}$$

where J_t denotes the value of an unadopted technology, $\Lambda_{t,t+1}$ is the household's discount factor and w_{st} represents the real wage for a unit of skilled labor. Thus, the optimality condition for

[2] Anzoategui (2018) elaborate that the presence of a congestion externality enables constant returns to scale in the generation of new technologies. This property simplifies aggregation, while inducing diminishing returns for the aggregate.

research and development can be stated as follows:

$$E_t \{\Lambda_{t,t+1} J_{t+1} \varphi_t\} - w_{st} = 0. \tag{8}$$

Using equation (6), the first order condition (8) implies

$$E_t \left\{\Lambda_{t,t+1} J_{t+1} \chi_t Z_t L_{srt}^{\rho_z - 1}\right\} = w_{st}, \tag{9}$$

stating that the discounted marginal benefit from an additional unit of labor has to equal the marginal costs of skilled labor. Importantly, due to the procyclicality of profits in intermediate goods production, the value of an unadopted technology also evolves procyclically. This property implies in combination with the assumption of sticky wages a procyclical movement of skilled labor employed in the R&D sector L_{srt} and thus investment in research and development.[3]

We include the possibility that technologies become obsolete and denote the survival rate for a given technology by ϕ. The stock of technologies Z_t evolves according to the following law of motion

$$Z_{t+1} = \varphi_t L_{srt} + \phi Z_t, \tag{10}$$

where $\varphi_t L_{srt}$ measures the newly created technologies and ϕZ_t the surviving technologies in period t . Combining (6) and (10), we can derive growth of the technology stock as

$$\frac{Z_{t+1}}{Z_t} = \chi_t L_{srt}^{\rho_z} + \phi, \tag{11}$$

where ρ_z refers to the elasticity of the growth rate of technologies with respect to research and development activity and is estimated in section (3).

2.3.2 Adoption of new technologies

This section describes the adoption mechanism, i.e. the process of converting existing technologies Z_t to technologies usable in production A_t. Crucially, only if an invention is adopted by firms it will generate productivity advances. Moreover, incorporating an endogenous adoption process in the model aims at capturing the empirical properties that technology adoption takes on average time and that the adoption of new technologies varies procylically. Modeling technology adoption in the form of an adoption sector, permits the endogenous modeling of technological diffusion, while avoiding issues related to aggregation.[4] Thus, a competitive group of adopters converts unadopted technologies into technologies usable in production. More specifically, adopters buy the rights to use the technology at the competitive price J_t, which corresponds to the value of an unadopted technology. The conversion of technologies into tech-

[3] R&D investment corresponds to the wage bill of skilled labor allocated to this sector $w_{st} L_{srt}$.

[4] More concretely, this approach avoids the need of keeping track of the fraction of firms which have adopted each of the respective technologies.

nologies which can be used in production requires input of skilled labor and takes time on average, where the conversion rate is subject to endogenous variation. The probability λ_t that an adopter successfully renders a product usable in any period equals to

$$\lambda_t = \lambda \left(Z_t L_{sat} \right), \tag{12}$$

where L_{sat} refers to skilled labor employed in technology adoption.[5] We assume $\lambda' > 0$ and $\lambda'' < 0$, which implies that the pace of adoption is an increasing and concave function of skilled labor allocated to this sector. Note that the specification of the adoption process entails that technological diffusion does not occur instantaneously but takes time on average. Let $\bar{\lambda}$ denote the steady state value of λ_t, then the average time until a new technology is adopted corresponds to $\frac{1}{\bar{\lambda}}$. Outside the steady state, the speed of adoption varies with the input of skilled labor L_{sat}. Note also that the adoption process is subject to a spillover effect from the total technology stock Z_t, implying that the efficiency of the adoption process increases in line with the state of the technology in the economy. This assumption guarantees the existence of a balanced growth path as the efficiency of the adoption process has to increase when the stock of technologies requiring adoption expands.

Once a technology has been rendered usable in production, the adopter sells the rights to use the technology to a monopolistically competitive intermediate goods producer which uses the good according to equation (4). Let Π_t^x denote the profit of an intermediate good firm from producing the good. The adopter sells the adopted technology at the competitive price V_t, which equals to the present discounted value of profits from producing the good

$$V_t = \Pi_t^x + \phi E_t \left\{ \Lambda_{t,t+1} V_{t+1} \right\}. \tag{13}$$

The adopter's maximization problem consists of choosing L_{sat} to maximize the value of an unadopted technology J_t:

$$J_t = \max_{L_{sat}} E_t \left\{ -w_{st} L_{sat} + \phi \Lambda_{t,t+1} \left[\lambda_t V_{t+1} + (1 - \lambda_t) J_{t+1} \right] \right\} \tag{14}$$

subject to condition (12). $w_{st} L_{sat}$ refers to total adoption expenditures, i.e. the expenditures on skilled labor allocated in the adoption process, while the second term in equation (14) denotes the discounted gains, which equals to the sum of adopted and unadopted technologies weighted by their respective probability. The corresponding first order condition can be expressed as follows:

$$Z_t \lambda_t' \phi E_t \left\{ \Lambda_{t,t+1} \left[V_{t+1} - J_{t+1} \right] \right\} = w_{st}. \tag{15}$$

Hence, marginal costs of adoption w_{st} equal the marginal gain from adoption expenditures,

[5] In estimating the model, we follow Anzoategui et al. (2018) and employ the functional form of the adoption rate as follows: $\lambda(\bullet) = \kappa_\lambda (\bullet)^{\rho_\lambda}$, where κ and ρ_λ are parameters and $0 < \rho_\lambda < 1$ applies.

i.e. the increase in the adoption probability times the discounted difference between the value of an adopted versus unadopted technology. Let us now turn to the evolution of adoption activity over the business cycle. Firstly, note that the term $V_t - J_t$ varies procyclically as future profits increase the value of adopted technologies V_t more strongly than the value of unadopted technologies J_t. From this property combined with stickiness in w_{st} follows the procyclicality of L_{sat}. Consequently, also the speed of adoption λ_t will evolve procyclically.

Since λ_t is not subject to adopter-specific characteristics, it is possible to sum across adopters in order to derive the law of motion of adopted technologies:

$$A_{t+1} = \lambda_t \phi \left[Z_t - A_t\right] + \phi A_t, \tag{16}$$

where $Z_t - A_t$ corresponds to the stock of unadopted technologies. Thus, tomorrow's stock of technology incorporated in production - and thus the endogenous component of TFP - equals to the sum of the stock of non-obsolete technologies surviving in the current period ϕA_t and the technologies newly adopted in this period $\lambda_t \phi \left[Z_t - A_t\right]$.

2.4 Households

The representative household saves in capital and riskless bond which are in zero net supply. The household rents capital to intermediate goods firms. Further, the model is subject to habit formation in consumption and households act as monopolistically competitive suppliers of differentiated types of labor. In addition to these standard properties, the household's problem is subject to the following, additional features. Firstly, the household supplies two types of labor: Skilled labor L^h_{st} used both in research and development and adoption and unskilled labor L^h_{ut} employed in the production of intermediate goods. Moreover, we assume that the household has a preference for holding the safe asset, which can be interpreted as a preference for liquidity. More specifically, bond holdings enter directly the utility function.[6] Further, we assume a liquidity demand shock $\varrho_t > 0$ which features transmission properties of a financial shock.[7] C_t denotes consumption, B_t riskless bond holdings and Π_t profits from ownership of monopolistically competitive firms. K_t refers to capital, Q_t to the price of capital, R^k_t to the rate of return on capital and D_t to the rental rate of capital. The households' decision problem can be stated as follows:

$$\max_{C_t, B_{t+1}, K_{t+1}, L^h_{ut}, L^h_{st}} E_t \sum_{\tau=0}^{\infty} \beta^{\tau} \left\{ log\left(C_{t+\tau} - bC_{t+\tau-1}\right) + \varrho_t B_{t+1} - \left[\frac{\upsilon_u \left(L^h_t\right)^{1+\varphi} + \upsilon_s \left(L^h_{st}\right)^{1+\varphi}}{1+\varphi}\right] \right\} \tag{17}$$

subject to

$$C_t = w^h_{ut} L^h_{ut} + w^h_{st} L^h_{st} + \Pi_t + R^k_t Q_{t-1} K_t + R_t B_t - B_{t+1}, \tag{18}$$

[6]This step follows Krishnamurthy and Vissing-Jorgensen (2012).

[7]The assumption of a shock to liquidity demand follows Fisher (2015). Accordingly, the liquidity demand shock corresponds to an explicit formulation of the risk shock in Smets and Wouters (2007).

where $R_t^k = \frac{D_t Q_t}{Q_{t-1}}$. Note that $\Lambda_{t,t+1}$ denotes the stochastic discount factor of the household given by $\Lambda_{t,t+1} \equiv \frac{\beta u'(C_{t+1})}{u'(C_t)}$, where $u'(C_t) = \frac{1}{C_t - bC_{t-1}} - \frac{b}{C_{t+1} - bC_t}$. Lastly, let ζ_t be the liquidity preference shock denoted in units of the consumption good $\zeta_t \equiv \frac{\varrho_t}{u'(C_t)}$. Thus, the first order conditions for capital and the riskless bond can be respectively derived as

$$1 = E_t \left\{ \Lambda_{t,t+1} R_{kt+1} \right\} \tag{19}$$

$$1 = E_t \left\{ \Lambda_{t,t+1} R_{t+1} \right\} + \zeta_t. \tag{20}$$

Equation (20) shows that the presence of the liquidity demand shock induces a distortion to the first order condition for the riskless bond. An increase in ζ_t affects the economy similar to an increase in risk: For a given riskless rate R_{t+1}, a rise in ζ_t triggers a precautionary savings effect in the sense that households lower their consumption in order to obey the first order condition via a fall in $\Lambda_{t,t+1}$. Furthermore, the shock to liquidity demand lowers investment demand since, as described by equation (19), the drop in $\Lambda_{t,t+1}$ causes an increase in the return on capital. The decrease of the stochastic discount factor also induces a decrease of R&D and adoption, as implied by equation (9) and (15). In conclusion, the liquidity demand shock ζ_t induces a positive comovement between consumption and investment. This can be further demonstrated by combining equation (19) and (20)

$$E_t \left\{ \Lambda_{t,t+1} \left(R_{kt+1} - R_{t+1} \right) \right\} = \zeta_t, \tag{21}$$

which states that a rise of ζ_t increases the interest rate spread $R_{kt+1} - R_{t+1}$ and thus highlights the similarity in terms of transmission mechanism to a financial shock.[8]

2.5 Standard DSGE model features

This section presents further key features of the model. For tractability, we focus on the resulting equilibrium conditions.

2.5.1 Intermediate goods firms: factor demands

This section outlines the factor demands resulting from the first order conditions of intermediate goods firms. Intermediate goods producers choose capital K_t^j, utilization U_t^j and labor L_t^j to minimize costs given the relative price of intermediate goods composite p_t^x, the price of capital Q_t, the rental rate D_t, the real wage w_t and the desired markup ς. The capital utilization decision is endogenized by assuming that the capital depreciation rate $\delta\left(U_t^j\right)$ is increasing and convex in capital utilization U_t^j.[9] The first order conditions resulting from the firm's cost minimization

[8] Anzoategui et al. (2018) provide empirical evidence for the high correlation between the model-implied liquidity demand shock and credit spreads.

[9] In endogenizing capital utilization, Anzoategui et al. (2018) follow the approach of Greenwood et al (1988).

problem for K_t^j, U_t^j and L_t^j respectively can be stated as:

$$\alpha \frac{p_t^x X_t^j}{K_t^j} = \varsigma \left[D_t + \delta \left(U_t^j \right) Q_t \right] \tag{22}$$

$$\alpha \frac{p_t^x X_t^j}{U_t^j} = \varsigma \delta' \left(U_t^j \right) Q_t K_t^j \tag{23}$$

$$(1-\alpha) \frac{p_t^x X_t^j}{L_t^j} = \varsigma w_{ut}. \tag{24}$$

The desired markup ς is assumed to be lower than the optimal unconstrained markup ϑ due to the potential threat of entry of imitators as commonly assumed by the literature.

2.5.2 Capital producers: investment

New capital goods are created using final output by competitive capital producers. The capital producers sell the newly created capital goods to households, which, in turn, rent the capital to firms. We denote by I_t the newly produced capital, by p_t^x the replacement price of capital, i.e. the relative price of converting final output into new capital, and by γ_y the growth rate of I_t in the steady state. Further, investment is subject to flow adjustment costs.[10] We assume an increasing and concave adjustment cost function $f\left(\frac{I_t}{(1+\gamma_y)I_{t-1}}\right)$ with the properties $f(1) = f'(1) = 0$ and $f"(1) > 0$. The corresponding first order gives Tobin's Q of investment, which states the ratio of the market value to capital to the replacement price:

$$\begin{aligned} \frac{Q_t}{p_t^k} = 1 + f\left(\frac{I_t}{(1+\gamma_y) I_{t-1}}\right) + \frac{I_t}{(1+\gamma_y) I_{t-1}} f'\left(\frac{I_t}{(1+\gamma_y) I_{t-1}}\right) \\ -E_t \Lambda_{t,t+1} \left(\frac{I_{t+1}}{(1+\gamma_y) I_t}\right)^2 f'\left(\frac{I_{t+1}}{(1+\gamma_y) I_t}\right), \end{aligned} \tag{25}$$

where $log(p_t^k)$ follows an AR(1) process subject to the parameters ρ_{pk} and σ_{pk}. The following equation presents the law of motion for capital

$$K_{t+1} = I_t + (1 - \delta(U_t)) K_t. \tag{26}$$

2.5.3 Price and wage setting

As in Smets and Wouters (2007), both nominal prices and wages are subject to staggered price setting according to Calvo adjustment rules. We denote the probability a firm cannot adjust its price by ξ_p and the probability a firm cannot adjust its wage by ξ_w. ι_p refers to the degree of indexation of prices to past inflation, while ι_w is the corresponding counterpart for wages. As previously outlined, households supply two types of labor (unskilled and skilled). We assume

[10] This approach follows Christiano et al. (2005).

both types of labor to be subject to the identical frequency of wage adjustment. Let us denote by π_t the inflation rate and by mc_t the marginal cost of final good producers, expressed in log deviation from steady state. From here, the price Phillips curve can be derived as

$$\pi_t = \kappa mc_t + \frac{\iota_p}{1+\iota_p\tilde{\beta}}\pi_{t-1} + \frac{\beta}{1+\iota_p\tilde{\beta}}E_t\left[\pi_{t+1}\right] + \epsilon\mu_t, \tag{27}$$

where $\tilde{\beta} = \frac{\beta}{1+\gamma_y}$ and $\kappa = \frac{\left(1-\xi_p\tilde{\beta}\right)\left(1-\xi_p\right)}{\xi_p\left(1+\iota_p\tilde{\beta}\right)}$. $\varepsilon\mu_t$ denotes a shock to final goods markup, which follows an AR(1) process with parameters ρ_μ and σ_μ. The Phillips curve for unskilled wages is given by

$$\begin{aligned}\left(1+\kappa_w\right)\tilde{w^u_t} = \frac{1}{1+\tilde{\beta}}\left(\tilde{w^u_{t-1}} + \iota_w\pi_{t-1} - \left(1+\tilde{\beta}\iota_w\right)\pi_t\right) + \frac{\tilde{\beta}}{1+\tilde{\beta}}E_t\left[\tilde{w^u}_{t+1} + \pi_{t+1}\right] \\ +\kappa_w\left(\tilde{muc}_t - \varphi\tilde{l^u_t}\right) + \epsilon\mu w_t,\end{aligned} \tag{28}$$

where $\kappa_w = \frac{\left(1-\xi_w\right)\left(1-\xi_w\tilde{\beta}\right)}{\xi_w\left(1+\tilde{\beta}\right)\left(1+\varphi\left(1+\frac{1}{\bar{mu}_w}\right)\right)}$ and $\bar{\mu}_w$ refers to to the steady state wage mark-up. The variables $\tilde{muc}$, $\tilde{w}$, l denote the marginal utility of consumption, as well as the unskilled wage and hours in log deviation from steady state respectively. $\epsilon\mu w_t$ is a shock to the wage mark-up, which follows an AR(1) process with parameters $\rho_{\mu w}$ and $\sigma_{\mu w}$. Replacing unskilled wages and labor for their skilled equivalents, the wage Phillips curve for skilled wages is identical.[11]

2.5.4 Monetary policy

Monetary policy is modelled in the form of a nonlinear Taylor rule which includes a zero lower bound constraint. More specifically, the central bank conducts monetary policy by setting the nominal interest rate R_{nt+1} according to

$$R^n_{t+1} = r^m_t\left(\left(\frac{\pi_t}{\pi^0}\right)^{\phi_\pi}\left(\frac{L_t}{L^{ss}}\right)^{\phi_y}R^n\right)^{1-\rho^R}\left(R^n_t\right)^{\rho^R} \tag{29}$$

subject to the zero lower bound constraint

$$R^n_{t+1} \geq 1, \tag{30}$$

where R^n denotes the steady state nominal rate, π^0 the central bank's inflation target, L_t total employment and L^{ss} employment in the steady state. Further, ϕ_π denotes the weight attributed to inflation gap, while ϕ_y refers to the weight on the capacity utilization gap in the Taylor rule.[12] Lastly, r^m_t follows an AR(1) process subject to the parameters ρ^{mp} and σ^{mp}.

[11] Note that in the model estimation, only unskilled wage setting is subject to wage markup shocks while the markup for skilled labor is assumed to be constant at its steady state level.

[12] We follow Anzoategui et al. (2018) in choosing the employment gap as economic slack measure in the Taylor rule. This approach permits us to facilitate estimation, while also capturing the realistic feature that monetary policy is conducted based on measures of slack which do not take into account the technology gap in terms of A_t.

2.5.5 Aggregation and equilibrium

The aggregate resource constraint can be derived as

$$Y_t = C_t + p_{kt}\left[1 + f\left(\frac{I_t}{(1+\gamma_y)\,I_{t-1}}\right)\right] I_t + G_t, \tag{31}$$

where G_t denotes government consumption. G_t is financed by lump sum taxes and follows the AR(1) process

$$log\left(\frac{G_t}{(1+\gamma_y)^t}\right) = (1-\rho_g)\,\bar{g} + \rho_g log\left(\frac{G_{t-1}}{(1+\gamma_y)^{t-1}}\right) + \epsilon_t^g. \tag{32}$$

Lastly, the labor market for skilled labor must clear in equilibrium:

$$L_{st}^h = L_{sat} + L_{srt}. \tag{33}$$

3 Estimation

We estimate this DSGE model with endogenous TFP mechanism as proposed by Anzoategui et al. (2018) on euro area data using Bayesian methods. Estimation is performed on quarterly data from 1999:I to 2007:IV. Due to the exceptional circumstances of the Great Recession and potential concomitant biases resulting from the crisis episode, we exclude the time period from 2008:I onward in the model estimation. The broader model-based analysis, by contrast, is based on the full sample (1999:I to 2017:II). We estimate the model using eight time series: The growth rates of respectively GDP, consumption, investment, wages, hours worked and R&D expenditures, as well as the series on inflation and the nominal risk-free rate. We define euro area in terms of the fixed composition concept (EA-12). The mixed-frequency of the data arising from annual data on R&D expenditure is accounted for by taking a Kalman filter approach. Appendix A.1 presents a detailed description of the data used in estimation.

We estimate the following technology parameters in the model. Regarding the key technological parameters in our model, we estimate the elasticity of the creation of new technologies with respect to research and development ρ_z. Further, by estimating the steady state growth rate of the economy g_y, also the average productivity of R&D $\bar{\chi}$ is pinned down. Moreover, following Anzoategui et al. (2018), all standard DSGE parameters except for the final goods markup are estimated.[13]

[13]The underlying intuition for calibrating the final goods markup are potential identification issues related to an additional markup in intermediate goods production.

3.1 Calibrated parameters

Table 1 presents an overview of the calibrated parameters and their respective values. In calibrating the model we closely follow the calibration approach by Anzoategui et al. (2018) for the US economy. We set the markups on intermediate (ς) and final goods (μ) to 1.18 and 1.1 respectively.[14] We calibrate the elasticity of substitution in intermediate goods ϑ to 1.37.[15] We calibrate the steady state government expenditure to GDP ratio $\frac{G}{Y}$ to 0.2 and the steady state depreciation rate δ to 0.02.

Regarding the parameters governing the endogenous technological process we calibrate the steady state adoption lag $\bar{\lambda}$, the obsolescence rate $(1-\phi)$ as well as the elasticity of the adoption probability λ with respect to adoption expenditures ρ_λ. More specifically, we set $\bar{\lambda}$ to generate an average adoption lag equal to 5 years.[16] We further calibrate an obsolescence rate $1-\phi$ of 2% (quarterly).[17] Lastly, we set the elasticity of adoption with respect to skilled labor ρ_λ to 0.95.[18]

Table 1: Calibrated parameter values

Parameter	Description	Value
δ	Capital depreciation	0.0200
$\frac{G}{Y}$	Steady state government consumption/output ratio	0.2000
μ	Steady state final goods mark up	1.1000
ς	Steady state intermediate goods mark up	1.1800
ϑ	Intermediate goods elasticity of substitution	1.3699
ϕ	Obsolescence rate	0.0200
$\overline{\lambda}$	Steady state adoption lag	0.0500
ρ_λ	Adoption elasticity	0.9500

[14] The share of R&D in GDP is increasing in the set magnitude of the markups and decreasing in ρ_λ. Thus, Anzoategui et al. (2018) propose a calibration choice of the markups at the lower end of the literature (see Jaimovich (2007)) in order to ensure a conservative calibration of ρ_λ.

[15] This value is very similar to the parameter choice of 1.35 in Anzoategui et al. (2018) which was calibrated to generate an elasticity of substitution of 3.85 between intermediate goods which is consistent with the estimates by Broda and Weinstein (2006).

[16] Anzoategui et al. (2018) propose this parameter choice as it is in line with the estimates in Cox and Alm (1996), Comin and Hobijn (2010) and Comin and Mestieri (2015).

[17] Anzoategui et al. (2018) point out that the set value corresponds to the average of the estimated obsolescence rate as estimated in terms of patent renewal rates (Bosworth (1978)) and the rate of decay of patent citations (Caballero and Jaffe (1993)).

[18] This calibration of ρ_λ is close to but slightly higher than in Anzoategui et al. (2018) in order to take into account the lower R&D to GDP ratio in the euro area as opposed to the US case.

3.2 Estimation results

Table 2 shows the prior and posterior distributions from the Bayesian estimation of our model parameters. For the standard parameters, we follow closely the choice of priors by Anzoategui et al. (2018) and Smets and Wouters (2007). Further, we estimate the elasticity of the R&D parameter ρ_z based on the prior proposed by Anzoategui et al. (2018) which follows a beta distribution centered around mean 0.6 (Griliches (1990)). The estimated standard model parameters are in line with the findings of the overall literature. Importantly, our estimate of the R&D elasticity ρ_z is in line with the Griliches (1990) and estimates.

Table 2: Prior and posterior distributions of estimated parameters

Parameter	Description	Dist	Prior		Posterior	
			Mean	St.Dev.	Mean	St.Dev.
ρ^R	Taylor rule smoothing	Beta	0.70	0.15	0.885	0.0384
ϕ_π	Taylor rule inflation	Gamma	1.50	0.25	1.320	0.2294
ϕ_y	Taylor rule labour	Gamma	0.30	0.10	0.348	0.1110
ϕ	Inverse Frisch elast.	Gamma	2.00	0.75	2.615	0.8314
f''	Investment adj. cost	Gamma	4.00	1.00	3.741	0.8025
$\frac{\delta'(U)}{\delta}$	Capital util. elas.	Gamma	4.00	1.00	4.148	0.9983
ξ_p	Calvo prices	Beta	0.50	0.10	0.562	0.1111
ξ_w	Calvo wages	Beta	0.50	0.10	0.654	0.0960
ι_p	Price indexation	Beta	0.50	0.15	0.204	0.0970
ι_w	Wage indexation	Beta	0.50	0.15	0.216	0.0937
μ_w	SS Wage markup	Normal	0.15	0.05	0.085	0.0591
b	Consumption habit	Beta	0.70	0.10	0.599	0.0523
ρ_z	R&D elasticity	Beta	0.60	0.15	0.540	0.1233
β^{est}	$100 \times (\beta^{-1} - 1)$	Gamma	0.25	0.10	0.392	0.1145
α	Capital share	Normal	0.30	0.05	0.248	0.0443
$100 * \gamma_y$	SS output growth	Normal	0.10	0.20	0.301	0.0359

4 Model dynamics and key drivers of economic fluctuations

We proceed to give an overview of the main model mechanisms and key drivers of economic fluctuations in this framework. Section (4.1) demonstrates which shocks are key in driving economic fluctuations. Section (4.2) presents the model dynamics following a shock to liquidity demand in the presence of the endogenous TFP mechanism as opposed to the model with purely exogenous total factor productivity.

Table 3: Variance decomposition

Variables	Liquidity Demand	Money	Govt Exp	Price of Capital	TFP	R&D	Mark up	Wage mark up
Output Growth	64.46	12.69	16.04	3.08	1.49	0.01	1.85	0.39
Consumption Growth	77.57	13.89	4.89	0.11	1.51	0.00	1.62	0.40
Investment Growth	39.84	11.29	3.22	40.44	1.57	0.03	2.90	0.72
Inflation	0.84	0.91	0.22	0.06	7.99	0.06	61.14	28.78
Nominal R	33.44	39.90	1.60	0.84	3.34	0.04	12.77	8.08
Hours	63.88	16.02	7.61	2.48	6.91	0.03	1.61	1.45
Endogenous TFP	71.62	15.84	0.70	0.46	0.79	0.73	9.72	0.13

4.1 Sources of model variation

Table 3 shows the variance decomposition of the key model variables.[19] The central finding is that the liquidity demand shock, interpretable as a shock which depresses consumption and favors safe asset holdings, represents the most important source of variation in this model: It accounts for more than 60% of the variation in output growth, for roughly 75% and 40% of the variation in consumption and investment growth respectively and for over 60% of the variation in hours worked. Crucially, demand shocks play an important role in explaining the variation in the endogenous total factor productivity component implying that demand side shocks exert important effects on the supply side. More specifically, 71.6% of the variation in endogenous total factor productivity are accounted for by the liquidity demand shock and 15.8% by the monetary policy shock. By contrast, the standard TFP shock, i.e. the shock to the exogenous component of total factor productivity, plays only a negligible role in explaining the variation of the key economic variables.

We now turn to the analysis of the historically key drivers of recessions. Figure 4 illustrates the historical development of GDP growth and the contributions of the standard TFP shock and the liquidity shock respectively. The historical decomposition demonstrates that the liquidity demand shock constitutes clearly the central driver of the recent recessions in the euro area. Technology shocks, instead, display a subordinate role in explaining recessions. This further supports the role of the liquidity demand shock in explaining economic fluctuations and the most important driver of recessions in the euro area.

[19] We take a shadow rate approach as the shadow rate provides a more comprehensive measure of the monetary policy stance, including the role of non-standard monetary policy measures. As a robustness check, we use an alternative non-linear model specification which imposes the ZLB constraint from which we extract smoothed variables and corresponding shock contributions using the iterative method developed by Anzoategui (2017). The corresponding results are highly similar to the findings in our baseline model, where the key difference constitutes the somewhat higher role attributed to the liquidity demand shock in explaining economic fluctuations in the nonlinear model, resulting from the inactivity of monetary policy at the zero lower bound.

Figure 4: Smoothed shocks from model with endogenous TFP mechanism. Data used as described in Appendix A.1.

4.2 Impulse response analysis: Endogenous TFP and business cycle persistence

This section illustrates the model dynamics and demonstrates the impulse responses following a shock to liquidity demand. We focus on the latter due to its high relevancy in explaining economic fluctuations and as it triggers a typical business cycle comovement of key economic variables (see section 4.1). Figure 5 shows the impulse responses of the key model variables to a one standard deviation liquidity demand shock. A rise in the demand for safe asset holdings brought about by the liquidity demand shock generates a fall in consumption and reduces the holding of the risky asset. Consequently, this depresses the safe real rate R_{t+1} and exerts upward pressure on the return to capital R^k_{t+1}. Capital investment falls. Importantly, the drop in aggregate demand following the liquidity demand shock depresses firm profits and consequently productivity enhancing investments, i.e. investment in R&D and technology adoption. Crucially, the model with endogenous total factor productivity dynamics displays a markedly stronger degree of business cycle persistence vis-à-vis a standard DSGE model with with exogenous productivity (red dashed line). More specifically, the output drop triggered by a liquidity demand shock is substantially stronger and also more persistent under endogenous TFP dynamics. The underlying cause is the presence of a strong feedback mechanism between the evolution

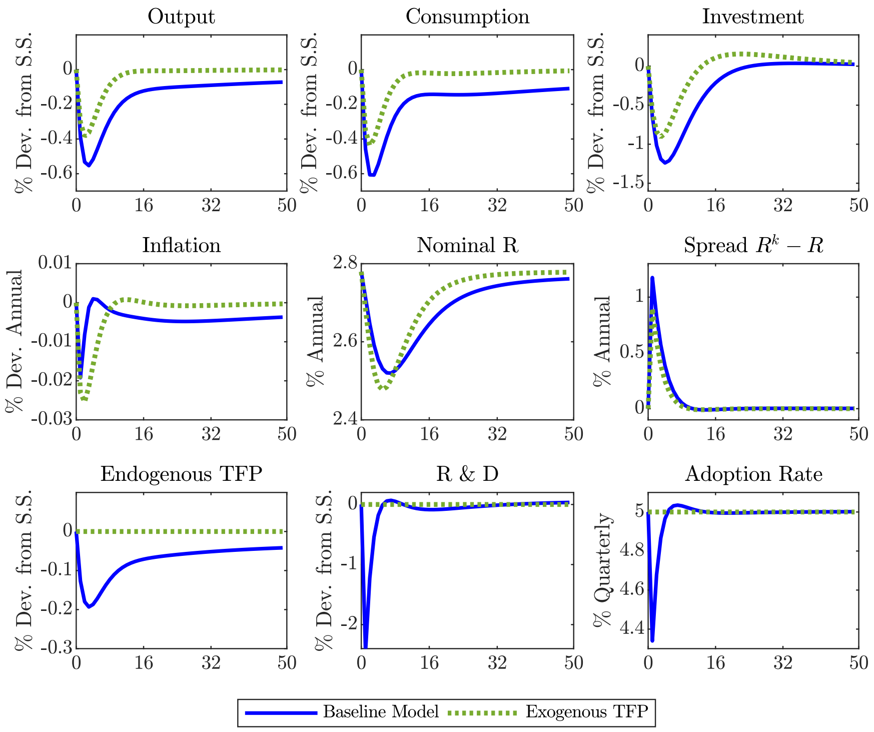

Figure 5: Impulse response to a 1 standard deviation liquidity demand shock

of TFP on the one side and overall economic conditions on the other side, which is absent in standard macroeconomic frameworks: The corresponding drop of both R&D and technology adoption activity following an adverse liquidity demand shock depresses total factor productivity, reinforcing the initial output drop. As a result, the presence of the endogenous TFP mechanism is capable of generating deep and persistent recessions and our estimated DSGE model with endogenous TFP mechanism can contribute both to explaining the depth and persistence of the recent euro area recessions and to the analysis of the sources underlying the euro area productivity slowdown.

4.3 Inflation implications: Muted inflation response due to the interaction of inflation and productivity dynamics

Let us now turn to the implications for inflation dynamics resulting from the presence of the endogenous productivity mechanism and the related interaction between inflation and productivity dynamics. Figure 6 illustrates the evolution of euro area core inflation and real GDP over the business cycle. It is striking that during the Great Recession, the downward adjustment of inflation was of minor magnitude vis-à -vis the marked drop in output. Moreover, also in the subsequent expansion, the observed reaction in inflation has been subdued in light of the sustained period of sound economic growth. Our model can match the observed patterns of inflation observed over the past decade: The response of inflation over the business cycle is

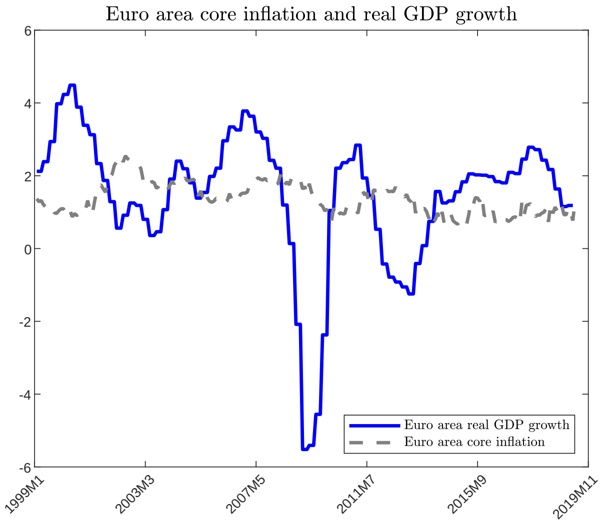

Figure 6: Inflation and GDP growth in the euro area (source: Eurostat; core inflation: HICP, annual rate of change; overall index excluding energy and unprocessed food; GDP growth: calendar and seasonally adjusted, chained volumes)

substantially muted as opposed to the standard model with exogenous total factor productivity as a result of the model-inherent interaction of inflation and productivity dynamics. More specifically, the reaction of inflation to a contractionary demand shock is negative, as is the case in standard New Keynesian DSGE models. However, a downturn will also be accompanied by a deceleration in productivity, raising price pressures and hence dampening the downward adjustment in inflation. Likewise, in the case of an expansionary liquidity demand shock, inflation would increase by less than in the framework with exogenous productivity as the price pressure resulting from increased demand are partly offset by decreased price pressures due to productivity improvements. Hence, the endogeneity of TFP in the model can also provide useful insights on potential drivers of the puzzling evolution of euro area inflation during the Great Recession and the subsequent recovery: The dampening effect resulting from the endogeneity of total factor productivity may have contributed to both the modest downward adjustment of inflation during the Great Recession and the subdued inflation response in the recent euro area expansion.

4.4 The role of the ZLB

Let us now address the implications of the presence of the zero lower bound constraint on the central bank's policy rate on economic dynamics, business cycle amplification and productivity developments. Figure 7 shows the economy's reaction to a large recessionary liquidity demand shock which induces the zero lower bound to bind.[20] Accordingly, the central effects of a binding

[20]The shock illustrated in Figure 7 constitutes a large shock in the sense that it corresponds to a 15 standard deviations liquidity demand shock.

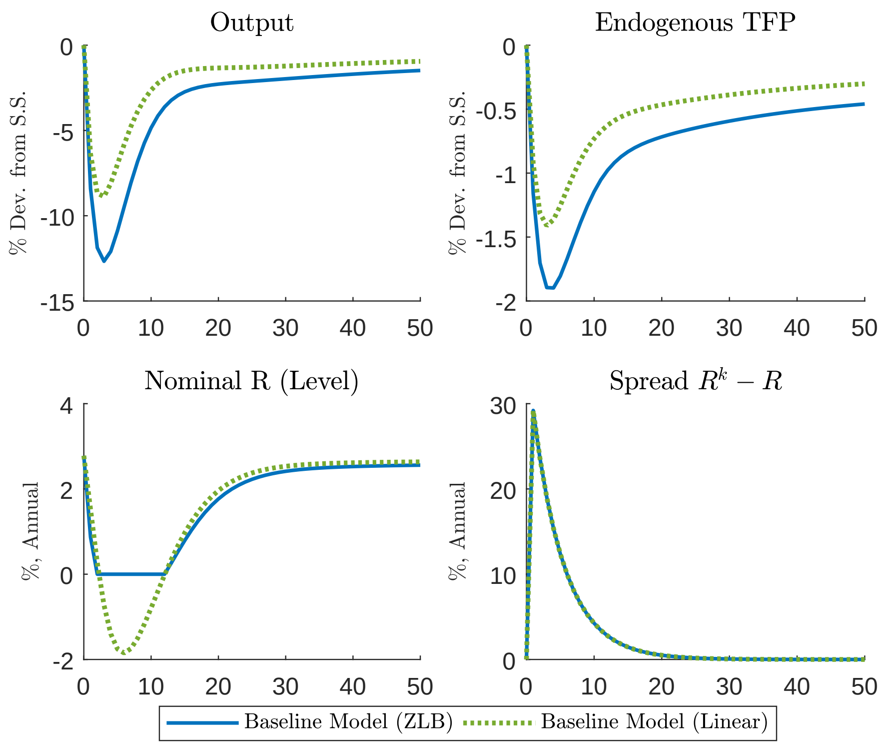

Figure 7: Effects of the ZLB in business cycle amplification

zero lower bound can be summarized as follows. As the shock in the economy is large and thus the corresponding shortfall in demand sufficiently pronounced, the required nominal interest rate in line with the central bank's policy rule falls below zero. With the optimal monetary policy rate in negative territory, a binding zero lower bound will constitute a significant obstacle to monetary policy in economic stabilization. The right uppermost column in Figure 7 demonstrates that the fall in total factor productivity will be even more marked relative to the linear endogenous DSGE model due to the binding constraints on the central bank's capability in policy intervention. This translates into a higher drop of aggregate demand, which depresses firm profits and thus the value of an unadopted and adopted technology respectively. The latter reduce research and development as well as firms' technology adoption activity, inducing a more pronounced fall in total factor productivity than in the linear baseline model. Crucially, a binding zero lower bound translates into a substantially larger drop in economic output. The first and obvious channel is the more severe shortfall in demand when monetary policy is constrained and hence ineffective in economic stabilization. The second underlying driver is the more intense decrease of total factor productivity as a reaction to a recessionary shock. In conclusion, both the scale and the persistence of the output drop are substantially larger in the case when monetary policy is constrained, emphasizing the role accruing to monetary policy in economic stabilization in this context. Crucially, in the presence of the endogenous TFP mechanism presented in section 4.2, a binding zero lower bound will exert more severe consequences than implied by standard macroeconomic workhorse models, due to the increased degree of business cycle persistence and resulting hysteresis effects in productivity. Thus, taking into account the endogeneity of productivity developments increases the negative impact of the ZLB due to its adverse impact not only on the demand-side but also on the evolution of the supply-side.

5 The euro area productivity slowdown: Evolution and key drivers of total factor productivity

This section analyses the productivity slowdown in the euro area from the perspective of this model. We focus on the evolution of the endogenous component of TFP, its empirical magnitude, as well as the main determinants of euro area total factor productivity. Based on these findings we seek to give insights on the key drivers of euro area total factor productivity and hence the productivity slowdown. Let us first address how model-implied productivity relates to empirically observable data. Recall from equation (5) that total factor productivity equals to $(A_t)^{\vartheta-1}\theta_t$ and thus consists of an exogenous component θ_t, i.e. a standard TFP shock, and an endogenous component $(A_t)^{\vartheta-1}$, which results from endogenous R&D and adoption. Labor productivity is directly empirically observable and model-implied labor productivity can be derived using equation (5) as:

$$\frac{Y_t}{L_t} = \underbrace{\underbrace{(A_t)^{\vartheta-1}}_{\text{Endog. TFP}} \underbrace{\theta_t}_{\text{TFP shock}}}_{\text{TFP}} \left(\frac{U_t K_t}{L_t}\right)^{\alpha}.$$

Consequently, model-implied labor productivity $\frac{Y_t}{L_t}$ can be decomposed into total factor productivity as the product of endogenous and exogenous TFP component on the one hand and capital intensity, as measured as utilization-weighted capital per hours worked $\frac{U_t K_t}{L_t}$ on the other hand.

5.1 Empirical magnitude of endogenous TFP in the euro area

This section demonstrates that the model-implied pattern of TFP is in line with empirically observed productivity measures and that the endogenous component of total factor productivity is empirically significant. Figure 8 presents the evolution of total factor productivity, its endogenous component, as well as labor productivity. Both TFP and its endogenous component are identified from the model, while detrended labor productivity is empirically observed. Firstly, we find that labor productivity and total factor productivity display a high degree of comovement throughout the sample, suggesting that the implied evolution of TFP is in line with empirically observable labor productivity developments. Differences between labor productivity and total factor productivity result from fluctuations in the degree of utilization-adjusted capital intensity. Importantly, the endogenous component of TFP explains a large share of total factor productivity and both series closely comove throughout the sample period, suggesting that the

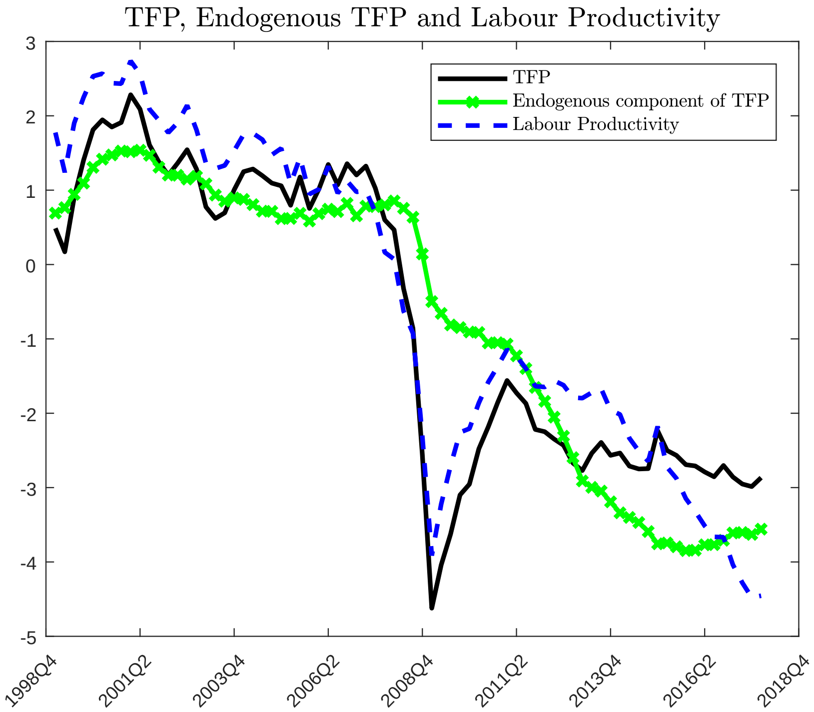

Figure 8: Evolution of total factor productivity, endogenous TFP and labor productivity

endogenous component of TFP is of empirically relevant magnitude. In particular in the pre-crisis period, the initial upswing following the Great Recession until roughly 2012:2, as well as towards the end of the sample period, the endogenous component of TFP nearly fully explains total factor productivity. Generally, the gap between total factor productivity and its respective endogenous component is attributed to exogenous TFP movements, i.e. the standard technology shock, which captures variation in total factor productivity not endogenously explicable by our model. Consequently, phases which are characterized by a relatively larger gap between TFP and its endogenous component are subject to a relatively higher importance of standard TFP shocks. That given, while endogenous TFP tracks total factor productivity closely throughout the sample, there is a more substantial unexplained wedge between TFP and its endogenous component during the Great Recession and also, albeit to a lesser extent, in the phase of roughly 2013:2 to 2016:4 than in the remaining periods. This suggests a more pronounced role of the TFP shock θ_t during these phases. A potential explanation for this observation is related to changes in labor utilization over the business cycle as in particular during the Great Recession many euro area firms used labor hoarding, i.e. instead of laying off workers adjusted their labor input by means of reductions in hours and in labor utilization (see for instance ECB (2012)). While our employment measure (total hours of employees) captures reductions along the intensive margin, it does not capture the utilization of the respective hours worked which the model attributes to exogenous shifts in total factor productivity.

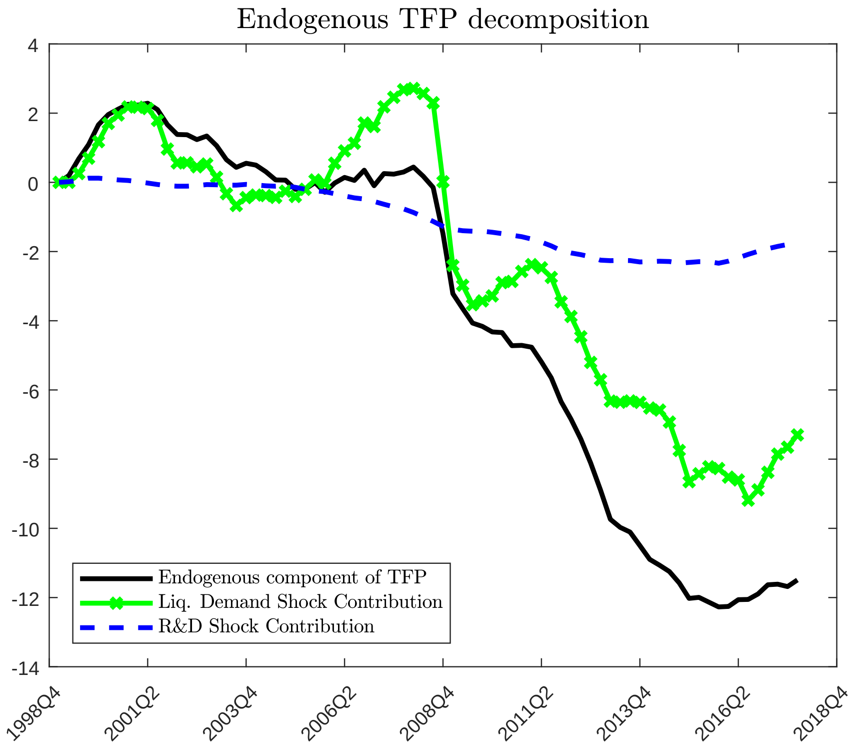

Figure 9: Endogenous TFP and main shock contributions

5.2 Determinants and evolution of endogenous total factor productivity

We now turn to a more detailed analysis of the evolution and most relevant drivers of endogenous total factor productivity. As already discussed in the context of the variance decomposition (Table 3), the liquidity demand shock constitutes the most important driver of euro area endogenous total factor productivity as it accounts for 71.6% of its variation. Figure 9 presents the evolution of endogenous TFP and the contribution of the liquidity demand shock and the shock to R&D efficiency respectively. We observe that the historical decomposition further confirms the key role of the liquidity demand shock in the evolution of endogenous TFP as both closely comove over the entire observation period. It is discernible that the decline in endogenous total factor productivity has already started in the early 2000s, which coincides with a persistent negative contribution of R&D efficiency over this period.[21] Crucially, the speed of decline in endogenous TFP accelerated substantially during the Great Recession and can be explained by a strong negative contribution of the liquidity demand shock. Starting from 2013 the substantial TFP decline came to a halt and from 2016 onward TFP improvements are discernible. The TFP increase is explained by an alleviating negative contribution of the liquidity demand shock in line with overall improving general economic conditions in the context of the expansion. Declines in R&D efficiency, however, further constitute a drag on productivity.

[21] The result that the slowdown in euro area productivity growth had set in already before the Great Recession is also a central finding proposed by Cette, Fernald and Mojon (2016).

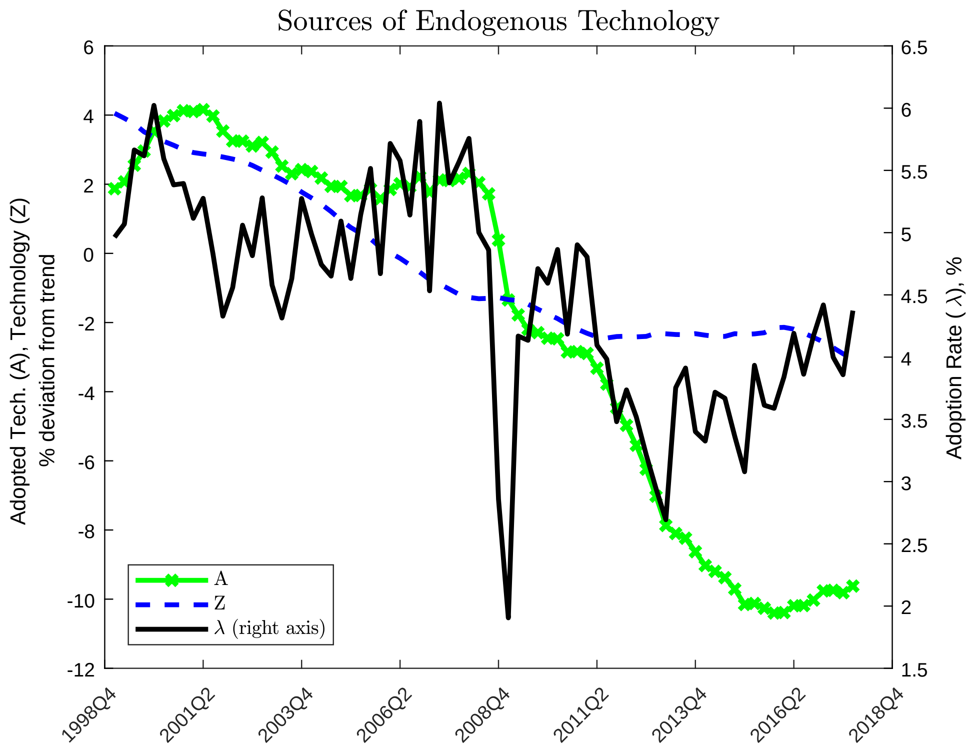

Figure 10: Endogenous TFP, R&D and technology adoption

5.3 Stagnant innovation versus slowing technology adoption?

Our model permits the decomposition of the euro area productivity slowdown into changes in R&D investment and technology adoption respectively. Figure 10 shows the evolution of the endogenous component of total factor productivity (green line), the stock of technologies (blue line) and the adoption rate (black line) over time. We observe that the main driving factor of the pre-crisis slowdown in euro area total factor productivity was the decline in the generation of new technologies through R&D activities, while the speed of technological diffusion as measured by the adoption rate was sound. The most relevant cause of the fall in productivity from the Great Recession onward, however, constituted a marked fall in technology adoption: The severity of the Great Recession substantially reduced firms' incentives to incorporate new technologies in the production process. Starting from about 2013, the degree of technological adoption has been increasing, in line with overall economic conditions and has represented the key driver of the starting recovery in total factor productivity.

6 Implications for euro area macroeconomic policy

We provided an analysis of euro area economic dynamics from the perspective of a DSGE model with endogenous total factor productivity mechanism in which total factor productivity evolves as the result of investment in R&D and technology adoption. Our results highlighted that when taking into account the endogeneity of total factor productivity, macroeconomic dynamics substantially differ in central aspects from standard DGSE models in which total factor productivity is exogenous. This section addresses the corresponding implications for macroeconomic policy in this context and in light of the identified main driving forces of the euro area productivity slowdown.

6.1 Demand-side fluctuations matter for the evolution of the supply-side

One of the main findings of this analysis, in line with the baseline model for the US case, is that demand-side shocks exert a significant influence on the evolution of productivity and that the latter displays a non-negligible degree of procylicality. This stands in sharp contrast to the underlying assumptions in standard macroeconomic frameworks, which assume purely supply-side determined productivity and hence rule out any direct effects from demand-side fluctuations to supply-side developments. This entails important policy implications. Firstly, our results suggest that negative demand effects in the recent euro area recession constitute an important contributor to the acceleration of the productivity slowdown in the euro area observed over the past decade. Moreover, our findings demonstrate that the feedback effects from the demand-side to productivity represent an important source of business cycle amplification and thus an important explanation of the depth and persistence of the recent recession in the euro area. Lastly, we document a substantial degree of procyclicality of euro area total factor productivity. Hence, from the perspective of our analysis, when assessing the business cycle position and the degree of under-utilization in the economy it is not sufficient to only take into consideration the extent of underutilization in production factors such as labor market slack and the deviation of the capital stock from its balanced growth path value but instead also the cyclical deviation of total factor productivity and its drivers through R&D and technology adoption from their respective long-run equilibrium levels. Standard output gap measures which only take into account the degree of underutilization in productive resources and do not factor in the corresponding cyclical shortfall in TFP may hence underestimate the degree of slack in the economy.

6.2 Flattening of the traditional Phillips curve relationship

A further important policy implication is the flattening of the Phillips curve relationship over the business cycle under procyclical productivity dynamics. More specifically, inflation falls by less in downturns and increases less pronouncedly in upswings vis-à-vis standard macroeconomic workhorse models (see Figure 5). The underlying mechanism is that procyclical movements in TFP offset to a large extent the effect of economic slack on inflation. In an expansion, the diminishing degree of economic slack exerts an inflationary effect on prices which is, however, counteracted by a corresponding procyclical rise in productivity, reducing cost pressures. In a downturn, in turn, the general deflationary impact of the lower degree of capacity utilization is partly offset by a procyclical productivity drop which correspondingly exerts upward pressure on costs. In sum, the inherent endogenous TFP mechanism alleviates the inflation response over the business cycle. As a result, the traditional Phillips curve relationship, which predicts a positive relationship between the degree of slack in the economy and inflation is muted under procyclical productivity dynamics. This feature contributes in explaining the lack of pronounced responses of inflation during the Great Recession as well as in the subsequent expansion.

6.3 Reducing the depth of recessions: Alleviating the feedback to R&D and technology adoption

As the results in the previous sections demonstrated, the second-round effects of a recessionary shock on total factor productivity via a drop in R&D and technology adoption activity constitute the key mechanism, which induces deep and highly persistent recessions in this framework. Hence, policies which aim at reducing the feedback from overall economic conditions to productivity-enhancing investments in innovation and adoption and the corresponding downward spiral unfolding in the economy could for instance constitute apt tools in preventing the occurrence of deep recessions. Subsidies supporting R&D and technological diffusion can constitute suitable policy options to achieve this aim as in the presence of subsidies, an adverse shock hitting the economy could only exert limited effect on productivity. This holds true as the negative shock does not feed through to the R&D sector or firms' choice of adopting new technologies in production as the subsidies prevent technology-enhancing investments to fall below a certain threshold. To ensure the long-run sustainability of the subsidies to innovation and diffusion the subsidies could be designed counter-cyclically and only be paid in the event of a downturn, leaving the long-term output path unaltered.

As equations (9) and (15) demonstrate, R&D and technology adoption fall procyclically due to the concomitant drop in the expected value of an adopted or respectively unadopted technology as a result of decreasing expectations about firm profits. That given, maintaining innovation and adoption activity could be achieved by alleviating the costs of R&D and technology diffusion in the form of a lump-sum transfer. This could be realized by compensating firms' and innovators' wage costs and hence employment of high skilled labor, preventing the procyclical drop in productivity and a corresponding large-scale output drop.[22] As holds true for the proposed design of policies promoting productivity growth in this context, it is important to note that adequately designed policies should tackle both the procyclical decrease in R&D and technology adoption given the two-stage nature of technology growth. However, in the case that possible subsidies to technological progress are constrained, for instance in the case of limited fiscal space, subsidies to technology adoption should be prioritized as technological diffusion are subject to a higher degree of procyclicality. This suggests a higher effectiveness of subsidies allocated to this sector in preventing persistent downturns, rendering them a natural priority for policy making. This

[22] The implicit assumption made here is that subsidy payments are conditional on actual increased innovation and adoption effort by firms. Put differently, firms cannot divert the subsidiy and use the transfer for other purposes.

notwithstanding, the potential effect of subsidies to R&D should not be underestimated given their longer-term effect on also the potential for future technology adoption, as the maximum level of adopted technologies A_t constitutes straightforwardly a subset of and is hence restricted by the total stock of invented technologies Z_t.

7 Conclusion

We estimate a medium-scale DSGE model with an endogenous total factor productivity mechanism as proposed by Anzoategui, Comin, Gertler and Martinez (2018) on euro area data to analyze the mechanisms underlying the high degree of business cycle persistence in the context of the recent euro area recession, as well as the sources of the euro area productivity slowdown. We find that modeling the evolution of total factor productivity endogenously as a result of productivity-enhancing investments in R&D and technology adoption substantially increases euro area business cycle persistence vis-à-vis standard macroeconomic models with purely exogenous total factor productivity. Furthermore, we find that the endogenous component of total factor productivity is empirically sizable and explains a high share of overall TFP in the euro area. Our results demonstrate a high degree of procyclicality of euro area total factor productivity. Regarding the evolution of euro area total factor productivity over time, we conclude that the slowdown in productivity has already set in in the early 2000s. During the Great Recession, however, we observe a marked acceleration of this decline. Concerning the main drivers of the slowdown in euro area productivity, we find that the fall in the efficiency of R&D investments in generating new innovations represents a main driving force in the pre-crisis phase, while starting from the Great Recession the liquidity demand shock, which favors safe asset holdings at the expense of consumption and the corresponding drop in firms' technology adoption constitutes the main contributing factor. This result crucially highlights the importance of demand-side shocks in explaining supply-side developments in the euro area. From 2015 onward, we document an increase in the endogenous TFP component, in line with overall improving economic conditions in the euro area. The diminishing efficiency of R&D investment in generating new innovations, however further constitute drags on euro area productivity. Finally, the endogenous productivity mechanism holds important implications for inflation in the euro area since its presence dampens the inflation response over the business cycle. More specifically, TFP falls when the economy is hit by a recessionary shock, raising production costs and muting the drop in inflation. This property contributes to the explanation of the negligible fall in inflation despite a severe output drop during the Great Recession. Likewise, productivity increases in an upswing in this setting and these procyclical productivity gains alleviate the rise in inflation in the event of an expansionary shock. Consequently, our results suggest that the procyclical increase of productivity has contributed to the sluggish response in euro area inflation in the current expansion.

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A Appendix

A.1 Data

The data used in the estimation are accessible from the Eurostat Database (ec.europa.eu/eurostat/de/data/database) and the ECB Statistical Data Warehouse (sdw.ecb.europa.eu). The model is estimated using series on real GDP, investment, consumption, hours worked, compensation of employees, total population and nominal interest rates. All series are denoted in terms of the euro area fixed composition (EA-12) and are - when applicable - seasonally- and calendar-adjusted.

Real GDP is denoted in terms of Million euros and chain linked volumes with reference year 2010. The series on consumption measures household and NPISH final consumption expenditure in Mio. Euros and current prices. Our measure of investment is gross fixed capital formation denoted in current prices. Hours worked correspond to total hours worked expressed in 1000 hours using the domestic employment concept. Compensation refers to compensation of employees (denoted in Mio. Euro and current prices). Population corresponds to the total population in the EA-12 countries and the GDP deflator refers to the price index. Lastly, the series on R&D investment is annual[23] and refers to business expenditure on research and development, where the business sector corresponds to the source of funds. We use as a proxy for the nominal interest rate the 3-months Euribor and the 3-months shadow rates as estimated by Kortela (2016)[24] in the ZLB episode.[25] Based on these data, we construct the series used in estimation as follows, where Δ denotes the temporal difference operator:

- Output growth $= 100 \times \Delta\ \text{LN}\left(\frac{\text{Real GDP } \times 1000}{\text{Population}}\right)$
- Consumption growth $= 100 \times \Delta\ \text{LN}\left(\frac{\frac{\text{Consumption} \times 1000}{\text{GDP deflator}}}{\text{Population}}\right)$
- Investment growth $= 100 \times \Delta\ \text{LN}\left(\frac{\frac{\text{Investment} \times 1000}{\text{GDP deflator}}}{\text{Population}}\right)$
- Real wage growth $= 100 \times \Delta\ \text{LN}\left(\frac{\frac{\text{Compensation} \times 1000}{\text{Hours}}}{\text{GDP deflator}}\right)$
- Growth rate of hours worked $= 100 \times \Delta\ \text{LN}\left(\frac{\text{Hours}}{\text{Population}}\right)$
- Inflation $= 100 \times \Delta\ \text{LN}\,(\text{GDP deflator})$
- Nominal interest rate $= \frac{1}{4} \times$ Euribor

[23] We deal with the mixed-frequency issue in the data by means of a Kalman-filter approach.
[24] The shadow rates estimated by Wu and Xia (2017) are used as a robustness check.
[25] We take a shadow rate approach as the shadow rate provides a more comprehensive measure of the monetary policy stance, including the role of non-standard monetary policy measures. As a robustness check, we use an alternative model specification which imposes the ZLB constraint and we extract smoothed variables and corresponding shock contributions using the method developed by Anzoategui (2017). The corresponding results are highly similar to the findings in our baseline model, where the key difference constitutes the somewhat higher role attributed to the liquidity demand shock in explaining economic fluctuations in the nonlinear model.

- Growth rate of R&D investment $= 100 \times \Delta \text{ LN}\left(\frac{\frac{\text{R\&D investment} \times 1000}{\text{GDP deflator}}}{\text{Population}}\right)$.

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