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# Fiscal Prudence: It's All in the Timing – Estimating Time-Varying Fiscal Policy Reaction Functions for Core EU Countries

*Tino Berger, Tore Dubbert, Ruben Schoonackers*

GEORG-AUGUST-UNIVERSITÄT
GÖTTINGEN

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# Fiscal prudence: It's all in the timing

## Estimating time-varying fiscal policy reaction functions for core EU countries


Tino Berger,[1] Tore Dubbert,[1,2] and Ruben Schoonackers[3]

[1] *University of Göttingen*

[2] *University of Münster*

[3] *National Bank of Belgium, Vrije Universiteit Brussel*



When estimating fiscal policy reaction functions (FRF), the literature has well recognized the importance of non-linearities. However, there is yet very little attempt to formally test for the presence and potential sources of a non-linear fiscal responsiveness. In this paper we address this gap by formally adressing model specification of the FRF in a panel of five EU countries. Employing a Bayesian stochastic model specification search algorithm, we provide formal evidence for time-varying fiscal prudence over the last 50 years. The primary balance responsiveness exhibits smooth but significant variation over time and thus confirms the necessity of a non-linear model. Moreover, the extended results show that dynamics can be partially linked to the interest rate growth differential and the level of public debt itself. However, no clear evidence is found in favor of the fiscal fatigue proposition.

## I. INTRODUCTION

With the policy rate at the zero lower bound the ability of monetary policy to encourage economic growth is limited. As a result, the role of fiscal policy to stabilize the economy has become increasingly important in recent years. Moreover, for euro area countries fiscal policy is the only instrument that allows for country-specific economic policy. There is an extensive and ongoing discussion in the literature on fiscal sustainability. While the importance of safe debt levels is well recognized, recent events seriously challenge the sustainability of public finances.

To counteract the consequences of the COVID-19 induced recession, governments responded with unprecedented spending. In the euro area, the government deficit increased to 8.8% of GDP in 2020 and the gross public debt ratio reached a level of 101.7% of GDP. With low economic growth and prolonged stimulus packages, these numbers are likely not to decline quickly over the next few years. Additionally, rising age-related public expenditures and low expected potential growth further challenge the sustainability of public finances.

In assessing sovereign vulnerabilities, stochastic debt sustainability analysis (DSA) frameworks play an important role. They make use of simulated stochastic debt trajectories that reflect the interplay of model-based projections for relevant macroeconomic variables with an expected fiscal policy response, based on the estimation of a fiscal policy reaction function (FRF) that describes how the primary balance responds to changes in public debt. Besides its importance for DSA, the estimation of a FRF yields information on the type and strength of fiscal policy reactions governments had in the past and can be helpful in providing signals for potential future sustainability issues. In order to obtain reliable debt projections, a correctly specified FRF is thus essential.

The FRF literature has well recognized the importance of non-linearities for correctly specifying the FRF. Ghosh et al. (2013), for example, find strong evidence for the existence of a nonlinear FRF that exhibits fiscal fatigue which is very well approximated by a cubic relationship between public debt and the primary balance. When the level of inherited debt increases, the primary balance responsiveness also increases but eventually starts to decrease and at high levels of debt finally becomes negative. Recent studies such as Fournier and Fall (2017) attempt to derive these thresholds endogenously by employing regime-switching models, while others such as Weichenrieder and Zimmer (2014), explicitly link the fiscal reaction to a specific event such as Euro membership.

Despite the emerging consensus regarding the importance of correctly modeling the FRF, there is yet very little attempt to formally test for the presence and the potential source of non-linearities. In this paper we address this gap in the literature by formally addressing model specification of the FRF in a panel of five EU countries. Specifically, we employ a Bayesian model specification search to test for time-variation in the responsiveness in the primary balance to the gross public debt ratio. The responsiveness parameter is allowed to vary according to a random walk and thus allows for various forms of non-linear reaction. We then test how much of the time-variation can be explained by the interest rate growth differential and the lagged squared debt ratio. The latter essentially tests for the fiscal fatigue proposition of Ghosh et al. (2013).

We find strong evidence for time-variation in the FRF over the last 50 years. The primary balance responsiveness to debt exhibits smooth but significant variation over time and thus confirms the necessity of a non-linear model. The dynamics can be partially linked to the interest rate growth differential. Less evidence is found in favor of the fiscal fatigue proposition.

The remainder of the paper is structured as follows. In Section II, we discuss the empirical set-up. More specifically, we focus on the role of FRFs in debt sustainability analysis and we elaborate on our empirical specification. Section III focuses on the econometric approach for estimating our FRF, while in Section IV results of our empirical analysis are discussed. Section V concludes.

## II. EMPIRICAL SET-UP

### A. Estimating a FRF: The basics

Is government policy in line with fiscal solvency? This is a question that features promintently in the academic and policy debate and boils down to assessing whether the debt-to-GDP ratio belongs to a dynamically stable trajectory.[1]

To analyze fiscal solvency, recall the public debt accumulation equation,

$$\Delta d_t \equiv d_t - d_{t-1} = \frac{r_t - g_t}{1 + g_t} d_{t-1} - pb_t, \tag{2.1}$$

where $d_t$ and $pb_t$ respectively stand for the debt-to-GDP and the primary balance ratio in period $t$. The interest rate on the outstanding amount of debt is represented by $r_t$ whereas nominal GDP growth equals $g_t$. From equation (2.1) one can immediately see that debt dynamics are driven by two opposing forces, (i) the interest-rate growth differential (IRGD) $(r_t - g_t)$ and (ii) the primary balance.

If then the fiscal reaction to debt is represented by

$$pb_t = \beta d_{t-1}, \tag{2.2}$$

[1] A very interesting overview of key economic principles and statistical methods used in debt sustainability analysis is given in Debrun et al. (2019). This section is indebted to their lecture.

one can derive that to ensure a dynamically stable public debt trajectory, i. e. a mean-reverting public debt ratio, on average the following condition needs to hold:

$$\beta > \frac{r-g}{1+g} \tag{2.3}$$

The fiscal reaction to debt - and estimating a FRF - can thus be used to assess the sustainability of public finances.

In a seminal paper, Bohn (1998) was the first to analyze this kind of FRF. More specifically, Bohn's (1998) model-based sustainability test (MBS) consists of estimating

$$pb_t = \beta d_{t-1} + X_t\gamma + \epsilon_t, \tag{2.4}$$

where $X$ captures a set of other determinants explaining the evolution in the primary balance and $\epsilon_t$ represents a white noise error term. Bohn (1998) showed that, under a set of regularity conditions, a positive primary balance reaction to changes in the debt ratio (i. e. $\beta > 0$) is sufficient evidence for an economy to be fiscally sustainable and satisfying its intertemporal budget constraint. Applications of Bohn's MBS differ mainly regarding the covariates included in $X$ and the empirical setting, i. e. the country and time coverage. Two interesting and comprehensive overviews of existing FRF studies are given by Berti et al. (2016) and Checherita-Westphal and Žďárek (2017).

Another major contribution to the FRF literature is the often cited paper of Ghosh et al. (2013). In their analysis, the authors argue that an average positive fiscal reaction to debt ($\beta > 0$) should be labeled as a "weak" sustainability criterion as this implies that an ever-increasing debt-to-GDP ratio is not excluded.[2] For instance, this is the case if the increase in the primary balance is lower than the IRGD. They advocate a stricter sustainability criterion - the public debt ratio converging to some finite proportion of GDP - and argue that a sufficient condition for this is a primary balance reaction that on average exceeds the interest-rate growth differential.

A key issue in the fiscal austerity debate - and in the estimation of FRFs - is whether the degree of fiscal responsiveness to public debt changes with the level of debt. Specifically, the hypothesis of fiscal fatigue has been tested. Ghosh et al. (2013), for example, find strong support for a nonlinear relationship between the primary balance and the lagged debt ratio that exhibits fiscal fatigue. More precisely, they find a cubic relation: At low levels of debt, the relationship between the primary balance and debt is barely existent. But as debt increases, the primary balance reacts

[2] This is in contrast to Bohn (1998), who considers $\beta > 0$ - under reasonable regularity conditions - to be a sufficient condition to meet fiscal solvency.

positively and increases (more than proportionally) with the stock of debt. Eventually, the response starts to weaken and even decreases at very high levels of debt. Thus, at very high debt levels, the fiscal effort - in the form of raising extra taxes or cutting primary spending - required to "keep up" with debt becomes unfeasable and/or undesirable. In more recent publications, Fournier and Fall (2017) confirm the fiscal fatigue property for a group of OECD countries, while Everaert and Jansen (2018) find it not to be a general characteristic of the FRF when allowing for country-specific fiscal reactions to public debt.[3] Testing for the presence of fiscal fatigue is important as this implies the existence of a debt level - the debt limit - where the debt dynamics become explosive and the government will inevitably default.[4]

By analyzing the fiscal fatigue property, the literature obviously recognizes that the primary balance reaction could display significant variation over time. However, accounting for a nonlinear relationship between the primary balance and public debt by adding potencies of the debt variable to the regression equation - as in Ghosh et al. (2013), where squared and cubic debt terms are added - only allows for a very specific, deterministic source of time variation. A time-varying policy response could also be due to different sources, such as the response to a changing IRGD. Others, like Weichenrieder and Zimmer (2014) have tried to link fiscal responsiveness to Euro membership.[5] More generally, explicitly allowing and testing for significant time variation in $\beta$ and - in a stochastic approach - linking it to a set of potential determinants could be very relevant. In the remainder of the paper, we will analyze this type of FRF.

The importance of analyzing whether or not there is significant time variation in $\beta$ is also recognized by Debrun et al. (2019) and relates to the long-term perspective when using FRFs as a test of fiscal sustainability. Debrun et al. (2019) state that in order for the outcome of FRF-based sustainability tests to be meaningful, the fiscal policy response to lagged public debt must be sufficiently systematic and stable over time. In other words, if the response is positive for a couple of years but becomes insignificant afterwards, no clear-cut indication can be given in terms of whether fiscal policy is sustainable or not - unless the time variation can be linked to conditions that are in correspondence with fiscal solvency.

So far, only few studies have modeled time-varying FRFs in a stochastic way. Among the notable exceptions are Legrenzi and Milas (2013), who employ a regime-switching model to investigate the

[3] As Everaert and Jansen (2018) note, this it at least not the case for the range of debt levels observed in their sample of 21 OECD countries over the period 1970-2014.

[4] This is the case even when a risk-free interest rate is assumed and thus abstraction is made from the endogeneity of the risk premium on government debt.

[5] In their panel regression, Weichenrieder and Zimmer (2014) find a systematic reduction in fiscal prudence when becoming a Eurozone member. However, their result is not robust to excluding Greece from the sample, which leads to the conclusion that Eurozone membership does not significantly decrease fiscal prudence.

relationship of the primary balance with debt and other variables for Greece, Ireland, Portugal and Spain. More closely related to our approach is Burger et al. (2011), who cast their FRF, featuring a time-varying fiscal response to debt, in state-space form, finding a time-dependent fiscal reaction for their South African sample. However, they do not formally test for the presence of time variation.

### B. The empirical specification

To identify a governments' fiscal reaction to a changing debt ratio, we employ a dynamic specification of the FRF. As noted by, amongst others, Everaert and Jansen (2018), the highly politicized nature of the public budgeting proces makes it hard to react immediately to changes in debt and other economic conditions. Moreover, as the implementation of budgetary policies and new fiscal measures takes time, the primary balance $pb_{it}$ is considered to be a very persistent series. A dynamic specification is thus highly justified,[6]

$$pb_{it} = \alpha_i + \delta_t + \phi pb_{i,t-1} + \beta_t d_{i,t-1} + X_{it}\gamma + \epsilon_{it}, \qquad \epsilon_{it} \sim N(0, \sigma_\epsilon^2) \tag{2.5}$$

where subscripts $i$ and $t$ respectively denote the $i$th country and $t$th period.

Country fixed effects $\alpha_i$ are included to account for country-specific time-invariant factors that affect the primary balance and are not included in $X_{it}$. Next to that, time-fixed effects $\delta_t$ are also present to control for the impact of global economic shocks such as the Financial and Economic Crisis of 2007-2008.

The vector $X_{it}$ represents a $1xk$ vector of $k$ explanatory variables that can have a direct impact on $pb_{it}$. The set of variables present in $X_{it}$ resembles standard choices in the literature (see, among others, Ghosh et al. (2013), Everaert and Jansen (2018), Berti et al. (2016), Checherita-Westphal and Žďárek (2017)). A first variable included in $X_{it}$ is a measure of the economic cycle, the output gap ($OG_{it}$), to control for the reaction of fiscal variables to the business cyle. Next to that, a measure of inflation ($\pi_{it}$) is added to account for bracket creep effects, i. e. in a progressive tax system where tax brackets are not fully indexed, rising inflation induces more than proportional changes in tax revenue (see, amongst others, Saez (2003)). An election cycle dummy variable ($elec_{it}$) is also taken into account to control for the possible presence of a political budget cycle, meaning that governments tend to increase their spending in election years to increase the

[6] By allowing for a dynamic specification, potential spurious regression issues are circumvented, i .e. by adding the lagged dependent variable a potential random walk of the dependent variable is nested in the model, leading to estimates that are valid even in the case of non-stationarity.

probability of being re-elected (see for example, Debrun et al., 2008). Finally, the implicit interest rate on the outstanding amount of public debt ($r_{it}$) is included to capture potential offsetting changes in the primary balance due to changing debt services in order to reach a nominal balance target.

Naturally, we are mainly interested in the relation between $pb_{it}$ and $d_{i,t-1}$ which represents the one-period-lagged debt-to-GDP ratio. We consider this relationship to be time-varying and allow the parameter $\beta_t$ to change over time according to a random walk process,

$$\beta_t = \beta_{t-1} + \eta_t, \quad \eta_t \sim N(0, \sigma_\eta^2). \tag{2.6}$$

This specification allows for a very flexible evolution of the parameter $\beta_t$ over time. A random walk process is particularly convenient to capture smooth transition and structural changes. As such, by letting $\beta_t$ evolve according to a random walk, we allow for frequent changes of a government's fiscal reaction to the debt ratio without forcing parameters to change.[7]

Consequently, the model that will be estimated and tested for the presence of time variation in the reaction of the primary balance to changes in the lagged public debt ratio is represented by equations (2.5)-(2.6).

Conditional on finding evidence for time variation in $\beta_t$, a model extension will be considered where we account for the possibility of observed variables playing a role in the determination of the time-varying path of $\beta_t$. More specifically, the following extended model will be estimated:

$$pb_{it} = \alpha_i + \delta_t + \phi pb_{i,t-1} + \beta_{it} d_{i,t-1} + X_{it}\gamma + \epsilon_{it}, \qquad \epsilon_{it} \sim N(0, \sigma_\epsilon^2). \tag{2.7}$$

$$\beta_{it} = \beta_t^* + G_{it}\kappa \tag{2.8}$$

$$\beta_t^* = \beta_{t-1}^* + \eta_t^*, \qquad \eta_t^* \sim N(0, \sigma_{\eta^*}^2). \tag{2.9}$$

In the model (2.7)-(2.9), the primary balance responsiveness to public debt ($\beta_{it}$) is modeled as a linear combination of a random walk component $\beta_t^*$ and a set of explanatory variables $G_{it}$. A first variable to be included in $G_{it}$ is the lagged public debt ratio ($d_{i,t-1}$) and its square term. By doing so, we explicitly take into account the possible presence of nonlinearities in the relation between public debt and the primary balance. Moreover, by including the squared debt term, which in fact implies a cubic relation between $pb_{it}$ and $d_{i,t-1}$, we are able to test the fiscal fatigue property as

[7] The fixed parameter specification constitutes a special case of the random walk process, with the time-varying parameter $\beta_t$ in equation (2.6) being constant for $\sigma_\eta^2 = 0$.

found in the seminal paper of Ghosh et al. (2013). An advantage of our approach, compared to Ghosh et al. (2013) and others, is that we do not consider the relationship to be deterministic but account for it in a stochastic way, i. e. acknowledging that other factors also drive the relation between debt and the primary balance. As such, if, empirically, a nonlinear relation is found, this is not the result of ignoring other potential sources of time variation.

As can be seen from equation (2.1), the IRGD plays an essential role in public debt management. A declining, but positive, IRGD differential reduces the primary surplus needed for debt stabilization. When the IRGD becomes negative, the debt ratio can decline even when running a primary deficit. Consequently, in this type of situation one could argue that the government's fiscal responsiveness to public debt fades. Therefore, the IRGD will be included in $G_{it}$. More specifically, we use the IRGD at the beginning of the period, i. e. $IRGD_{i,t-1}$, as this is the relevant indicator that impacts on the discretionary fiscal policy behavior in period $t$.

Note that other possible determinants of the time-varying responsiveness of the primary balance to public debt, not present in $G_{it}$, are captured by the random walk process $\beta_t^*$. Testing for the presence of significant time variation in $\beta_t^*$ can therefore be very interesting. If no significant time variation is found, this implies the variables in $G_{it}$ fully explain the existing time variation in $\beta_t$, $\sigma^2_{\eta^*}$ will equal zero and $\beta_t^*$ becomes a constant.

## C. Data and Sources

In the empirical analysis a balanced panel of yearly data is used for 5 core EMU countries, covering a period from 1970-2019. The included countries are Austria, Belgium, France, Germany and the Netherlands. The choice of countries is limited to - as we believe - a somewhat homogeneous group of countries. The reason being that as our model (2.5)-(2.6) indicates, we assume a homogenous primary balance reaction to the included covariates (see section III for details on why this is important). Extending the number of countries would probably contradict that assumption.

The main data source for our analysis is the AMECO database. For the fiscal variables $pb_{it}$, $d_{i,t-1}$ and $r_{it}$, data before 1995 are retropolated using the historical public finance database prepared by Mauro et al. (2015). The inflation variable $\pi_{it}$ is constructed using the GDP deflator while the $IRGD$ represents the difference between $r_{it}$ and the nominal GDP growth rate. The $OG_{it}$ is also taken from AMECO and is calculated using the commonly agreed production function methodology (for more details on this methodology, see Havik et al., 2014). Finally, data on $elec_{it}$ are taken from the Database of Political Institutions (DPI) version 2017, and where necessary complemented with data from older versions.

## III. ESTIMATION METHODOLOGY

To estimate our empirical model represented by equations (2.5) - (2.6) or the extended model, (2.7) - (2.9), a number of methodological or econometrical choices need to be made. In what follows, some details are provided on these choices and on the actual methodology used to estimate the different models.

### A. The choice of a homogeneous panel specification

When considering debt-to-GDP ratios, the variation over time is often limited. By increasing the covered time period, this could, at least partially, be overcome. However, in our empirical model the size of the time-varying parameter vector $\beta = (\beta_1, \beta_2, ..., \beta_T)'$ grows linearly with the number of time periods. As such, increasing the sample size along the time dimension generally does not lead to an identification improvement. Hence, to mitigate the degree of uncertainty around the estimated path of debt coefficients $\beta_t$ and to ensure that there is sufficient information present in the data, the number of observations needs to be increased along the cross-sectional dimension. Of course, to benefit from this a homogeneous reaction to debt will be assumed.

However, as shown by Everaert and Jansen (2018), unmodeled slope heterogeneity in the reaction to lagged public debt can lead to the false conclusion that fiscal fatigue is present in the data.[8] Taking into account their results, we will therefore limit our sample to what we believe to be a somewhat homogeneous group of countries.

### B. Dealing with endogeneity issues

When estimating our empirical specification, a potential source of reverse causality or endogeneity is the relationship between $pb_{it}$ and $OG_{it}$. Fiscal policy, and thus $pb_{it}$, has an impact on the state of the economy, making the output gap an endogeneous regressor. If not properly accounted for, this might induce (severely) biased estimates. In order to deal with this endogeneity issue, a two-step instrumental variable procedure is employed. The first step constitutes an auxiliary regression that involves regressing $OG_{it}$ on the exogeneous covariates in $X_{it}$ and following Berti

[8] If there are countries with a weaker reaction to increases in public debt, these countries will eventually end up with a higher debt level. Estimating a homogeneous debt reaction will therefore incorrectly capture this as the presence of fiscal fatigue, while in fact this can be explained by unmodeled slope heterogeneity.

et al. (2016) the first and second lag of $OG_{it}$ as instruments for $OG_{it}$.[9] In the second step and for the remainder of the analysis, in the vector $X_{it}$ we replace $OG_{it}$ by the fitted values of the first-step regression, $\widehat{OG}_{it}$.

### C. Cross-sectional dependencies in the error term

In macroempirical analysis cross-sectional dependencies are more likely to be the rule than the exception, because of strong economic linkages between countries (see Westerlund and Edgerton, 2008). Empirically, this results in significant cross-sectional correlation in the error terms. To deal with this, country and year fixed effects $(\alpha_i, \delta_t)$ are employed in equations (2.5) and (2.7). As noted by Eberhardt and Teal (2011), for country and year effects to be efficacious in dealing with cross-sectional correlated error terms, an identical impact of the existing cross-sectional dependence across all countries in the sample needs to be assumed. As our sample is limited to a homogeneous group of core EU countries, we believe this assumption not to be too stringent.

To test whether the included fixed effects adequately control for the presence of cross-sectional dependencies, the average of the country-by-country cross-correlation in the estimated error terms, $\widehat{\epsilon}_{it}$, is calculated. Next to that, we test for the presence of first-order serial correlation in $\epsilon_{it}$, using the Cumby and Huizinga (1992) test, the reason being that significant autocorrelation would render $d_{i,t-1}$ and its powers endogenous.[10]

### D. Formally testing for time variation in the baseline model

In our empirical specifications, we assume $\beta_t$ to be time-varying. More precisely, we assume that $\beta_t$ follows a random walk process. As such, we are estimating a time-varying parameter model. A key issue for the model specification is whether the fiscal policy responsiveness truly varies over time or is constant.

Stated otherwise, the question whether the time variation in $\beta_t$ is relevant implies testing $\sigma_\eta^2 = 0$ against $\sigma_\eta^2 > 0$, which constitutes a non-regular testing problem as the null hypothesis lies on the boundary of the parameter space. This motivates employing a Bayesian stochastic model specification search (SMSS) algorithm. In a Bayesian setting, each of the potential models is assigned a prior probability and the goal is to derive the posterior probability for each model

[9] Given the rather high $R^2$ of the auxiliary regression, the chosen instruments can be regarded as strong. Results from the auxiliary regressions are available upon request.

[10] As $d_{it}$ is impacted by a contemporaneous shock in the $pb_{it}$.

conditional on the data. The modern approach to Bayesian model selection is to apply Monte Carlo Markov Chain (MCMC) methods by jointly sampling model indicators and parameters. Frühwirth-Schnatter and Wagner (2010) developed this model selection approach for Unobserved Components (UC) models. Their approach relies on a non-centered parameterization of the UC model in which (i) binary stochastic indicators for each of the model components are sampled together with the parameters and (ii) the standard inverse gamma (IG) prior for the variances of innovations to the time-varying components is replaced by a Gaussian prior centered around zero for the standard deviations. In what follows, the exact implementation applied to our baseline model ((2.5)-(2.6)) is outlined.[11] [12]

### 1. *Non-centered parameterization*

As argued by Frühwirth-Schnatter and Wagner (2010), a first piece of information on the hypothesis whether the variance of innovations to a state variable is zero or not can be obtained by considering a non-centered parameterization. This implies rearranging the random walk process for the time-varying parameter $\beta_t$, i. e. equation (2.6):

$$\beta_t = \beta_0 + \sigma_\eta \tilde{\beta}_t, \tag{3.1}$$

$$\tilde{\beta}_t = \tilde{\beta}_{t-1} + \tilde{\eta}_t, \quad \tilde{\beta}_0 = 0, \quad \tilde{\eta}_t \sim N(0,1), \tag{3.2}$$

where $\beta_0$ is the initial value of $\beta_t$ if this coefficient varies over time ($\sigma_\eta > 0$), while being the constant value of $\beta_t$ in case that there is no time variation ($\sigma_\eta = 0$).

A crucial aspect of the non-centered parameterization is that it is not identified: The signs of $\sigma_\eta$ and $\tilde{\beta}_t$ can be exchanged without affecting their product. This implies that (i) in the situation where $\sigma_\eta > 0$, the marginal likelihood and therefore the marginal posterior distribution are bimodal with modes $+\sigma_\eta$ and $-\sigma_\eta$ and (ii) when $\sigma_\eta = 0$, the marginal likelihood and posterior will be unimodally centered around zero. As such, allowing for non-identification of $\sigma_\eta$ provides useful insights about the degree of time variation governing the debt ratio coefficient.

### 2. *Parsimonious specification*

In the non-centered parameterization, the question whether the fiscal responsiveness to the debt ratio varies over time or not can be expressed as a standard variable selection problem. To this

[11] This can easily be extended to the more refined specification for $\beta$, represented by equations (2.8)-(2.9).

[12] The implementation and description of this approach draws heavily on earlier work from the authors, such as Berger et al. (2016) and Everaert et al. (2017).

end, a binary indicator that can take the values 0 or 1 is introduced and sampled together with the model's other parameters (see Frühwirth-Schnatter and Wagner, 2010). More precisely, (3.1) becomes

$$\beta_t = \beta_0 + \lambda \sigma_\eta \tilde{\beta}_t, \tag{3.3}$$

where $\lambda \in \{0, 1\}$ is the binary indicator. If $\lambda = 0$, the time-varying component of $\beta_t$ drops, implying a constant debt ratio coefficient. That is, $\beta_t = \beta_0$ for all $t$. If $\lambda = 1$, the parameters $\{\tilde{\beta}_1, \tilde{\beta}_2, ..., \tilde{\beta}_T\}$ and $\sigma_\eta$ (together representing the time-varying component of $\beta_t$) are sampled along with the remaining parameters. We assume a uniform prior distribution for the binary indicator, making both candidate models - the one with a time-varying and the one with a constant debt ratio coefficient - equally likely a priori. Hence, the prior probability is set to $p_0 = 0.5$.

### *3. Gaussian priors centered at zero*

Our Bayesian estimation approach requires choosing prior distributions for the model parameters. When using the standard inverted Gamma (IG) prior for the variance parameter, the choice of the shape and scale hyperparameters - that define this distribution - has a strong influence on the posterior distribution when the true value of the variance is close to zero (see Frühwirth-Schnatter and Wagner, 2010 and Everaert et al., 2017). As a result, this choice of prior distribution has a tendency to overstate $\sigma^2_\eta$, especially if the true value of $\sigma^2_\eta$ is small.[13] In other words, the actual degree of time variation would be overstated.

When making use of the non-centered parameterization in (3.1)-(3.2) , where $\sigma_\eta$ is a regression coefficient, this issue can be resolved. In fact, this allows us to replace the standard IG prior on the variance parameter $\sigma^2_\eta$ by a Gaussian prior centered at zero on $\sigma_\eta$. As the standard deviation $\sigma_\eta$ is centered around zero both for $\sigma^2_\eta > 0$ and $\sigma^2_\eta = 0$, this makes sense. Frühwirth-Schnatter and Wagner (2010) show that the posterior density of $\sigma_\eta$ is much less sensitive to the hyperparameters of the Gaussian distribution and is not pushed away from zero when $\sigma^2_\eta = 0$.

## E. Estimating the FRF using a Markov Chain Monte Carlo algorithm

For the baseline specification, the system of equations represented by (2.5), (3.3) and (3.2) constitutes a state-space model, where the measurement equation is represented by (2.5) and the

[13] More specifically, as the IG distribution does not have probability mass at zero, using it as a prior distribution tends to push the posterior density away from zero.

state equation for $\beta_t$ by (3.3) and (3.2). Due to the presence of the time-varying parameter, $\beta_t$, and the utilization of the SMSS outlined above, this state-space model is non-standard. We follow Everaert et al. (2017) and employ a Gibbs sampler to estimate the parameters of the state-space model. More specifically, by simulating draws from conditional distributions, thereby breaking the complex estimation problem into easier to handle pieces, a MCMC algorithm is used to obtain approximations of intractable marginal and joint posterior distributions:

For convenience, define $\theta \equiv (\beta_0, \sigma_\eta, \alpha', \delta', \phi, \gamma')'$, $\beta \equiv (\beta_1, \beta_2, ..., \beta_T)'$ and $\tilde{\beta} \equiv (\tilde{\beta}_1, \tilde{\beta}_2, ..., \tilde{\beta}_T)'$, where $\gamma \equiv (\gamma_1, \gamma_2, ...\gamma_k)'$ with $k$ being the number of control variables contained in the predictor matrix $X$. Next, define a data matrix $Y = (pb, d_{-1}, X)$, where $pb, d_{-1}$ and $X$ contain all observations $i = 1, 2, ..., N$, $t = 1, 2, ..., T$ of $pb_{it}, d_{i,t-1}$ and $X_{it}$. That is, observations are stacked over cross sections and time periods, with the cross-sectional being the slower index. The resulting MCMC scheme is then given by the following blocks:[14] [15]

1. Sample the binary indicator $\lambda$ from $p(\lambda|\tilde{\beta}, Y)$, marginalizing over the parameters in $\theta$ and $\sigma^2_\epsilon$, then sample the unrestricted parameters in $\theta$ and $\sigma^2_\epsilon$.

2. Sample the random walk component $\tilde{\beta}$ from $p(\tilde{\beta}|\lambda, \theta, \sigma^2_\epsilon, Y)$

3. Perform a random sign switch for $\sigma_\eta$ and the elements in $\tilde{\beta}$. That is, draw from $\{-1, 1\}$ with equal probability of both outcomes and multiply by $\sigma_\eta$ and $\tilde{\beta}$, implying a 50 percent chance of $\sigma_\eta$ and $\tilde{\beta}$ being multiplied by (-1). The time-varying parameter vector can then be constructed from its components (based on equation (3.3)).

Given a sufficiently long burn-in phase, the MCMC scheme outlined above produces samples of the parameters that converge to the intractable joint and marginal posterior distributions. We set the total number of Gibbs iterations to 200,000, with a burn-in phase of 80,000. We store every 10th of the remaining 120,000 draws, leaving us with 12,000 retained draws.

## IV. EMPIRICAL RESULTS

Turning to the empirical results, we first discuss our baseline model in Section IV A. In Section IV B, the model extension is considered, where we allow observed variables to impact on the time-varying path of the primary balance responsiveness.

[14] Further details of this procedure are laid out in the appendix.

[15] In a separate appendix, more details on the MCMC scheme for the extended model, represented by equation (2.7)-(2.9), are outlined.

## A. Baseline specification

The baseline specification refers to the pure random walk model and is represented by equations (2.5), (3.1) and (3.2). As our Bayesian estimation approach requires choosing prior distributions for the model parameters, we will first discuss our prior choices. Then, the results of the SMSS procedure are analyzed, followed by a discussion of the model the SMSS procedure favours, i. e. the parsimonious model.

### 1. *Prior choices*

Summary information on the prior distributions for the unknown parameters is reported in Table I. For the variance $\sigma_\epsilon^2$ of shocks hitting the primary balance in equation (2.5), an inverse Gamma prior distribution is used, that is $\sigma_\epsilon^2 \sim IG(c_0, C_0)$, where the shape $c_0 = \frac{v_0}{2}NT$ and scale $C_0 = c_0\sigma_0^2$ parameters are calculated from the prior belief $\sigma_0^2$ and the prior strength $v_0$, which are expressed as a fraction of the sample size $NT$.[16] Our prior belief for $\sigma_\epsilon$ is 1.18, implying that 90% of primary balance shocks lie between -1.99 and 1.99%.[17] Note that the prior is fairly loose as the strength of $\sigma_\epsilon^2$ is set to $\nu_0 = 0.05$.

For the remaining parameters, Gaussian prior distributions, $N(a_0, V_0)$, are used. Technically, we assume Gaussian parameters and the inverted Gamma distributed regression error variance to jointly follow a dependent Normal-inverted Gamma distribution a priori. This implies the normally distributed parameters to depend on $\sigma_\epsilon^2$.[18] $V_0$ then equals $\sigma_2^2 A_0$. When discussing our Gaussian prior choices, first consider the time-varying fiscal responsiveness to the lagged public debt ratio, $\beta_t$. For $\beta_0$, the prior is given by $\beta_0 \sim N(0, 1.18^2 * 0.32^2)$ (with $\sigma_\epsilon \approx 1.18$), which reflects our belief that if no time variation is present in $\beta_t$ (i. e. $\sigma_\eta = 0$), then fiscal responsiveness ranges from roughly $-0.62$ to 0.62. This covers a wide range of parameter values found in the literature.[19] For the standard deviation $\sigma_\eta$ of the innovations to the time-varying part in $\beta_t$, a Gaussian prior centered at zero is chosen as well ($\sigma_\eta \sim N(0, 1.18^2 * 0.1^2)$). Note that the prior standard deviation of 0.1 implies a very loose prior as it allows that 90% of the innovations to $\beta_t$ lie between $-0.19$ and 0.19. Simulations of the random walk specification for $\beta_t$, based on the prior distribution for $\sigma_\eta$, reveal that the resulting random walk process covers all possible realistic values for the debt

[16] Since the prior is conjugate, $v_0 NT$ can be interpreted as the number of "fictitious" observations used to construct the prior belief $\sigma_0^2$ (see also Iseringhausen and Vierke, 2018).

[17] The choice of the prior belief for the standard deviation of $\sigma_0 \approx 1.18$ is based on a standard regression for $pb_{it}$, estimated with Ordinary Least Squares, where the debt ratio coefficient, $\beta$, enters the equation as a constant.

[18] More formally, it holds that $\theta \sim N(a_0, \sigma_\epsilon^2 A_0)$ and $\sigma_\epsilon^2 \sim IG(NT\frac{\nu_0}{2}, NT\frac{\nu_0}{2}$, where $\theta \equiv (\beta_0, \sigma_\eta, \alpha', \delta', \phi, \gamma')'$. Details are provided in appendix A.

[19] Again, we refer the reader to the excellent literature review of Checherita-Westphal and Žďárek (2017).

TABLE I. Prior choices for the baseline specification

**Gaussian priors**

| $\sim N(a_0, \sigma_\epsilon^2 A_0)$ | | $a_0$ | $\sqrt{A_0}$ | 5% | 95% |
|---|---|---|---|---|---|
| Initial state | $\beta_0$ | 0 | 0.32 | $-0.62$ | 0.62 |
| Standard deviation state error | $\sigma_\eta$ | 0 | 0.1 | $-0.19$ | 0.19 |
| AR(1) parameter | $\phi$ | 0.7 | 0.32 | 0.06 | 1.30 |
| Parameters of control variables and fixed effects | $(\gamma', \alpha', \delta')'$ | $\underline{0}$ | $0.32I$ | $-0.62$ | 0.62 |

**Inverted Gamma prior**

| $\sim IG(NT\frac{\nu_0}{2}, NT\frac{\nu_0}{2}\sigma_0^2)$ | | $\sigma_0$ | $\nu_0$ | 5% | 95% |
|---|---|---|---|---|---|
| Measurement error variance | $\sigma_\epsilon$ | 1.18 | 0.05 | 0.90 | 2.36 |

Notes: For the inverted Gamma prior, we display the prior belief about standard deviation $\sigma_0$ instead of the corresponding variance parameter as this is easier to interpret. Likewise, we report $\sqrt{A_0}$ instead of $A_0$ for the Gaussian priors. For the priors on $\gamma$, $\underline{0}$ is a $K$ x 1 vector of zeros, and $I$ is the identity matrix of dimension $K$x$K$, with $K$ being the number of control variables and fixed effects.

ratio coefficient.[20]

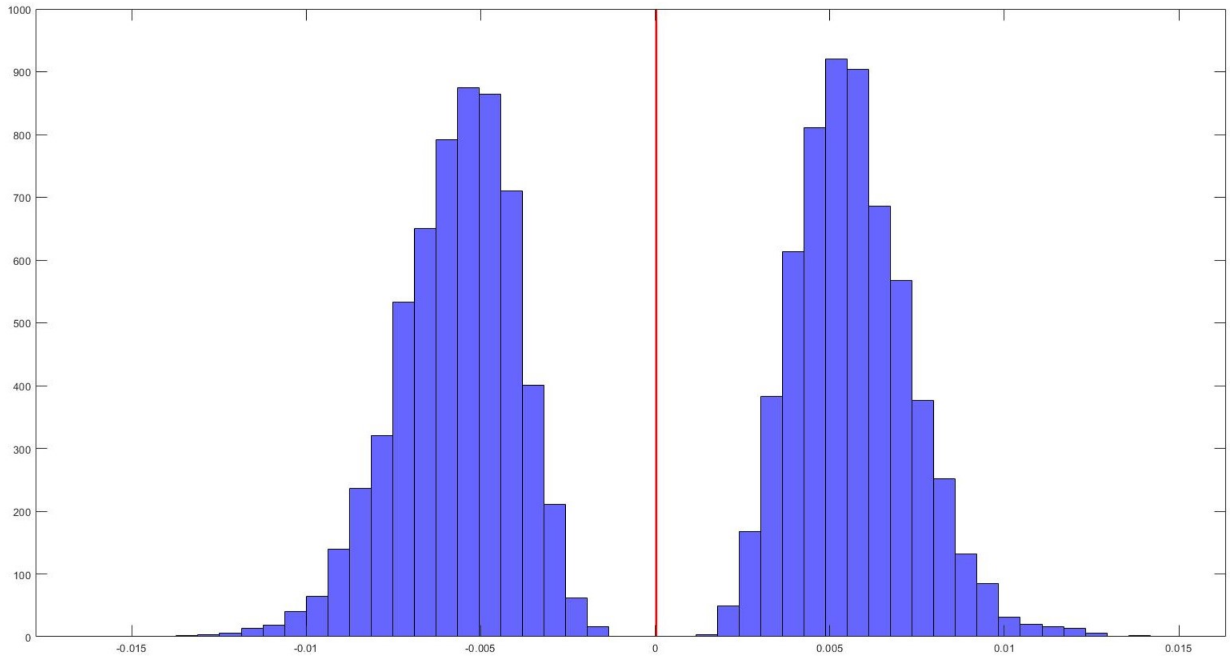
For the coefficient on the lagged primary balance, $\phi$, a Gaussian prior centered around 0.7 is chosen, roughly in line with estimates found in the literature (see for example Everaert and Jansen, 2018). Although the prior is not centered around 0, we are equally uninformative for $\phi$, implying a 90% prior density interval that roughly ranges from 0.06 to 1.30. For the other parameters, i. e. the coefficients on the control variables and the country and time fixed effects, the prior distribution is centered around zero, with the prior standard deviation $\sqrt{A_0}$ being 0.32. As a result, the 90% prior density interval spreads from approximately $-0.62$ to 0.62, thereby covering a wide range of parameter values found in the literature.

### *2. Stochastic model specification search*

First, we estimate the unrestricted model, represented by equations (2.5), (3.1) and (3.2). That is, we set the binary indicator $\lambda$ in (3.3) to 1 to generate a posterior distribution for the standard deviation ($\sigma_\eta$) of the shocks to $\beta_t$. If this distribution is bimodal, with low or no probability mass at zero, this can be taken as a first indication of a time-varying primary balance reaction to public debt. Figure 1 presents the resulting posterior distribution. Obviously, a clear-cut bimodality in

[20] The simulation results are available upon request.

FIG. 1. Posterior distribution for $\sigma_\eta$, when the binary indicator $\lambda = 1$.




the posterior distribution, with almost no probability mass at zero, is present. This indicates that $\sigma_\eta^2$ indeed appears to be greater than zero.

As a more formal test for the presence of time variation, we next sample the stochastic binary indicator $\lambda$ along with the unknown parameters. For the binary indicator $\lambda$, we choose a Bernoulli prior distribution with a prior probability $p_0$ of being included in the model, i. e. $p(\lambda = 1) = p_0$. As our benchmark, we set $p_0$ to 0.5, implying indifference between a time-varying and a constant debt ratio coefficient a priori. We further analyze results for the more informative priors $p_0 = 0.25$ and $p_0 = 0.75$. The posterior inclusion probability for the binary indicator is then calculated as the average selection frequency over all iterations of the Gibbs sampler.[21] By looking at the posterior inclusion probability, we obtain valuable information on the question whether time variation is present in the debt ratio coefficient or not.

Table II displays posterior inclusion probabilities for $\lambda$ for different prior variances of $\sigma_\eta$ and different prior inclusion probabilities. In the baseline case (see Table I), $A_0$ is set to 0.01 and $p_0 = 0.5$. The posterior inclusion probability of the stochastic binary indicator clearly exceeds 50% and is almost equal to 1. Clearly, based on this result, time variation is present in the fiscal responsiveness to public debt. As a first robustness check, we further consider other values for $A_0$,

[21] In other words, the posterior inclusion probability is the ratio of iterations in which $\lambda = 1$ relative to the absolute number of draws.

TABLE II. Posterior inclusion probabilities for the binary indicator $\lambda$

| Priors | | Posterior |
|---|---|---|
| $p_0$ | $A_{0,\sigma_\eta}$ | $\lambda$ |
| 0.25 | 0.001 | 0.9992 |
| 0.25 | 0.01 | 0.9979 |
| 0.25 | 0.1 | 0.9938 |
| 0.25 | 1 | 0.9772 |
| 0.25 | 10 | 0.9399 |
| 0.5 | 0.001 | 0.9999 |
| **0.5** | **0.01** | **0.9991** |
| 0.5 | 0.1 | 0.9985 |
| 0.5 | 1 | 0.9925 |
| 0.5 | 10 | 0.9835 |
| 0.75 | 0.001 | 0.9999 |
| 0.75 | 0.01 | 0.9997 |
| 0.75 | 0.1 | 0.9994 |
| 0.75 | 1 | 0.9978 |
| 0.75 | 10 | 0.9928 |

Note: Results are based upon various prior inclusion probabilities for $\lambda$, including a non-informative prior, i. e. $p_0 = 0.5$.

given the non-informative prior inclusion probability of $\lambda$, $p_0 = 0.5$: For a somewhat stricter prior variance $A_0 = 0.001$, i. e. when placing more weight on values near zero, and a variety of looser prior variances of 0.1, 1 and 10, results are almost equal. In particular, being less informative with respect to $\sigma_\eta$ by increasing $A_0$ hardly brings down the probability of a time-varying fiscal reaction to debt. Thus, even for the very uninformative prior, where $A_0 = 10$, the posterior inclusion probability still amounts to 98.35%. Moreover, the high probability of a time-varying fiscal reaction remains when being more informative with respect to $p_0$: As expected, when setting $p_0 = 0.75$, posterior inclusion probabilities for $\lambda$ are even higher. Even when we set $p_0 = 0.25$, so that our model favors the finding of no time variation in the fiscal reaction to debt a priori, the posterior inclusion probability clearly exceeds 90% for all four values of $A_0$. Our evidence regarding time variation in $\beta_t$ is thus very convincing.[22]

### 3. *Results parsimonious model*

As can be seen from the results in Table II, the SMSS procedure clearly favors a model with the stochastic binary indicator $\lambda$ set to 1, and where the debt ratio coefficient is allowed to vary over time. In what follows, results of this parsimonious model are discussed.[23]

Table III shows the estimation results for our set of control variables included in $X_{it}$. More precisely, as coefficients are sampled along with the other parameters, we report the posterior means as well as the 5th and 95th percentiles of the marginal posterior distributions. The results are broadly in line with the existing literature on FRFs. In particular, we find a positive reaction of the primary balance to an increasing output gap, indicating that fiscal policy is on average countercyclical and thus can be considered to be an effective stabilization tool.[24] Moreover, inflation is found to have a positive impact on the primary balance, which could be linked to bracket creep effects. Somewhat counterintuitive, according to our results an increase in the interest cost on servicing the public debt would lead to a lower primary balance. As this implies interest costs to rise, one would expect an offsetting impact of the primary balance - as our set of core EU countries is bounded by the nominal deficit rule. Although the mean of the coefficient on the election cycle variable shows that governments tend to increase their spending in election years, the 90% highest posterior density interval clearly encompasses zero. We thus refrain from statements on the effect of a potential political budget cycle. Finally, the posterior distribution for the lagged primary balance coefficient clearly indicates a pronounced sluggishness in the budgeting process.

Note that the bottom of table III contains information on the possible presence of autocorrelation and cross-sectional dependence in the error term. We follow Everaert and Jansen (2018) in employing the Cumby and Huizinga (1992) test to examine first-order serial correlation in the error terms. An advantage of this test is that it is valid even in the presence of instrumented regressors (and heteroscedasticity). The results suggest that there is no first-order autocorrelation present in the residuals. Related to instrument validity, this implies the lagged endogenous variables are

[22] While in this paper we focus on a group of what we labeled “core” EU countries, we additionally tested whether a time-varying fiscal response to debt was present in a sample of Southern EU countries, namely Greece, Italy, Portugal and Spain. However, for this sample, the finding of time variation is mixed at best, with a posterior inclusion probability of the stochastic binary indicator being approximately 0.36 in the baseline model. Results are available upon request.

[23] The model is labeled the “parsimonious” model as $\lambda$ is fixed and thus not sampled along with the other parameters.

[24] From a policy point of view, we can make no inference on the relative strength of automatic stabilizers and discretionary fiscal policy. When interested in the relative importance of discretionary fiscal policy as a stabilization tool, one could opt to use the cyclically adjusted primary balance as a dependent variable. This is, however, not the scope of this paper.

TABLE III. Posterior distribution of main parameters in the parsimonious baseline model
Sample: 1970-2019, 5 core EU countries

| Parameter | | Posterior mean | 5% | 95% |
|---|---|---|---|---|
| *Slope parameters* | | | | |
| Output gap | $\gamma_1$ | 0.347 | 0.224 | 0.468 |
| Inflation | $\gamma_2$ | 0.142 | 0.066 | 0.218 |
| Election cycle | $\gamma_3$ | -0.134 | -0.388 | 0.122 |
| Implicit interest rate | $\gamma_4$ | -0.186 | -0.275 | -0.096 |
| Lagged primary balance | $\phi$ | 0.522 | 0.435 | 0.608 |
| *Variance parameters* | | | | |
| State error variance | $\sigma^2_\eta$ | $3.5e{-}5$ | $1.0e{-}5$ | $7.5e{-}5$ |
| Measurement error variance | $\sigma^2_\epsilon$ | 1.339 | 1.149 | 1.550 |
| **Residual diagnostics** | | | | |
| Cumby-Huizinga autocorrelation test statistic | 0.824 | (0.36) | | |
| Average pairwise cross-sectional correlation coefficient | -0.076 | | | |

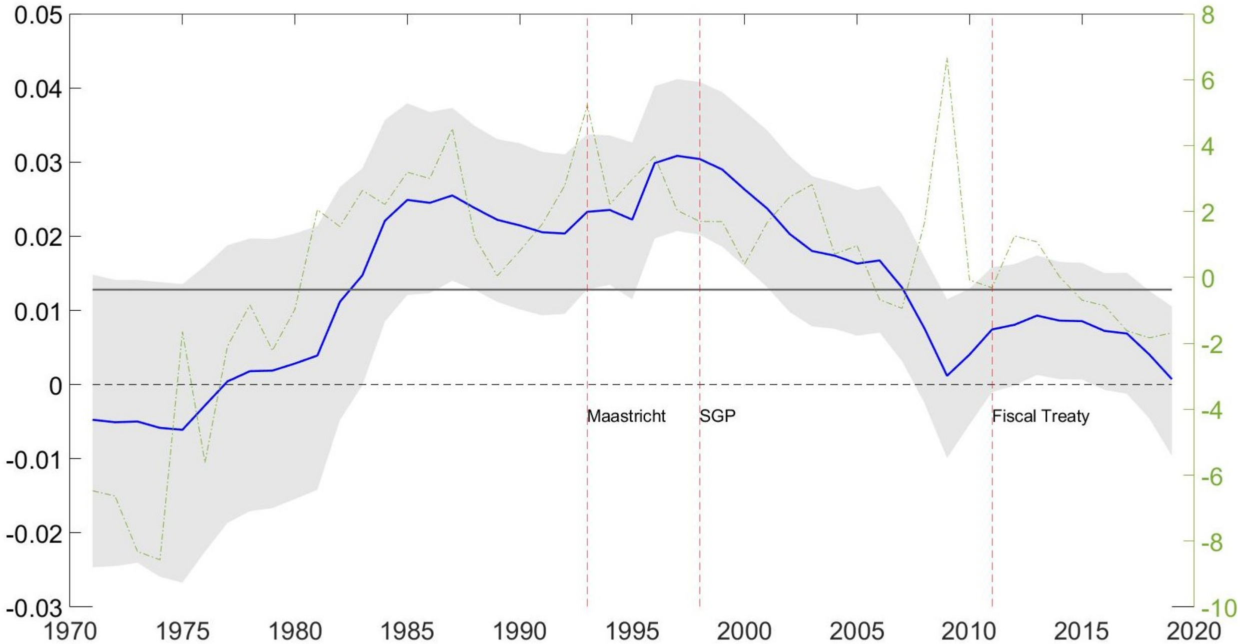
Note: For the Cumby-Huizinga test, the corresponding p-value is put in brackets.

predetermined. Moreover, and equally important, the presence of serial correlation would have rendered $d_{t-1}$ and its powers endogenous. Next to that, the calculated average pairwise correlation in the estimated errors is relatively small, indicating that including country and time fixed effect is sufficient to deal with the possible presence of cross-sectional correlation in the errors.

Of course we are mainly interested in the estimated time-varying path of the debt ratio parameter, $\beta_t$, which is displayed in Figure 2. The blue line represents the average of the posterior distribution of the time-varying fiscal responsiveness to the public debt ratio, with the shaded area showing the evolution of the 90% highest posterior density interval. The average fiscal responsiveness over time is displayed as a gray line and amounts to 0.013, indicating that Bohn (1998)'s weak sustainability criterion has been fulfilled on average. It should be noted that this value is clearly located near the lower end of the spectrum of debt ratio coefficient estimates found in the literature.

The path shows a weak fiscal reaction to debt in the seventies - with fiscal policy barely responding to changes in debt, as indicated by the 90% highest posterior density interval. However, starting in the beginning of the eighties, the fiscal reaction picked up substantially, with a first peak in the mid-eighties. Subsequently, fiscal responsiveness seemed to stabilize for a certain period,

FIG. 2. Time-varying $\beta_t$ in the baseline specification




Notes: The blue line represents the posterior mean of $\beta_t$ with the 90% highest posterior density interval as shaded area (left y-axis), while the green line represents the interest-rate growth differential in percent (sample country average, right y-axis). The average debt ratio coefficient is depicted as a gray line. Some milestones of European integration have been added as vertical lines, including the Maastricht Treaty, the Stability and Growth Pact (SGP) as well as the more recently implemented Fiscal Treaty.

followed by a small increase towards the end of the nineties. The small growth in fiscal responsiveness seems to coincide with the period between signing the Maastricht Treaty and the start of the common currency, a possible explanation being that countries needed to fulfill the convergence criteria for adopting the Euro. Afterwards, while the Stability and Growth Pact required continued fiscal efforts from goverments, it seems that fiscal responsiveness dropped signficantly. This preliminary finding confirms the results of Weichenrieder and Zimmer (2014), who relate the drop in fiscal responsiveness after entering the Eurozone to the frequent breaches of the 3% deficit rule, the implicit weakening of the rules and the moral hazard effects from implicit bailout guarantees. The Fiscal Treaty, enforced in 2013, does not appear to have reinforced fiscal prudence, at least according to our anecdotal evidence.

The European Monetary Union has led to a narrowing of spreads among member countries (see amongst others, Turner and Spinelli, 2011), resulting in a downward effect on the IRGD. As such, the downward trend in fiscal responsiveness after Eurozone acceptance could be due to a decreasing

IRGD. We therefore also plot the IRGD - averaged over our sample countries - in figure 2 in green, with the corresponding values on the right y-axis. Comparing its evolution with the path of the debt ratio coefficient is instructive: In particular, one might argue that the unsubstantial fiscal responsiveness in the seventies might stem from the negative IRGDs at that time. Likewise, the increase in fiscal responsiveness in the eighties as well as the fall after the introduction of the Euro is roughly accompanied by movements of the IRGD in the same direction. A notable exception to this apparent correlation is the spike in IRGDs in the aftermath of the Financial and Economic Crisis of 2007-2008, implied by both lower growth rates and higher refinancing costs in the sample countries as spreads widened. This was due to a sharp increase in public debt ratios and growing concerns from financial markets regarding countries' ability to pay back their debts.

### B. Model extension: Drivers of a time-varying debt coefficient $\beta$

As results from the baseline specification show, there is clear evidence of significant time variation in $\beta_t$. In a model extension, represented by equations (2.7), (2.8) and (2.9), we therefore model the time-varying fiscal reaction to public debt as a linear combination of a random walk component and a set of covariates (see Section II B for more details.), which leads to a country-specific $\beta_{it}$. This enables us to shed some light on potential drivers of the observed time-variation in a country's fiscal responsiveness to public debt.

Moreover, by formally testing for time variation in the random walk component by means of the SMSS algorithm, we are able to determine whether there is significant time variation left that cannot be explained by the variables included in $G_{it}$.

#### *1. Choice of variables included in $G_{it}$*

As elaborated upon in Section II B, our analysis focuses on the role of (i) the IRGD and (ii) the level of the public debt ratio in explaining the time variation in fiscal responsiveness to public debt.

- **IRGD:** Focusing on the IRGD is an obvious choice as it plays an essential role in public debt management.[25] If the implicit interest rate on the outstanding amount of debt increases, and thus if debt service costs rise, governments are forced to react stronger to rising public

[25] As argued in Section II B, we will employ the IRGD at the beginning of period $t$, $IRGD_{i,t-1}$, as this is the relevant indicator that impacts on the discretionary fiscal policy behavior in $t$.

debt ratios in order to prevent an explosive debt path. On the contrary, a higher nominal GDP growth rate tends to lower the debt-to-GDP ratio by increasing the denominator. A lower primary balance will thus be needed to stabilize the public debt ratio. All in all, higher economic growth makes any public debt position more sustainable (ceteris paribus), which justifies a lower fiscal responsiveness to debt. In our empirical analysis, we also allow for an asymmetric government reaction to positive and negative IRGDs. If the IRGD $< 0$, and nominal interest rates are expected to remain below growth rates for a long time, public debt may have no fiscal costs and only limited welfare costs (see Blanchard (2019) for an interesting discussion on this topic). On the contrary, a positive and increasing IRGD will lead to a higher primary surplus needed to stabilize or reduce debt. As such, this should lead to an increase in fiscal responsiveness.

- **Lagged debt ratio:** As stated before, an important element in the fiscal austerity debate is whether fiscal responsiveness is impacted by the level of debt itself. By including the lagged debt ratio in $G_{it}$ we actually allow for the presence of nonlinearities in the relation between $pb_{it}$ and $d_{i,t-1}$, that are caused by the level of public debt itself. More specifically, taking into account the level of the lagged debt ratio as a covariate in $G_{it}$ implies in fact a parabolic relationship between $pb_{it}$ and $d_{i,t-1}$.

To see this, first consider the non-centered parameterization for equation (2.9),

$$\beta_t^* = \beta_0^* + \lambda\sigma_{\eta^*}\tilde{\beta}_t, \tag{4.1}$$

$$\tilde{\beta}_t = \tilde{\beta}_{t-1} + \tilde{\eta}_t, \quad \tilde{\beta}_0 = 0, \qquad \tilde{\eta}_t \sim N(0,1). \tag{4.2}$$

The extended model is then represented by equations (2.7), (2.8), (4.1) and (4.2), as elaborated upon more thoroughly in appendix B. Now assuming that $d_{i,t-1}$ is the only covariate contained in $G_{it}$, we can write

$$pb_{it} = \alpha_i + \delta_t + \phi pb_{i,t-1} + \underbrace{(\beta_0^* + \lambda\sigma_{\eta^*}\tilde{\beta}_t + d_{i,t-1}\kappa)}_{\beta_t} d_{i,t-1} + X_{it}\gamma + \epsilon_{it}.$$

Thus, in this case $\beta_0^*$ captures the constant, linear component of the debt ratio coefficient while $\kappa$ captures the impact of the quadratic term. A positive but decreasing response of the primary balance to rising debt - and thus a first indication of fiscal fatigue, would show up as $\kappa < 0$.

Next, and in line with Ghosh et al. (2013), we will allow for a cubic specification to test for the presence of fiscal fatigue in our sample. Analogously to the explanation above, this can be done by including the square of $d_{i,t-1}$ in $G_{it}$. A negative coefficient on the squared debt term in $G_{it}$ could be seen as evidence for fiscal fatigue.

Finally, recall that an advantage of our approach - compared to Ghosh et al. (2013) and others - is that we also acknowledge that other factors have an impact on $\beta_t$. They are captured by the random walk component. As such, possible nonlinearities caused by the actual level of public debt are not the result of ignoring other sources of time variation.

### *2. Prior choices*

As for the baseline model, our Bayesian estimation approach requires choosing prior distributions for the model parameters in the extended specification. For the parameters already present in the baseline specification, the prior choices are retained. For the new parameter vector $\kappa$, a Gaussian prior centered around zero is chosen with the prior standard deviations $\sqrt{A_0}$ being approximately 0.32. Hence, for $\kappa$ we are also highly uninformative for these parameters as the 90% prior density interval ranges from approximately $-0.62$ to 0.62.

### *3. Stochastic model specification search*

As already mentioned, using the SMSS algorithm allows us to make inferences about the importance of including the random walk component in the extended specification for $\beta$, i. e. equation (2.8). Results for the SMSS are reported in the upper panel of Table IV. Various specifications are estimated, which differ in the variables included in $G_{it}$. Results show that for all specifications, the posterior inclusion probability $p(\lambda|data)$ of the stochastic binary indicator clearly exceeds 50% and even fluctuates around 90%. This indicates that there is significant time variaton left in the fiscal responsiveness to the public debt ratio that cannot be explained by the variables in $G_{it}$. However, note that in all specifications, the posterior inclusion probability $p(\lambda|data)$ drops with respect to the baseline model, due to the inclusion of covariates explaining a share of the time variation in $\beta_t$. Similarly, the posterior mean of the variance of innovations to the random walk component, $\sigma_\eta^2$, falls for most specifications. Both can be interpreted as preliminary signs that the variables included in $G_{it}$ are indeed explaining part of the observed time variation in fiscal prudence.

## *4. Results parsimonious model*

The discussion above shows that the SMSS obviously favors a model where the stochastic binary indicator is set to 1 in (4.1). The lower panel of Table IV reports the results for this parsimonious model. More precisely, it presents the posterior mean and the 5th and 95th percentile of the marginal posterior distributions of the impacts, $\kappa$, - over different combinations of variables included in $G_{it}$ - on $\beta_{it}$.

When looking at the results, one immediately notices that the posterior distributions of the coefficients $\kappa$ are centered around small numbers. This, however, does not imply that the impact of the included variables is negligible. As the determinants included in $G_{it}$ are trying to explain part of the time variation in $\beta$ - which is on average equal to 0.013 in our baseline model - it is logical that coefficients are much smaller.[26]

Our empirical results show that the IRGD seems to have no clear impact on a government's fiscal responsiveness. Although the posterior mean has the right positive sign, over the different specifications the 90% highest posterior density interval contains zero (see specifications 1, 5 and 7). However, as the distribution is not centered around zero, this could still be taken as a weak sign that an increase in the IRGD leads to a higher fiscal responsiveness. Moreover, this result could be due to an asymmetric reaction of governments to positive and negative IRGDs. When the IRGD is negative, results clearly show no impact of this determinant on fiscal responsiveness. On the contrary, when the IRGD is positive, an increase in it leads to a rise in fiscal responsiveness. This is expected as a growth in a positive IRGD enlarges the cost for governments of being fiscally irresponsible. This can mainly be seen in specification 2, while in specification 6 and 8 the posterior distribution includes zero but is firmly skewed to the right, with the majority of the probability mass located in the positive area.

Finally, results on potential nonlinearities in the fiscal reaction to the public debt ratio show that - at least for our sample - governments tend to respond more when the debt ratio is high. This is clearly confirmed when only including the level of the debt ratio in $G_{it}$ (see specification 3, 5 and 6). When explicitly testing for fiscal fatigue, and thus including a squared debt term in $G_{it}$, our findings do not provide evidence for the fiscal fatigue proposition of Ghosh et al. (2013) (see specifications 4, 7 and 8). Our results are closer to Everaert and Jansen (2018), who also do not find fiscal fatigue to be a robust characteristic of the fiscal reaction function. However, this does not imply that there is no such debt threshold from where fiscal effort becomes unfeasible or

[26] More precisely, the coefficient vector $\kappa$ measures the impact on $\beta$ of a one %-point increase in the corresponding variable.

TABLE IV. Results extended model

Sample: 1970-2019, 5 core EU countries

| | Specification 1 | | | Specification 2 | | | Specification 3 | | | Specification 4 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Stochastic model specification search** | | | | | | | | | | | | |
| $\sigma^2_{\tilde{\eta}}$ | $3.4e{-5}$ | $9.0e{-6}$ | $7.6e{-5}$ | $3.9e{-5}$ | $1.1e{-5}$ | $8.5e{-5}$ | $2.9e{-5}$ | $6.5e{-6}$ | $6.7e{-5}$ | $3.0e{-5}$ | $6.8e{-6}$ | $6.8e{-5}$ |
| $p(\lambda\|data)$ | 0.978 | | | 0.988 | | | 0.891 | | | 0.887 | | |
| **Results posterior distributions for $\kappa$ in the parsimonious model** | | | | | | | | | | | | |
| | Mean | 5% | 95% | Mean | 5% | 95% | Mean | 5% | 95% | Mean | 5% | 95% |
| IRGD | 0.0007 | -0.0005 | 0.002 | - | - | - | - | - | - | - | - | - |
| IRGD<0 | - | - | - | -0.0008 | -0.0036 | 0.0022 | - | - | - | - | - | - |
| IRGD>0 | - | - | - | 0.001 | 0.000 | 0.003 | - | - | - | - | - | - |
| Debt | - | - | - | - | - | - | 0.0002 | $4.2e{-5}$ | 0.0003 | -0.0005 | -0.0013 | 0.0003 |
| Debt$^2$ | - | - | - | - | - | - | - | - | - | $3.8e{-6}$ | -3.7$e{-7}$ | $7.9e{-6}$ |

Table IV, continued

| | Specification 5 | | | Specification 6 | | | Specification 7 | | | Specification 8 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Stochastic model specification search** | | | | | | | | | | | | |
| $\sigma^2_{\tilde{\eta}}$ | $2.9e{-5}$ | $6.1e{-6}$ | $6.6e{-5}$ | $3.5e{-5}$ | $8.4e{-6}$ | $7.9e{-5}$ | $2.9e{-5}$ | $6.4e{-6}$ | $6.8e{-5}$ | $3.6e{-5}$ | $9.0e{-6}$ | $8.0e{-5}$ |
| $p(\lambda\|data)$ | 0.820 | | | 0.911 | | | 0.805 | | | 0.895 | | |
| **Results posterior distributions for $\kappa$ in the parsimonious model** | | | | | | | | | | | | |
| | Mean | 5% | 95% | Mean | 5% | 95% | Mean | 5% | 95% | Mean | 5% | 95% |
| IRGD | 0.0002 | -0.0011 | 0.0015 | - | - | - | 0.0002 | -0.0011 | 0.0015 | - | - | - |
| IRGD<0 | - | - | - | -0.0019 | -0.005 | 0.001 | - | - | - | -0.0018 | -0.0048 | 0.0012 |
| IRGD>0 | - | - | - | 0.0008 | -0.0008 | 0.0023 | - | - | - | 0.0007 | - 0.0008 | 0.0022 |
| Debt | 0.0002 | $2.5e{-5}$ | 0.0003 | 0.0002 | 4.6e-5 | 0.0004 | -0.0005 | -0.0014 | 0.0003 | -0.0005 | -0.0013 | 0.0003 |
| Debt$^2$ | - | - | - | - | - | - | $3.8e{-6}$ | -3.1$e{-7}$ | $7.9e{-6}$ | $3.6e{-6}$ | $-5.4e{-7}$ | $7.7e{-6}$ |

Notes: $p(\lambda|data)$ represents the posterior inclusion probability for the random walk component of the non-centered parameterization. Further, posterior moments are displayed for the variance of the random walk component and for the set of parameters $\kappa$ in the parsimonious model.

undesirable. But for the debt ratios observed in our homogeneous sample of core EU countries - and when allowing for other determinants driving fiscal responsiveness - we do not find any signs of the fiscal fatigue property.

## V. CONCLUSION

The fiscal policy response to the COVID-19 crisis has put severe pressure on public finances in the EU. Against the backdrop of low expected potential economic growth and sharply rising age-related public expenditures, this has revived the debate on the sustainability of public finances. Estimating FRFs and empirically analyzing whether countries react to a growing public debt ratio by tightening the fiscal policy stance can shed light on a country's degree of fiscal prudence.

The FRF literatue has well recognized the importance of non-linearities for correctly specifying the FRF. A key issue is whether the degree of fiscal responsiveness changes with the level of debt. Specifically, as introduced by Ghosh et al. (2013), the hypothesis of fiscal fatigue has been tested, implying that at a certain debt level the fiscal response starts to weaken and even decreases.

In this paper, we formally test for the presence and potential sources of non-linearities by allowing for a time-yvaring fiscal responsiveness to debt. This approach is related to commonly used FRF specifications that embed the fiscal fatigue proposition, but is more flexible as it allows nonlinearities in the fiscal reaction to debt to arise stochastically by means of a time-varying parameter model.

Having employed a Bayesian SMSS testing procedure to formally test for the presence of time variaton in the responsiveness in the primary balance to the gross public debt ratio, we find strong evidence for time-variation in the FRF over the last 50 years. Governments' fiscal stance to debt exhibits smooth but significant variation over time and thus confirms the necessity of a non-linear model.

In a model extension, we explicitly try to make inferences about potential driving forces of the time varyings fiscal responsiveness. As such, we are able to test for the presence of fiscal fatigue in a stochastic way, i. e. acknowledging the potential presence of other sources of time variation.

Our results provide preliminary evidence that the fiscal response to debt seems to be partly explained by changes in the IRGD, at least when the IRGD is positive. In that case, an increase in the IRGD reinforces the cost of being fiscally irresponsible. Governments will therefore react by tightening their fiscal policy stance.

When allowing for nonlinearities caused by the level of public debt, our model does not provide robust evidence of the fiscal fatigue proposition of Ghosh et al. (2013). On the contrary, the results indicate that - for our sample - governments tend to increase fiscal responsiveness when the debt ratio increases. As such, these results are more in line with the findings of Everaert and Jansen (2018), who also do not find fiscal fatigue to be a robust characteristic of the FRF. However, this does not imply that no such debt threshold exists from which the fiscal effort becomes unfeasible or undesirable. It is just not observed in our sample of public debt ratios.

Our findings further indicate that a significant fraction of the time variation governing the fiscal reaction coefficient is not explained by our set of predictors. Future research on potential other sources of the observed time variation could therefore be very clarifying and help in explaining countries' fiscal stances to debt. More precisely, it could be interesting to look explicitly into the relevance of financial market pressure and the role of political economy determinants, such as the political orientation of governments.

Given their prominence in stochastic DSA, a correctly specified FRF is of utmost importance. In our analysis, we propose a careful assessment of whether potential parameter instability should be accounted for in the sample of interest. Our results clearly indicate that time-varying FRFs appear to be an adequate choice.

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**Appendix A: Gibbs sampling procedure pure random walk model**

In this section, we provide details on the Gibbs sampling algorithm for the "pure random walk model". The full model in this case consists of the equations (2.5), (3.3) and (3.2), restated here for convenience (with the slight notational difference that the regressor matrices corresponding to the fixed effects are now contained in $X$, the parameters $\alpha \equiv (\alpha_1, \alpha_2, ..., \alpha_N)'$ and $\delta \equiv (\delta_2, \delta_3..., \delta_T)'$ thus contained in $\gamma$):

$$
\begin{aligned}
pb_{it} &= \phi pb_{i,t-1} + \beta_t d_{i,t-1} + X_{it}\gamma + \epsilon_{it}, && && \epsilon_{it} \sim N(0, \sigma_\epsilon^2), && \text{(A1)}\\
\beta_t &= \beta_0 + \lambda \sigma_\eta \tilde{\beta}_t, && && && \text{(A2)}\\
\tilde{\beta}_t &= \tilde{\beta}_{t-1} + \tilde{\eta}_t, && \tilde{\beta}_0 = 0, && \tilde{\eta}_t \sim N(0,1), && \text{(A3)}
\end{aligned}
$$

In what follows we provide details on the MCMC algorithm employed to jointly sample the time-varying parameter vector $\beta$, the hyperparameters collected in $\theta$ and $\sigma_\epsilon^2$ and the stochastic binary indicator $\lambda$. The outlined procedure is based on Frühwirth-Schnatter and Wagner (2010) and Berger et al. (2016).

**1. Sampling the stochastic binary indicator and the hyperparameters**

In this block, we sample the stochastic binary indicator $\lambda$ and the hyperparameters, collected in $\theta$ and $\sigma_\epsilon^2$. For notational convenience, define a general regression model

$$y = \chi^m \theta^m + e, \quad e \sim N(0, \Sigma), \tag{A4}$$

where $y$ is the dependent variable vector and $\chi$ is an unrestricted predictor matrix corresponding to the parameter vector $\theta \equiv (\beta_0, \sigma_\eta, \phi, \gamma')'$. For both $y$ and $\chi$, observations are stacked over cross-sectional and time units, that is, over $i = 1, 2, ..., N$ and $t = 1, 2, ..., T$, with $i$ being the slower index. Correspondingly, $\chi^m$ and $\theta^m$ are the restricted predictor matrix and parameter vector, where $\sigma_\eta$ and its associated predictor vector are excluded from $\theta$ and $\chi$ if the binary indicator $\lambda$ is zero. The covariance matrix of the error term $e$ is a diagonal matrix simply given by $\Sigma = diag\left(\sigma_\epsilon^2 I_{NT}\right)$, where $I_{NT}$ is the identity matrix of dimension $NT$ with $N$ and $T$ being the numbers of cross-sectional and time units in the sample, respectively. $\sigma_\epsilon^2$ is a scalar. Thus, we assume homoscedasticity.

Note that simply drawing from $p(\lambda|\theta, \sigma_\epsilon^2, \tilde{\beta}, y, \chi)$ and $p(\theta, \sigma_\epsilon^2|\lambda, \tilde{\beta}, y, \chi)$ does not yield an irreducible Markov chain as a draw of $\lambda = 0$ implies that $\sigma_\eta$ will also be zero, which leads to the

Markov chain having absorbing states. We follow Frühwirth-Schnatter and Wagner (2010) in resolving this by marginalizing over the parameters in $\theta$ and $\sigma_\epsilon^2$ when drawing $\lambda$ and subsequently sampling from $p(\theta, \sigma_\epsilon^2 | \lambda, \tilde{\beta}, y, \chi)$.

The posterior distribution of $\lambda$ is obtained from Bayes' rule:

$$p(\lambda|\tilde{\beta}, y, \chi) \propto f(y|\lambda, \tilde{\beta}, \chi)p(\lambda), \tag{A5}$$

where $f(y|\lambda, \tilde{\beta}, \chi)$ is the marginal likelihood of the regression model in (A4), having integrated out $\theta$ and $\sigma_\epsilon^2$, and $p(\lambda)$ is the prior distribution of $\lambda$.

Given homoscedasticity, a dependent Normal-inverted Gamma prior with $\theta^m \sim N(a_0^m, A_0^m \sigma_\epsilon^2)$ and $\sigma_\epsilon^2 \sim IG(c_0, C_0)$, with $c_0$ and $C_0$ being the shape and scale parameters of the prior distribution for the measurement error variance, is conjugate, implying the closed form solution of the marginal likelihood[27]

$$f(y|\lambda, \tilde{\beta}, \chi) \propto \frac{|A_T^m|^{0.5}}{|A_0^m|^{0.5}} \frac{\Gamma(c_T) C_0^{c_0}}{\Gamma(c_0) \left(C_T^m\right)^{c_T}}, \tag{A6}$$

where

$$a_T^m = A_T^m \left((\chi^m)' y + (A_0^m)^{-1} a_0^m\right),, \tag{A7}$$

$$A_T^m = \left((\chi^m)'\chi^m + (A_0^m)^{-1}\right)^{-1}, \tag{A8}$$

$$c_T = c_0 + \frac{NT}{2}, \tag{A9}$$

$$C_T = C_0 + 0.5\left(y'y + (a_0^m)' (A_0^m)^{-1} a_0^m - (a_T^m)' (A_T^m)^{-1} a_T^m\right). \tag{A10}$$

The above can then be applied to the state-space model in equations (A1), (A2) and (A3).

Inserting (A2) into (A1) yields

$$pb_{it} = \phi pb_{i,t-1} + \beta_0 d_{i,t-1} + \lambda \sigma_\eta \tilde{\beta}_t d_{i,t-1} + X_{it}\gamma + \epsilon_{it}, \qquad \epsilon_{it} \sim N(0, \sigma_\epsilon^2), \tag{A11}$$

which can be written as

$$\underbrace{pb_{it}}_{y_{it}} = \underbrace{\begin{bmatrix} d_{i,t-1} & \lambda\tilde{\beta}_t d_{i,t-1} & pb_{i,t-1} & X_{it} \end{bmatrix}}_{\chi_{it}^m} \underbrace{\begin{bmatrix} \beta_0 \\ \sigma_\eta \\ \phi \\ \gamma \end{bmatrix}}_{\theta^m} + \epsilon_{it}. \tag{A12}$$

[27] Note that we follow Berger et al. (2016) in employing a *dependent Normal-inverted Gamma prior* due to the assumption of homoscedasticity. Hence, the prior variance parameters $V_0 \equiv \sigma_\epsilon^2 A_0$ cannot simply be interpreted as the prior covariance matrix of the normally distributed parameters, as $V_0$ depends on $\sigma_\epsilon^2$. Details can be found in Koop (2003), who uses precision instead of variance parameters, however (and therefore works with Normal-Gamma, not Normal-inverted Gamma distributions).

Note that the second elements of $\chi_{it}^m$ and $\theta^m$ are excluded (set to zero) if $\lambda = 0$, while for $\lambda = 1$, $\sigma_\eta$ is sampled along with the other parameters in $\theta$. The marginal likelihood $f(y|\lambda, \beta)$ is then given by (A6), and the stochastic binary indicator $\lambda$ can be sampled from the Bernoulli distribution:

$$p(\lambda = 1|\beta, y, \chi) = \frac{f(\lambda = 1|\beta, y)}{f(\lambda = 0|\beta, y) + f(\lambda = 1|\beta, y)}. \tag{A13}$$

Given $\lambda$, $\theta^m$ and $\sigma_\epsilon^2$ can then be sampled jointly from $\theta^m, \sigma_\epsilon^2 \sim NIG(a_T^m, A_T^m, c_T, C_T)$, where the posterior moments are given by (A7), (A8), (A9) and (A10).

### 2. Sampling the time-varying parameter

In this block, we employ the forward-filtering backward-sampling procedure of Carter and Kohn (1994) to sample the time-varying component $\tilde{\beta}$ given $\theta$, $\sigma_\epsilon^2$ and $\lambda$. Our conditional linear Gaussian state-space model is given by:

$$y_t = H_t^m s_t^m + e_t, \qquad\qquad e_t \sim MN(0_N, R), \tag{A14}$$

$$s_t = F s_{t-1} + K_t v_t, \qquad s_0 \sim N(b_0, V_0), \qquad v_t \sim N(0, Q), \tag{A15}$$

where $y_t$ is an $N$ x 1 vector of observations and $H_t^m$ is the restricted version of the predictor matrix, with $s_t^m$ being the corresponding time-varying parameter vector, for which $H_t^m = H_t$ and $s_t^m = s_t$ in the unrestricted case. The matrices $\chi, F, K, R, Q$ as well as the expected value and variance of the initial state $s_0$, that is, $b_0$ and $P_0$, are assumed to be known (conditioned upon). The disturbances $e_t$ and $v_t$ are assumed to be serially uncorrelated and independent of each other for $t = 1, 2, ..., T$. For details on the linear Gaussian state-space model, we refer to Durbin and Koopman (2012).

We can then employ the Kalman filter on this linear Gaussian state-space model to filter the unknown state $s_t$ (forward-filtering). $s_t$ can then be sampled from its conditional distribution (backward-sampling), as described in Carter and Kohn (1994).

Rearranging terms in equation (A11) and restating the state equation (A3) yields the unrestricted conditional state-space model for $\tilde{\beta}_t$:

$$\overbrace{pb_{it} - \phi pb_{i,t-1} - d_{i,t-1}\beta_0 - X_{it}\gamma}^{y_{it}} = \overbrace{d_{i,t-1}\lambda\sigma_\eta}^{H_t^m} \overbrace{\tilde{\beta}_t}^{s_t^m} + \overbrace{\epsilon_{it}}^{e_{it}}, \qquad \epsilon_{it} \sim N(0, \overbrace{\sigma_\epsilon^2}^{R}), \tag{A16}$$

$$\underbrace{\tilde{\beta}_t}_{s_t} = \underbrace{1}_{F} \underbrace{\tilde{\beta}_{t-1}}_{s_{t-1}} + \underbrace{1}_{K_t} \underbrace{\tilde{\eta}_t}_{v_t}, \qquad \tilde{\eta}_t \sim N(0, \underbrace{1}_{Q}), \tag{A17}$$

Notice that $s_t^m$ is a scalar as we assume the time-varying parameter to be homogeneous across countries, as outlined above. Stacking observations over $i = 1, 2, ..., N$, this can be written as

$$\overbrace{\begin{bmatrix} pb_{1t} - pb_{1,t-1}\phi - d_{1,t-1}\beta_0 - X_{1t}\gamma \\ \vdots \\ pb_{Nt} - pb_{N,t-1}\phi - d_{N,t-1}\beta_0 - X_{Nt}\gamma \end{bmatrix}}^{y_t} = \overbrace{\begin{bmatrix} d_{1,t-1}\lambda\sigma_\eta \\ \vdots \\ d_{N,t-1}\lambda\sigma_\eta \end{bmatrix}}^{H_t^m} \overbrace{\tilde{\beta}_t}^{s_t^m} + \overbrace{\begin{bmatrix} \epsilon_{1t} \\ \vdots \\ \epsilon_{Nt} \end{bmatrix}}^{e_t}, \tag{A18}$$

$$\overbrace{\begin{bmatrix} \epsilon_{1t} \\ \vdots \\ \epsilon_{Nt} \end{bmatrix}}^{e_t} \sim \left( \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix}, \sigma_\epsilon^2 \overbrace{\begin{bmatrix} 1 & & \\ & \ddots & \\ & & 1 \end{bmatrix}}^{R} \right) \tag{A19}$$

$$\underbrace{\tilde{\beta}_t}_{s_t} = \underbrace{1}_{F} \underbrace{\tilde{\beta}_{t-1}}_{s_{t-1}} + \underbrace{1}_{K_t} \underbrace{\tilde{\eta}_t}_{v_t}, \tag{A20}$$

$$\underbrace{\tilde{\eta}_t}_{v_t} \sim N(0, \underbrace{1}_{Q}), \tag{A21}$$

The time-varying component $\tilde{\beta}_t$ is initialized with mean and variance $b_0 = 0$ and $P_0 = 0.00001$. By doing so, we ensure that the time-varying parameter $\beta_t$ is initialized with its first value, $\beta_0$.

The unobserved state vector $\tilde{\beta}$ is then extracted using standard forward-filtering and backward-sampling. Instead of taking the entire $N$ x 1 observational vector $y_t$ as the item of analysis, we follow the univariate treatment of the multivariate series approach of Durbin and Koopman (2012), in which each of the elements in $y_t$ is brought into the analysis individually. This offers significant computational gains and reduces the risk of the prediction error variance matrix becoming nonsingular during the Kalman filter procedure.

In the restricted model, that is, for $\lambda = 0$, $\chi^m$ and $s^m$ are empty. Thus, no forward-filtering and backward-sampling is applied. In this case, $\tilde{\beta}_t$ is sampled directly from its prior, that is, from (A3).

Lastly, given its components $\beta_0, \sigma_\eta$ and $\tilde{\beta}$, the time-varying parameter vector $\beta$ can be constructed from (A2).

**Appendix B: Gibbs sampling procedure extended model**

In this section, we lay out the Gibbs sampling procedure for the "extended model", where the time-varying parameter equation contains a set of covariates $G$. Formally, this entails employing the non-centered parameterization for $\tilde{\beta}_t$ and introducing a stochastic binary indicator, sampled along with the other parameters, analogous to the model in equations (2.5), (3.3) and (3.2) referred to in section III E and appendix A (we will refer to this model as the "simpler model" below). This implies that the extended model is comprised of the following set of equations (analogous to the notation in appendix A):[28]

$$pb_{it} = pb_{i,t-1}\phi + d_{i,t-1}\beta_{it} + X_{it}\gamma + \epsilon_{it}, \qquad \epsilon_{it} \sim N(0, \sigma_\epsilon^2), \tag{B1}$$

$$\beta_{it} = \beta_t^* + G_{it}\kappa, \tag{B2}$$

$$\beta_t^* = \beta_0^* + \lambda\sigma_{\eta^*}\tilde{\beta}_t, \tag{B3}$$

$$\tilde{\beta}_t = \tilde{\beta}_{t-1} + \tilde{\eta}_t, \qquad \tilde{\eta}_t \sim N(0, 1), \tag{B4}$$

where (2.9) has been replaced by (B3) and (B4) and $G$ is a set of covariates potentially driving the time variation in the fiscal reaction to debt. By sampling the stochastic binary indicator $\lambda$ along with the other parameters, we obtain useful information as to whether the time-varying component $\sigma_{\eta^*}\tilde{\beta}_t$ contains any further information beyond that in the covariates $G$.

To simplify notation, we now include the parameters of the covariates $G$, that is $\kappa$, in the parameter vector $\theta$, so that $\theta \equiv (\beta_0, \sigma_\eta, \phi, \gamma', \kappa')'$, with $\kappa \equiv (\kappa_1, \kappa_2, ..., \kappa_s)$, where $s$ is the number of explanatory variables included in the state equation, and $\tilde{\beta} \equiv (\tilde{\beta}_1, \tilde{\beta}_2, ..., \tilde{\beta}_T)'$. Analogous to the simpler model, the MCMC scheme splits the estimation problem into three blocks where the parameters are drawn from conditional distributions:

1. Sample the binary indicator $\lambda$ from $p(\lambda|\tilde{\beta}, Y)$, marginalizing over the parameters in $\theta$ and $\sigma_\epsilon^2$, then sample the unrestricted parameters in $\theta$ and $\sigma_\epsilon^2$.

2. Sample the time-varying parameter vector $\tilde{\beta}$ from $p(\tilde{\beta}|\lambda, \theta, \sigma_\epsilon^2, Y)$

3. Perform a random sign switch for $\sigma_{\eta^*}$ and the elements in $\tilde{\beta}$. That is, draw from $\{-1, 1\}$ with equal probability of both outcomes and multiply by $\sigma_{\eta^*}$ and $\tilde{\beta}$, implying a 50 percent chance of $\sigma_{\eta^*}$ and $\tilde{\beta}$ being multiplied by (-1). $\beta^*$ and $\beta$ can then be constructed from their components.

[28] In addition to the sources mentioned in appendix A, this section draws from Iseringhausen and Vierke (2018).

In what follows, we lay out this MCMC scheme in more detail. Given the similarity of this approach with that of the simpler model, the following sections are mainly concerned with elaborating on the differences between the two.

### 1. Sampling the stochastic binary indicator and the hyperparameters

Analogously to the procedure in the pure random walk case, insert (B2) in (B1), using the expression for $\beta_t^*$ in (B3) to obtain

$$\underbrace{pb_{it}}_{y_{it}} = \underbrace{\begin{bmatrix} d_{i,t-1} & d_{i,t-1}\lambda\tilde{\beta}_t & d_{i,t-1}G_{it} & pb_{i,t-1} & X_{it} \end{bmatrix}}_{\chi_{it}^m} \underbrace{\begin{bmatrix} \beta_0^* \\ \sigma_{\eta^*} \\ \kappa \\ \phi \\ \gamma \end{bmatrix}}_{\theta^m} + \epsilon_{it}. \tag{B5}$$

Thus, $\theta^m$ now additionally contains the parameters of the covariates in the state equation $\kappa$, and the sampling scheme laid out in section A 1 can be employed.

### 2. Sampling the time-varying parameter

As before, in this block we set up the conditional state-space model for $\beta_t^*$:

$$\overbrace{pb_{it} - \phi pb_{i,t-1} - d_{i,t-1}\beta_0^* - d_{i,t-1}G_{it}\kappa - X_{it}\gamma}^{y_{it}} = \overbrace{d_{i,t-1}\lambda\sigma_{\eta^*}}^{H_t^m} \overbrace{\tilde{\beta}_t}^{s_t^m} + \overbrace{\epsilon_{it}}^{e_{it}}, \qquad \epsilon_{it} \sim N(0, \overbrace{\sigma_\epsilon^2}^{R}), \tag{B6}$$

$$\underbrace{\tilde{\beta}_t}_{s_t} = \underbrace{1}_{F} \underbrace{\tilde{\beta}_{t-1}}_{s_{t-1}} + \underbrace{1}_{K_t} \underbrace{\tilde{\eta}_t}_{v_t}, \qquad \tilde{\eta}_t \sim N(0, \underbrace{1}_{Q}), \tag{B7}$$

for each $i = 1, 2, ..., N$ and $t = 1, 2, ...T$. Given this conditional state-space model, the time-varying parameter $\tilde{\beta}_t$ is sampled just as in the baseline model in section A 2.

Lastly, given $\beta_0^*$, $\sigma_{\eta^*}$ and $\tilde{\beta}$, $\beta^*$ and $\beta$ can be constructed from their components.

As for the simpler model, we set the total number of Gibbs iterations to 200,000, with a burn-in phase of 80,000, keeping every 10th draw of the remaining 120,000, which leaves us with 12,000 retained draws.