Varazdin Development and Entrepreneurship Agency
in cooperation with
Victoria University, Melbourne Australia
University North, Croatia
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Economic and Social Development

19th International Scientific Conference on Economic and Social Development

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Book of Proceedings

ISSN 1849-7535
9 771849 753006

Melbourne, 9-10 February 2017

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MODELLING OF THE POLITICAL BUDGET CYCLE AND THE IMPACT OF TRANSPARENCY

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ABSTRACT
This paper models the political budget cycle with stochastic differential equations. The paper highlights the development of future volatility of the budget cycle. In fact, I confirm the proposition of a less volatile budget cycle in future. Moreover, I show that this trend is even amplified due to higher transparency. These findings are new evidence in the literature on electoral cycles. I calibrate a rigorous stochastic model on public deficit-to-GDP data for several countries from 1970 to 2012.
Keywords: *Stochastic Modelling, Political Budget Cycle, Transparency*

1. INTRODUCTION

The study of the 'traditional' political budget cycle is well established in economic literature since the publication of the seminal paper by Nordhaus (1975). Polite-economy models propose that politicians have incentives to focus on the period shortly before elections. They tend to do so as voters are easily affected in their economic well-being by government policies. This pattern is commonly known as the 'political budget cycle' (PBC).
This paper extends the existing PBC literature in line with recent research by Herzog & Haslanger (2014, 2016). The new research takes into consideration the impact of transparency through e-governance, the Internet, and social media. In general, I study whether the PB-cycle is less volatile in future and whether this is due to higher transparency.
This paper utilizes a stochastic modelling approach of the PBC model. I calibrate the model based on public deficit data from 1970 to 2012 for different countries. I forecast the PBC and evaluate the volatility across time periods with a t-tests. Hence, this approach is novel and different to the econometric estimation of the PBC in relation to transparency by Herzog & Haslanger (2016).
To my knowledge, this paper is the first that models and analyses the problem of the PBC in respect to transparency in a stochastic framework. In order to study this case, first I build a stochastic model and calibrate it. In a second step, I forecast the PBC. Finally, I compare the variance of the deficit-to-GDP cycle between the historical data period and the forecasting horizon. In addition, I include transparency dynamics in an extended model. I expect an smaller PB-cycle in the extended stochastic model.
The study of transparency and the development of transparency measures is a new topic in the literature of budget cycles. It is mainly due to a growing public demand of transparency in government processes since the onset of the Internet age. Therefore, the role of the Internet has gained importance in the political process even in political election campaigns all around the world. This new demand of higher public transparency by citizens and their implications on the budget cycle, however, is difficult to measure. Overall, I demonstrate the proposition that transparency mitigates the political budget cycle.
The paper is structured as follows: in the section 2, I review the literature. The model is introduced in section 3. Finally, I discuss the simulation results in section 4. Section 5 concludes the paper.

2. LITERATURE REVIEW

Seminal papers on the topic of political budget cycles are by MacRae (1977), Alesina (1988), Rogoff & Sibert (1988), Nordhaus (1989) and Persson & Tabellini (1990). Despite this well-established literature there is remarkably little literature on the issue of transparency and the political budget cycles. To my knowledge, the only exception is Klomp & De Haan (2011) amd the recent research by Herzog & Haslanger (2014, 2016).

The origin of the political budget cycle literature is the seminal article by Nordhaus (1975). He studied why politicians spend more money in upcoming elections despite an obvious economic trade-off. Governments have to 'chose between present welfare and future welfare' (Nordhaus 1975). The main finding was that unemployment rates will rise in the beginning and fall in the second half of a government's term and that the opposite is true for public expenditure. Paldam (1979) find similar actions during an election period. This means 'a restrictive policy in the beginning of an election period followed by an expansive phase later on' (Paldam, 1979). Hence, governments try to make the immediate time before elections as good as possible for their voters in order to be re-elected. This theoretical argument coined the idea of the political budget cycle in general.

Broadly speaking, my paper is in line with this research, however, goes beyond in respect of two dimensions. First, I study the relationship of the political budget cycle and transparency. Second, I study the consequences within a newly designed stochastic model. Thus, I extend the existing literature and give evidence in line with recent research by Herzog & Haslanger (2016).

There exists empirical literature in relation to this paper. According to Rogoff (1990) governments 'engage in a consumption binge, in which taxes are cut, transfers are raised and government spending is distorted towards projects with high immediate visibility'. Although this behavior seems to influence the decisions of voters, there is evidence that expansionary fiscal policy actions do not necessarily create higher well-being (Alesina, Roubini & Cohen 1997). However, those policies someway create positive psychological feedback to human behavior and the overall economy. Drazen (2002) states that although there is 'agreement that aggregate economic conditions affect election outcomes (...), there is significant disagreement on about whether there is opportunistic manipulation'. In other words, it is hard to determine whether politicians have the power to shape economic conditions in a way that influences voters' behavior. The empirical literature demonstrates that the political budget cycle is more noticeable in developing countries (Shi & Svensson 2006, Grier 2008, Ames 1987, and Rojas-Suarez, Canonero & Talvi 1998). One explanation of this phenomenon is either the higher trade-openness (Murao 2014) or perhaps the lower transparency in developing countries. The last explanation is the proposition of this paper.

3. THE MODEL

The following model simulates the PB-cycle using a mean-reverting stochastic differential equation with seasonality and a jump component. The model is calibrated under the real-world using historical public deficit-to-GDP data from 1970 to 2012. In a second step, I conduct a Monte Carlo simulation using the calibrated model. The simulation results are finally evaluated and statistically tested. The modelling and simulation is conducted in MATLAB (Appendix B).

The deficit-to-GDP cycle exhibit a prominent seasonal component, along with mean-reversion. In addition, the PBC displays jumps during periods of recessions. Therefore, I have to account for both components inside the stochastic model. The PBC is modeled according to the following rule:

$$PBC(t) = f(t) + X(t) \ , \tag{1}$$

where $PBC(t)$ denotes the public deficit-to-GDP over time, $f(t)$ is the deterministic seasonal component of the model and $X(t)$ captures the stochastic part of the model.

The modelling of the seasonal component $f(t)$ is as follows:

$$f(t) = s_1 \sin(2\pi t) + s_2 \cos(2\pi t) + s_3 sin(4\pi t) + s_4 \cos(4\pi t) + s_5 \qquad (2)$$

where s_i , i = 1,…,5 are estimated constant parameters. These five parameters are estimated by a dynamic OLS regression. I calibrate this model for selective countries such as Australia, Canada, Sweden, Spain, Netherlands, the United Kingdom and the United States. I use the public deficit-to-GDP data over the period from 1970 to 2012.
The stochastic component $X(t)$ is modelled as an stochastic mean-reverting Ornstein-Uhlenbeck process with jumps

$$dX(t) = (\alpha - \kappa X_t)dt + \sigma dW_t + J(\mu_J, \sigma_J)d\Pi(\lambda) \ , \qquad (3)$$

where the parameter α and κ are the mean-reversion parameters. The term W_t is a standard Brownian motion and σ denotes the volatility. The jump size is $J(\mu_J, \sigma_J)$ with normal distribution and mean μ_J and standard deviation σ_J. The jump is modeled with a standard Poisson process $\Pi(\lambda)$, and has jump intensity of λ.
In a final step, I extend the benchmark model of equation [3] with a transparency parameter. According to the paper hypothesis and the evidence by Herzog & Haslanger (2016), transparency reduce the variance of the political budget cycle. This means that the volatility, σ, is lower. Indeed, I model transparence by a new parameter θ, and included this term in equation [3]:

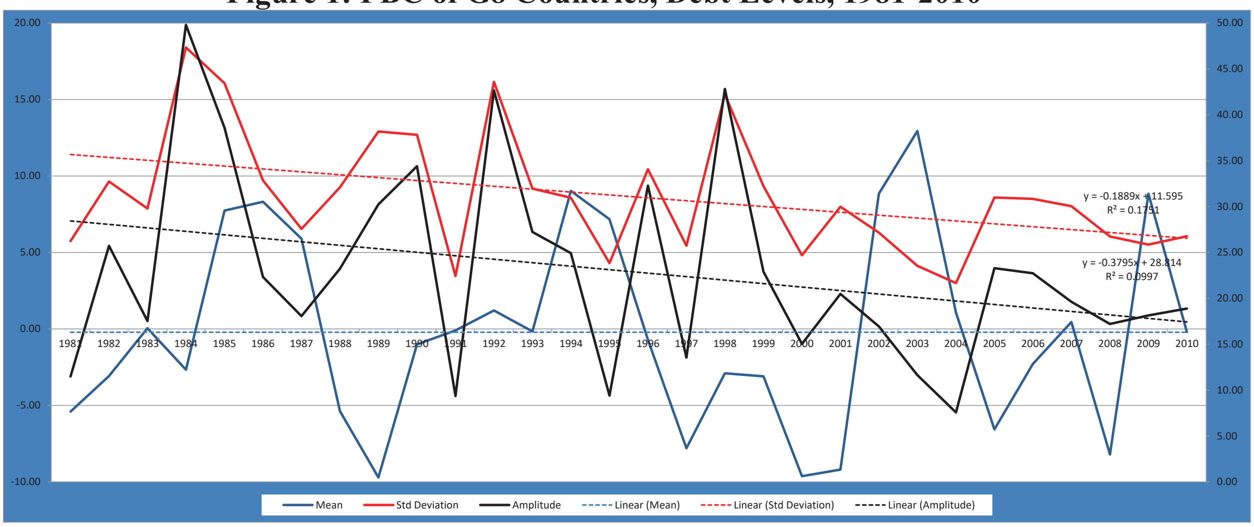
$$dX(t) = (\alpha - \kappa X_t)dt + \theta * \sigma dW_t + J(\mu_J, \sigma_J)d\Pi(\lambda) \, . \qquad (4)$$

In the extended model, I choose for $\theta = 0.9$. This imitates a 10 percent decline in the simulated volatility based on the historical data due to transparency while the jump size is still unaffected. The calibrated and estimated model according to equation [1] is finally discretized for forecasting purposes. The model simulation is performed without the seasonal trend. The simulation is conducted for approximately 20 years with 10 000 trials by utilizing Monte Carlo's method. At the end of the Monte Carlo simulation, I add the seasonality back on the simulated paths and plot the results.

4. SIMULATION RESULTS AND DISCUSSION

According to Herzog & Haslanger (2014), the political budget cycle (PBC) is getting less volatile especially in terms of the amplitude and standard deviation for more than 100 countries, including G8 (Figure 1). However, the ups and downs of the cycle itself, measured by the mean value, are almost unchanged over the past three decades. Whether this trend is due to higher transparency remains to study.

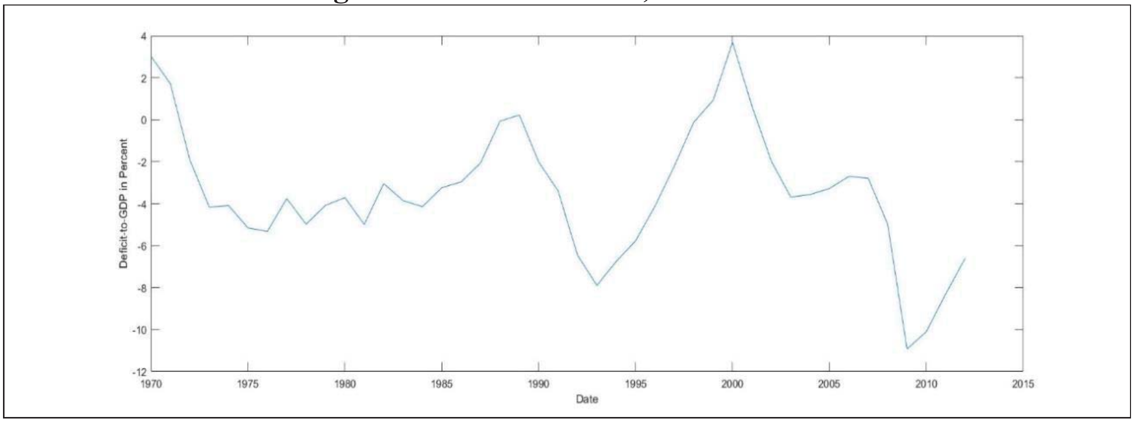
Figure 1: PBC of G8 Countries, Debt Levels, 1981-2010



Source: OECD, author's calculation.

The model simulation is based on real-world deficit-to-GDP data (Appendix A). In the following, I demonstrate the methodology for the United Kingdom (UK). In Figure 2, you see the deficit-to-GDP cycle from 1970 to 2012. Undoubtedly, the UK deficit-to-GDP has large swings in particular in the last decade. Around the millennium year 2000, there was a surplus due to an economic boom and the IT-bubble aligned with the public auction of mobile frequencies to private telecom providers. In 2009 on the other hand, the so-called 'great recession' moved the deficit-to-GDP significantly downwards. This was due to public expenditures to stabilize the financial system and a fiscal stimulus package in response to the financial and economic crisis of 2007-2008.

Figure 2: PBC of the UK, 1970 to 2012



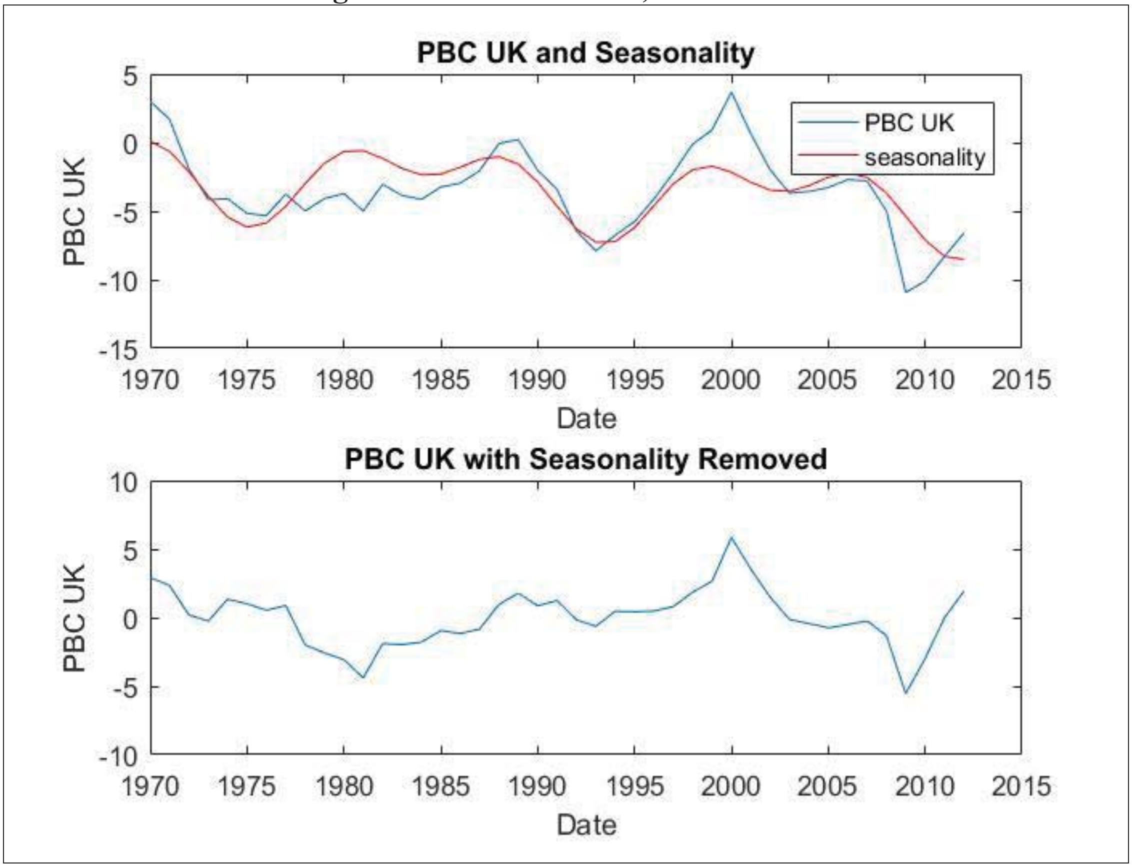
Source: IMF, illustration author.

Despite the large swings in the deficit-to-GDP ratio in recent decades, I attempt to study whether the volatility in the PB-cycle is declining and what is the role of public transparency. The stochastic model is calibrated on the historical deficit-to-GDP from 1970 to 2012 (Appendix A). Based on the calibration, I simulate the future development of the deficit-to-GDP.

The top-panel in Figure 3 illustrates the deficit-to-GDP of the UK (blue line) together with the estimated seasonal trend (red line). The seasonal trend is estimated and computed by sophisticated smoothing and OLS methodology (Appendix B). The bottom-panel in Figure 3 subtracts the seasonal trend from the deficit-to-GDP ratio. Finally, I obtain the so-called de-trended deficit-to-GDP curve. This de-trended time-series is utilized for the stochastic simulation in the next step.

Figure following on the next page

Figure 3: PBC of the UK, 1970 to 2012

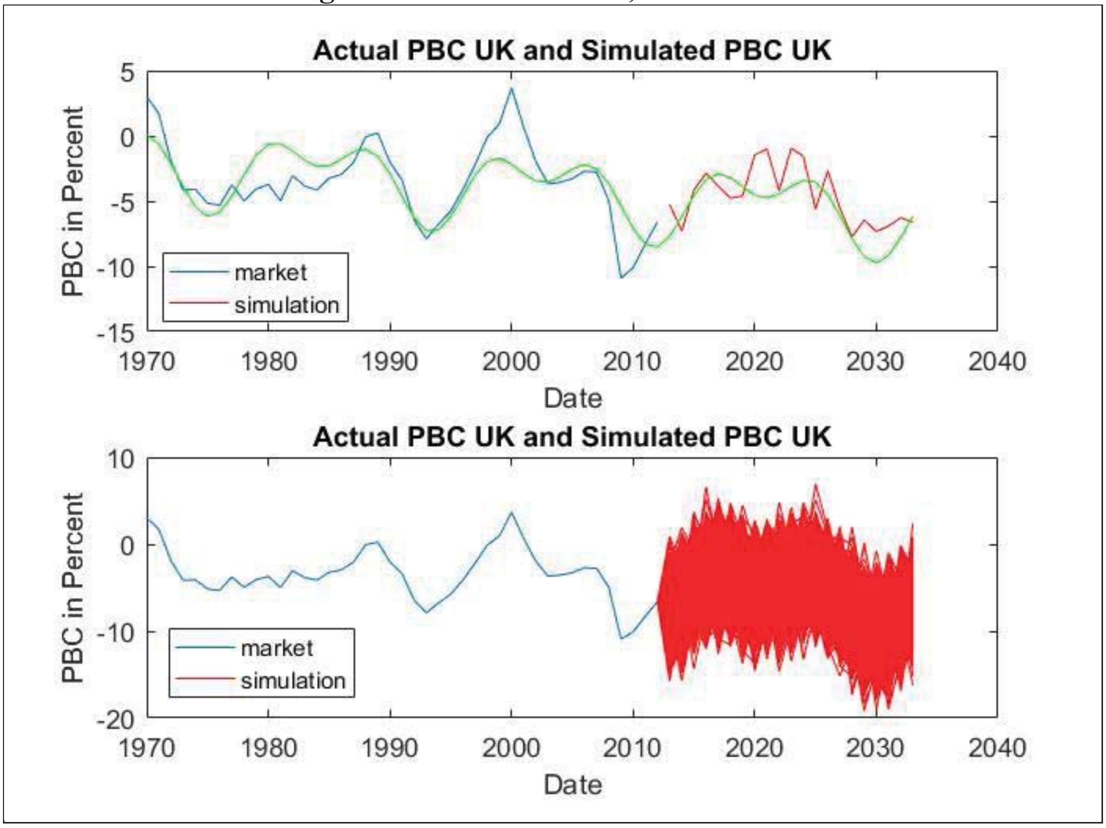


Source: author's calculation.

The stochastic simulation is based on the Monte Carlo method of equation [3]. The MATLAB code for this simulation is in Appendix B. The simulation runs 10 000 trials and uses the most likely outcome (average) of all simulations. Finally, I add the seasonal trend component to the simulated curve and obtain the final dynamics of the deficit-to-GDP over 20 years.
The top-panel in Figure 4 illustrates the Monte Carlo simulation. The blue curve is again the historical deficit-to-GDP data from 1970 to 2012. The green curve represents the seasonal trend including the forecast from 2013 to 2030. The red line denotes the simulated deficit-to-GDP based on the historical model parameters. It turns out that the simulation based on historical data contains already a declining volatility of the deficit-to-GDP ratio in the future. Thus the red curve is less volatile than the blue despite the whole simulation is based on the data period from 1970 to 2012. The bottom-panel contains all Monte Carlo simulations of the deficit-to-GDP ratio over the forecasting horizon of about 20 years. I use the mean scenario in the top-panel (red curve) which is the most likely outcome of all Monte Carlo simulations.

Figure following on the next page

Figure 4: PBC of the UK, 1970 to 2012



Source: author's calculation.

This stochastic simulation model is run for the following set of countries: UK, US, Canada, Japan, Sweden, Netherlands, Italy, Austria and Spain. The country selection is due to data availability. Most other countries have either shorter time-series or a significant data break, for instance in Germany due to the reunification in 1990. The simulation result for all countries is summarized in Table 1.

Table 1: Summary of Model I: Benchmark

	UK	US	Canada	Japan	Sweden	Netherlands	Italy	Austria	Spain
Variance PBC 1970 to 2012	9.4584	8.4789	11.5214	11.2294	18.2281	5.4892	12.1141	3.3766	11.4396
Variance PBC Forcasting Horizont	4.8002	5.2192	3.7824	5.7766	11.0498	3.7776	3.3585	3.2651	6.1178
Test of Difference: p-value	0.0245	0.0008	0.0000	0.0000	0.7353	0.0160	0.0000	0.1049	0.1304
Test of Difference: t-value	-2.4299	-3.9515	6.8670	-8.4636	-0.3428	-2.4939	14.6307	-1.6987	-1.5772
Evaluation of Difference	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No

Source: Own simulations and computations. Significance test at 5% level.

Source: author's calculation.

The first row denotes the variance of the deficit-to-GDP ratio in the calibrated model based on historical data. The second row displays the variance of the deficit-to-GDP based on the simulated model. It turns out that the future variance is lower in all cases despite the model dependence on historical data. The bottom rows demonstrate the test of significance. For the majority of countries, the variance is already significantly lower in the benchmark model. Keep in mind, the benchmark model does not contain any transparency parameter. Only for three countries Sweden, Austria, and Spain the variance is not significantly different. Consequently, I run the extended version of my stochastic model according to equation [4]. The extended model includes the transparency parameter and computes the significance tests again. The transparency parameter is set at 0.9, which means a 10 percent increase in transparency. The result of this simulation is summarized in Table 2. The countries of interest are Sweden, Austria, Spain – the three outliers in my benchmark model above. Now, the result is a significantly lower variance for all countries, including Sweden, Austria and Spain.

Table 2: Summary of Model II: Higher Transparency

A 10% reduction in Vola due to Higher Transparency

	Sweden	Austria	Spain
Variance PBC 1970 to 2012	18.2281	3.3766	11.4396
Variance PBC Forcasting Horizont	17.7075	2.7454	6.1290
Test of Difference: p-value	0.0295	0.0427	0.0421
Test of Difference: t-value	-2.3443	-2.1643	-2.1712
Evaluation of Difference	YES	YES	YES

Source: Own simulations and computations.
Significance test at 5% level.

Source: author's calculation.

In summary, I confirm the hypothesis in this paper, however, with a completely different model in contrast to the econometric evaluation of Herzog & Haslanger (2014, 2016). In fact, I find the mitigation of the PBC within a stochastic framework based on historical data. If I include a transparency parameter in the stochastic model, the overall result is even more significant. In fact, the hypothesis is confirmed at a significance level of 5 percent for all countries. Consequently, transparency will mitigate the amplitude and thus variance of the public budget cycles over time and across countries. Of course, the model has limitations. But most of the limitations are excellent topics for further research. One issue is the data limitation and the sensitivity of the calibrated model on the future path of simulations. Despite these limitations, my finding completes the picture of the recent econometric findings by Herzog & Haslanger (2016). Hence, further research is needed but there is preliminary evidence of the PBC-transparency hypothesis.

5. CONCLUSION

The paper demonstrates that transparency mitigates the variance of the public budget cycle over time and across countries. My theoretical finding is in-line with recent econometric research based on large samples such as of 99 developing and 34 OECD countries. However, the utilized stochastic model has the advantage that all simulations are based on historical data. Hence, the simulation of the deficit-to-GDP ratio is replicating all historical trends accordingly. Overall, the model proposition is verified. I do not reject the hypothesis that transparency will mitigate the public budget cycle in future.

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Appendix

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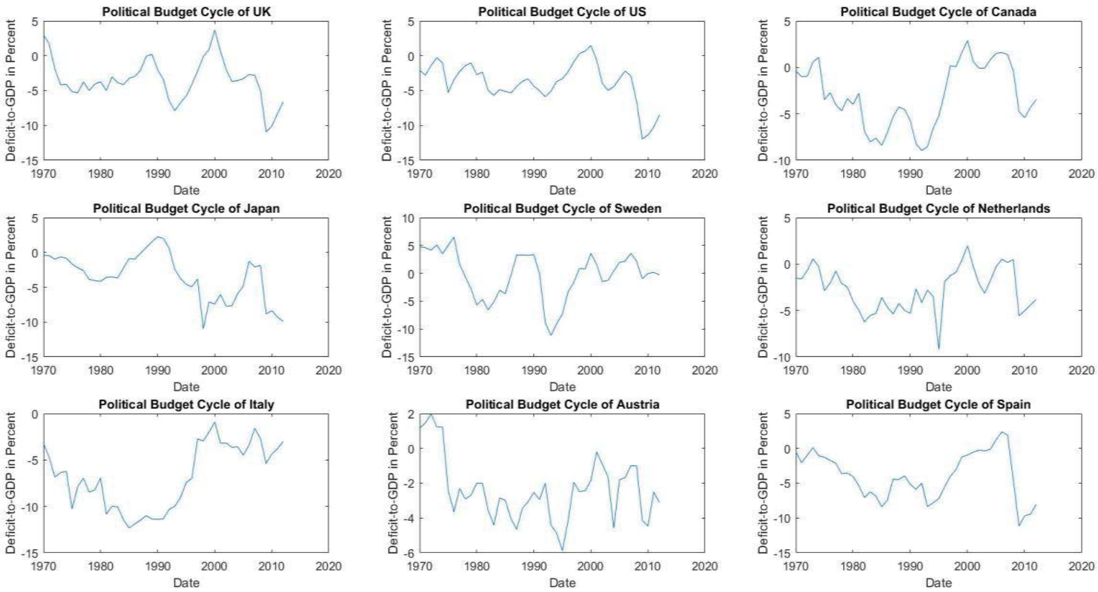
Appendix A: Overview of Budget Cycle in Selected Countries from 1970 to 2012



Appendix B: Stochastic Simulation Model: MATLAB Code

```
%% PBC Stochastic Simulation Model
figure;
plot(year1,UK);
title('PBC');
xlabel('Date');
ylabel('Deficit-to-GDP in Percent');
PriceTimes = yearfrac(year1(1), year1);

%% Model Calibration
seasonMatrix = @(t) [sin(2.*pi.*20*t) cos(2.*pi.*20*t)
sin(4.*pi.*20*t) ...
     cos(4.*pi.*20*t) t ones(size(t, 1), 1)];
 C = seasonMatrix(PriceTimes);
 seasonParam = C\UK;

% Plot PBC and seasonality
figure;
subplot(2, 1, 1);
plot(year1,UK);
title('PBC UK and Seasonality');
xlabel('Date');
ylabel('PBC UK');
hold on;
plot(year1, C*seasonParam, 'r');
hold off;
legend('PBC UK', 'seasonality');

% Plot de-seasonalized PBC
X = UK-C*seasonParam;
subplot(2, 1, 2);
plot(year1, X);
title('PBC UK with Seasonality Removed');
xlabel('Date');
ylabel('PBC UK');
```

```
% The model for $X_t$ needs to be discretized in order to conduct the
calibration. The discretized equation is:
% $X_t=\alpha \Delta t + \phi X_{t-1} + \sigma \xi$
% with probability $(1 - \lambda \Delta t)$ and, $X_t=\alpha \Delta t +
\phi X_{t-1} + \sigma \xi + \mu_J + \sigma_J \xi_J$ with probability
$\lambda \Delta t$, where $\xi$ and $\xi_J$ are independent standard normal
random variables, and $\phi = 1 - \kappa \Delta t$.
% The density function of $X_t$ given $X_{t-1}$ is [1,4]:
% $f(X_t|X_{t-1}) = (\lambda \Delta t) N_1(X_t|X_{t-1}) + (1 - \lambda
\Delta t) N_2(X_t|X_{t-1})$
% $N_1(X_t|X_{t-1}) = (2 \pi (\sigma^2 + \sigma_J^2))^{-\frac{1}{2}}
\exp(\frac{-(X_t - \alpha \Delta t - \phi X_{t-1} - \mu_J)^2}{2 (\sigma^2 +
\sigma_J^2)})$  $N_2(X_t|X_{t-1}) = (2 \pi \sigma^2)^{-\frac{1}{2}}
\exp(\frac{-(X_t - \alpha \Delta t - \phi X_{t-1})^2}{2 \sigma^2})$
% Learning Toolbox(TM) is well suited to solve the above maximum likelihood
problem.

% PBC at t, X(t)
Pt = X(2:end);
% PBC at t-1, X(t-1)
Pt_1 = X(1:end-1);
% Discretization
dt = 1/365;

% PDF for discretized model
mrjpdf = @(Pt, a, phi, mu_J, sigmaSq, sigmaSq_J, lambda) ...
    lambda.*exp((-(Pt-a-phi.*Pt_1-mu_J).^2)./ ...
    (2.*(sigmaSq+sigmaSq_J))).* (1/sqrt(2.*pi.*(sigmaSq+sigmaSq_J)))
+ ...
    (1-lambda).*exp((-(Pt-a-phi.*Pt_1).^2)/(2.*sigmaSq)).* ...
    (1/sqrt(2.*pi.*sigmaSq));

lb = [-Inf -Inf -Inf 0 0 0];
ub = [Inf 1 Inf Inf Inf 1];

% Initial values
x0 = [0 0 0 var(X) var(X) 0.5];
% Solve maximum likelihood
params =
mle(Pt,'pdf',mrjpdf,'start',x0,'lowerbound',lb,'upperbound',ub,...
    'optimfun','fmincon');

% Obtain calibrated parameters
alpha = params(1)/dt
kappa = params(2)/dt
mu_J = params(3)
sigma = sqrt(params(4)/dt)
sigma_J = sqrt(params(5))
lambda = params(6)/dt

%% Monte Carlo Simulation
PriceDates = year1;
rng default;

%Transperency Model II
```

```
%sigmaT = 0.90; include as a product sigmaT*sigma in simulation equ.
below!
nPeriods = 2+20;
nTrials = 10000;
n1 = randn(nPeriods,nTrials);
n2 = randn(nPeriods, nTrials);
n3 = randn(nPeriods, nTrials);
j = binornd(1, lambda*dt, nPeriods, nTrials);
SimPrices = zeros(nPeriods, nTrials);
SimPrices(1,:) = X(end);
for i=2:nPeriods
    SimPrices(i,:) = alpha*dt + (1-kappa*dt)*SimPrices(i-1,:) + ...
                    +sigma*sqrt(dt)*n1(i,:) +
j(i,:).*(mu_J+sigma_J*n2(i,:));
End

% Add back seasonality
SimPriceDates = daysadd(PriceDates(end),0:nPeriods-1);
SimPriceTimes = yearfrac(PriceDates(1), SimPriceDates);
CSim = seasonMatrix(SimPriceTimes);
logSimPrices = SimPrices + repmat(CSim*seasonParam,1,nTrials);

% Plot simulated PBC
figure;
subplot(2, 1, 1);
plot(year1,UK);
hold on;
plot(SimPriceDates(2:end), logSimPrices(2:end,1), 'red');
seasonLine = seasonMatrix([PriceTimes;
SimPriceTimes(2:end)])*seasonParam;
plot([PriceDates; SimPriceDates(2:end)], seasonLine, 'green');
hold off;
title('Actual PBC UK and Simulated PBC UK');
xlabel('Date');
ylabel('PBC in Percent');
legend('market', 'simulation');

PricesSim = exp(logSimPrices);
subplot(2, 1, 2);
plot(PriceDates,UK);

hold on;
plot(SimPriceDates, logSimPrices, 'red');
hold off;
title('Actual PBC UK and Simulated PBC UK');
xlabel('Date');
ylabel('PBC in Percent');
legend('market', 'simulation');

% Computation of Variance and Test of Significance
var(UK)
var(logSimPrices(2:end,1))
[H,P,CI,STATS] = ttest(logSimPrices(2:end,1),mean(UK))
[P,H] = signtest(logSimPrices(2:end,1),mean(UK))
[P,H] = signtest(UK,mean(logSimPrices(2:end,1)))
```