Impact of Partial Calibration on DSGE Estimation: An Illustration Using Smets and Wouters (2007)'s Model

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Abstract

Using the model of Smets and Wouters (2007), we illustrate the sensitivity of estimates to calibration errors in the estimation of dynamic stochastic general equilibrium models. To do so, we consider different estimations of the model using simulated data. One consists in using the true values of the calibrated parameters, the others in modifying by ±1% the value of one calibrated parameter only. The comparison of the estimates obtained in the former estimation and in the others shows that the effect on the estimates ranges from -0.4% to 1.3% for a one-percent increase, and from -0.3% to 0.5% for a one-percent decrease. The size and the sign of the effects depend on the choice of the miscalibrated parameter. The relative sensitivity of the estimates and the pattern of the sign effect of the calibration error also differ between the calibrated parameters. The estimates are not all equally affected by a miscalibration. Most of these results remain valid in the case of a ±10% change in the calibrated values, although the magnitude of the effects, their signs and the relative sensitivities may change. For some parameters, the effects of calibration errors are small compared to the estimation bias.

1 Introduction

Estimation of macroeconomic models typically involves two types of parameters: those meant to be estimated and those whose values are calibrated, i.e. held fixed during estimation. Calibration is generally motivated by two reasons. The first one is that the researcher may have a strong prior on some parameters, the prior being itself based on estimates from previous studies which have reached a consensus. The second reason is more technical: it could be that some parameters are simply not identifiable and thus must be assigned a value for the other parameters to be estimable. Given the prevalence of calibration in macroeconomic modelling, it is crucial to evaluate its impact on estimation. In particular, it is useful to measure the sensitivity of estimates to miscalibrations. This is the goal of the analysis carried out in this project, which focuses on dynamic stochastic general equilibrium (DSGE) models. Our aim is to assess the sensitivity of estimates to calibration errors, that is, to check how the estimates of parameters in DSGE models change as the values of some fixed[1] parameters deviate from their true values.

The remainder of the report is structured as follows. Section 2 describes the methodology and the model used in the applications. Section 3 presents and discusses the results. Section 4 contains additional remarks. Section 5 concludes.

[1]The expressions *fixed parameter* and *calibrated parameter* will be used indistinctly in this report.

2 Methodology and Model

2.1 Description of the methodology

We wish to evaluate the sensitivity of estimates to calibration errors. To do so, our methodology, which partially relies on Iskrev (2019), is the following. Consider a DSGE model which contains several parameters, some of which are initially calibrated. First, we estimate the model on real data and store the values (posterior modes and/or means) of the estimated parameters. For the calibrated parameters, values are chosen from the literature. Second, we simulate the estimated model. Note that we know the true values of the parameters underlying the data-generating process. In a third step, we re-estimate the model using the simulated data, first with the same values for the fixed parameters as in the data-generating process (*control case*), then after modifying the value of one fixed parameter only, the other fixed parameters remaining at their true values (*perturbated case*). We then compare the free parameters' estimates resulting from the two estimations: any difference in the estimates is interpreted as the effect of a calibration error on a given fixed parameter on the estimation.

The estimation is conducted under the Bayesian approach, which has become standard in the estimation of DSGE models compared to the maximum likelihood method. Throughout the analysis, the parameters in which we are interested are the modes of the posterior distributions of the free parameters; hence, the effect of calibration will be evaluated in terms of differences in the estimated mode of the posterior distribution between the control case and the perturbated cases. All the estimations and simulations are performed with the Dynare software.[2]

Modifying the values of the calibrated parameters requires choosing the magnitude of the perturbations. We consider perturbations in percentage points; more specifically, we consider a deviation of $\pm 1\%$ from the true value of each calibrated parameter separately. The effect of calibration on the estimates is also evaluated in percentage points, that is, we measure the percentage change in the estimates following a one-percent increase or decrease in the value of a given calibrated parameter. Although such a measurement unit provides good insights into the sensibility of estimates to calibration errors, it may be misleading due to the differences in variability associated to different parameters' estimates. Thus, to account for those differences in variability in sensitivity measurement, we also measure the changes in estimates in units of standard deviations. The standard deviations considered are the ones resulting from the estimation on real data. Besides, in order to assess the sensitivity of estimates to the *magnitude* of calibration errors, we also consider a deviation of $\pm 10\%$ from the true values of the calibrated parameters.

Two remarks are worth making at this stage. First, the analysis is based on simulated data rather than on real data. Since we know how the data are generated, we know the true values of all the parameters, be they calibrated or not. This feature is important since we explicitly seek to evaluate the effect of a *miscalibration* on the resulting estimates. Such a task obviously requires knowing the true values of the calibrated parameters. Besides, as we know the true values of the free parameters, we are able to evaluate whether the impact of a miscalibration is severe or not. That is, we can compare the estimates' sensitivity to calibration errors relatively to the potential bias in the parameters' estimates and, thus, check whether calibration only has a marginal effect on the whole estimation process.

Second, we consider changes in the value of one fixed parameter at a time, the other fixed parameters being held at their true values. Hence, we do not allow the other calibrated parameters to adjust

[2] All the code on which our work is based can be found on this GitHub repository. The different scripts are described here. The code mainly inherits from Smets & Wouters' replication files, as well as from Prof. Pfeifer's collection of DSGE models (link).

following a perturbation in the value of a fixed parameter. Depending on the interdependence between the fixed parameters, this might have some consequences in the measurement of the sensitivity of estimates to calibration.

2.2 Model

The above methodology is applied to the model developed in Smets and Wouters (2007) (hereafter SW). It is a medium-scale DSGE model which contains many frictions (sticky nominal prices and wages, habit formation in consumption, investment adjustment costs, variable capital utilization and fixed costs in production). The model contains 14 endogenous variables whose dynamics is driven by seven orthogonal structural shocks: total factor productivity, investment-specific technology, risk premium, exogenous spending, price mark-up, wage mark-up and monetary policy shocks. To estimate the model, the authors use seven macroeconomic US data series observed quarterly from 1966:1 to 2004:4. These observed variables are the log difference of real GDP, real consumption, real investment and the real wage, log hours worked, the log difference of the GDP deflator, and the federal funds rate.

Their model features 36 parameters, five of which are calibrated in the estimation procedure. These fixed parameters are the depreciation rate (δ), the exogenous spending-GDP ratio (g_y), the steady-state mark-up in the labor market (λ_w) and the curvature parameters of the Kimball aggregators in the goods and labor markets (ε_p and ε_w). These are the calibrated parameters on which we will introduce calibration errors to assess their impact on estimates. In the estimation procedure, the parameters δ and g_y are calibrated because they are difficult to estimate, while λ_w, ε_p and ε_w are so because they are not identified. It is therefore even more interesting to look at the impact of a calibration error on these parameters, as there does not seem to be much certainty about their true value, which means that a calibration error is very likely. A description of the parameters is given in Appendix A.

In order to simulate the model, values must be assigned to the fixed and free parameters. For the fixed parameters, we use the same calibrated values as in SW: 0.025 for δ, 0.18 for g_y, 1.5 for λ_w, 10 for ε_p and ε_w For the free parameters, we replicate the estimation done in SW and use the resulting estimates reported in Appendix B. Using the estimated model, we generate series of data for the seven observable variables over approximatively 250 periods. Several re-estimations of the model are then performed on simulated data, which differ by the values chosen for the calibrated parameters. One estimation consists in using the true values from the known data-generating process, the others consist in increasing or decreasing by one percent the value of one calibrated parameter, the other parameters remaining fixed at their true values. In order to reduce the stochastic sampling variability, the estimations are made on 100 simulated samples; for each parameter, the estimate actually considered is then the average over the 100 estimated posterior modes obtained.

3 Results

We quantify the sensitivity of the estimates to calibration errors. Our benchmark case consists in modifying the value of the calibrated parameters by $\pm 1\%$ from their true value. We first present the results in which changes in estimates are expressed in percentage points (Section 3.1) and in standard deviation units (Section 3.2). In order to assess the sensitivity of the estimates to the *size* of the calibration errors, we then consider a higher percentage change ($\pm 10\%$) in the calibrated values (Section 3.3). We finally discuss the results (Section 3.4).

3.1 Effects measured in percentage points

The results corresponding to changes measured in percentage points are reported in Figure 1. In each panel, the blue (resp. red) bars represent the percentage change in the parameters' estimates following a one-percent increase (resp. decrease) in the value of a calibrated parameter from its true value, the other calibrated parameters being unchanged.

For the majority of parameters, the estimates are most sensitive to calibration errors on the steady-state wage mark-up (λ_w) and the depreciation rate (δ). In particular, a one-percent increase in the value of one of these two parameters leads to a change in several parameters' estimates higher than 0.3% in absolute value. The estimates are less sensitive to a calibration error on the spending-GDP ratio (g_y), as all estimates vary by less than 0.2% in absolute value following a one-percent increase or decrease in g_y. The case is even more extreme regarding calibration errors on the curvature parameters (ε_p and ε_w): none of the estimates is sensitive to a perturbation in either ε_p or ε_w, except for ξ_p, σ_l and ξ_w.

The parameters' estimates are not all equally affected by a change in the value of the calibrated parameters. For instance, following a one-percent positive change in λ_w, the estimates of σ_l, φ, $\bar{l}$ and the time preference rate ($100(\beta^{-1}-1)$) vary by way more than 0.5%, while the effect on the estimates of the persistence of the wage markup shock (ρ_w) and the productivity shock (ρ_a) is nearly zero. Besides, the set of parameters whose estimates are the most sensitive to a miscalibration depends on the calibrated parameter subject to a perturbation. For the parameter g_y, this set includes ψ and r_y; for λ_w and δ, it includes σ_l, φ, ρ_r, $\bar{l}$ and $100(\beta^{-1}-1)$.

For a given estimate, the magnitude of the effect depends on the choice of the miscalibrated parameter. For instance, the impact of a one-percent increase and decrease in λ_w on the estimate of the investment adjustment cost (φ) is 0.8% and -0.3% respectively, whereas the same calibration errors on the spending-GDP ratio g_y have no impact.

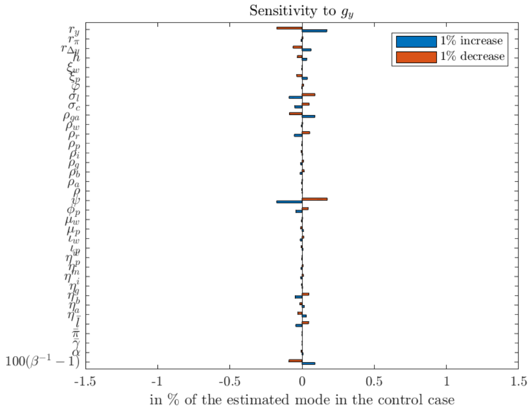
The sign effect of the calibration error displays different patterns depending on the miscalibrated parameter. For g_y and the curvature parameters ε_p and ε_w, the effects on the estimates of a one-percent increase and decrease are symmetrical. This is not the case for the calibrated parameters λ_w and δ: for several estimates, the effects of a positive and negative deviation may have either the same sign or different sizes.

3.2 Effects measured in standard deviations

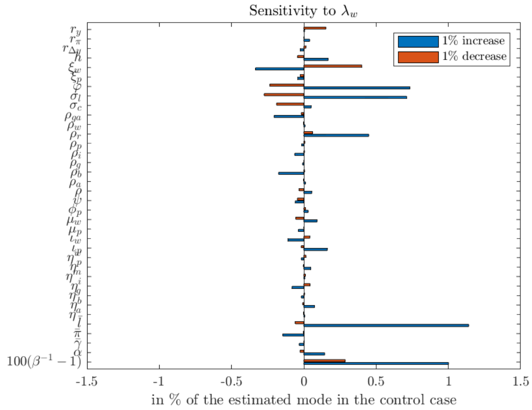
The results corresponding to changes measured in units of standard deviations of the initial estimates are depicted in Figure 2.

For most parameters, the estimates are most sensitive to calibration errors on λ_w and δ. In particular, a one-percent increase in the value of one of these two parameters leads to a change in several estimates higher than 0.01 standard deviation in absolute value. The estimates are less sensitive to a calibration error on g_y, as all estimates (except for ρ_g) vary by less than 0.01 standard deviation in absolute value following a $\pm 1\%$ deviation in g_y. Calibration errors on the curvature parameters (ε_p and ε_w) again have very little effect on the parameters' estimates, except for ξ_p, ξ_w, σ_l, ρ_w and μ_w.

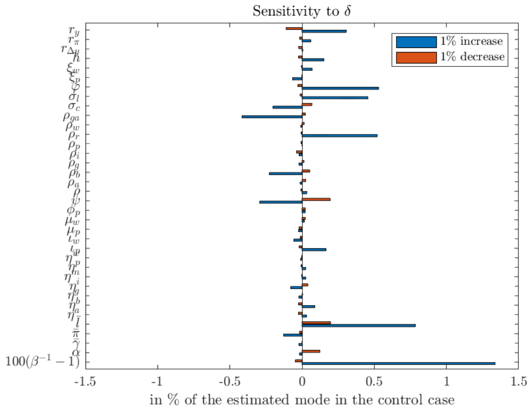
The parameters' estimates are not all equally affected by a change in the value of the calibrated parameters. For instance, following a one-percent positive change in the steady-state wage mark-up λ_w, the estimates of h, φ, σ_l and the time preference rate ($100(\beta^{-1}-1)$) vary by more than 0.02 standard deviation, while the effect on the estimate of the productivity shock η^a is nearly zero. Besides, the



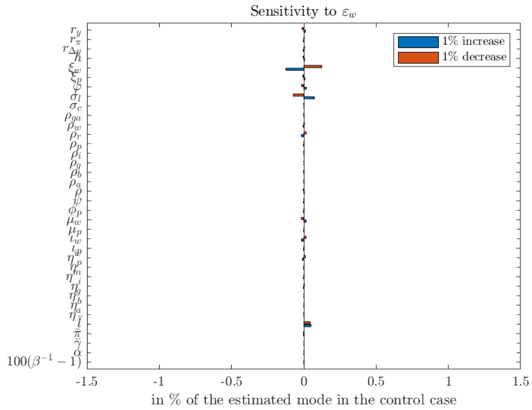
(a) Exogenous spending-GDP ratio (g_y)



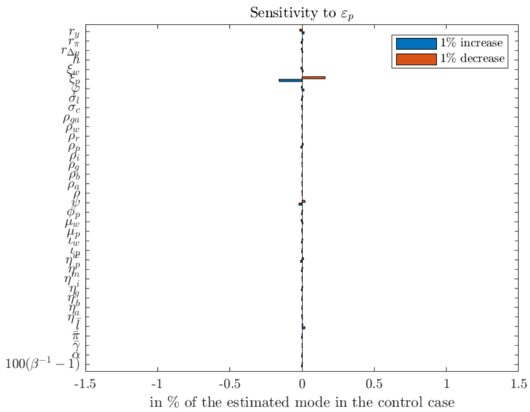
(b) Steady state labor market mark-up (λ_w)



(c) Depreciation rate of capital (δ)



(d) Kimball parameter for wages (ε_w)



(e) Kimball parameter for prices (ε_p)

Figure 1: Changes in the estimated modes of the posterior distributions of the free parameters due to a $\pm 1\%$ deviation on the respective calibrated parameter. Expressed in % of the estimated modes in the control case.

set of parameters whose estimates are the most sensitive to a miscalibration depends on the calibrated parameter subject to a perturbation. For the spending-GDP ratio g_y, this set includes ρ_g, ϕ_p and η^g; for λ_w (resp. δ), it includes h, ξ_w, φ, σ_l and the time preference rate (resp. h, σ_c, ρ_{ga}, ρ_g, ρ_a and the time preference rate). Hence, even after controlling for the estimates' variability in the sensitivity measurement, there are still some differences in the degree of sensitivity between estimates.

For a given estimate, the magnitude of the effect depends on the choice of the miscalibrated parameter. For instance, the impact of a one-percent increase and decrease in λ_w on the estimate of the Calvo parameter for wages (ξ_w) is -0.03 and 0.039 standard deviations respectively, whereas the same calibration errors on g_y have no impact.

The sign effect of the calibration error displays different patterns depending on the calibrated parameter. For g_y and the curvature parameters (ε_p and ε_w), the effects of a one-percent increase and decrease on the estimates are symmetrical. This is not the case for the calibrated parameters λ_w and δ: for several estimates, the effects of a positive and a negative change may have either the same sign or different sizes.

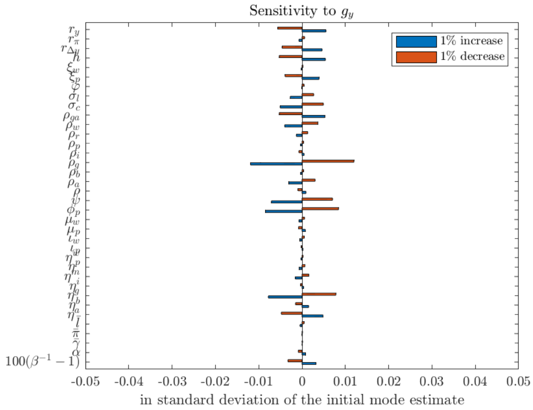
Hence, both measurement units mostly provide similar results. One reason is that the results in Figure 2 are approximately those in Figure 1 divided by the coefficient of variation of the corresponding estimates. As the coefficients of variation do not depend on the calibrated parameters, changing the measurement unit does not modify neither the ranking of the calibrated parameters with respect to the size of their miscalibration impact, nor the sign effect of the calibration errors.

However, the *relative* sensitivity of the estimates is not robust to the choice of the measurement unit. For instance, when changes are measured in units of standard deviations, the estimate of the persistence of the spending shock (ρ_g) appears to be more sensitive to a one-percent increase in δ than that of the persistence of the risk premium shock ρ_b (-0.025 versus -0.008 standard deviation), while the opposite is true when changes are measured in percentage points (nearly 0% versus -0.3%). Likewise, when changes are expressed in percentage points, the estimate of the steady state hours worked ($\bar{l}$) is the most sensitive one to a one-percent increase in the value of λ_w (1.2% change), which is not the case when changes are measured in standard deviation (0.012 standard deviation). We observe that the estimates associated with a relative high (resp. low) coefficient of variation experience a fall (resp. rise) in their relative sensitivity to miscalibrations when the measurement unit changes from percentage points to standard deviations (see Table 3 in Appendix B for the values of the coefficient of variation). As a result of a change in the hierarchy of the estimates' sensitivities, the set of parameters whose estimates are the most sensitive to a miscalibration of a given calibrated parameter depends on the measurement unit. This result shows that the conclusion we draw on the relative sensitivity of the various estimates crucially depends on whether or not we control for the variability of these estimates in the sensitivity measurement, that is, on either we evaluate the changes in estimates in percentage points or in units of standard deviations.

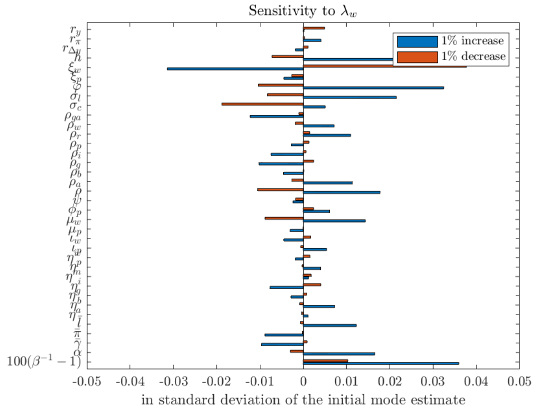
3.3 Results for a $\pm 10\%$ deviation in the calibrated values

The results corresponding to a $\pm 10\%$ deviation of the calibrated parameters from their true values are reported in Figures 4 and 5 in Appendix D.

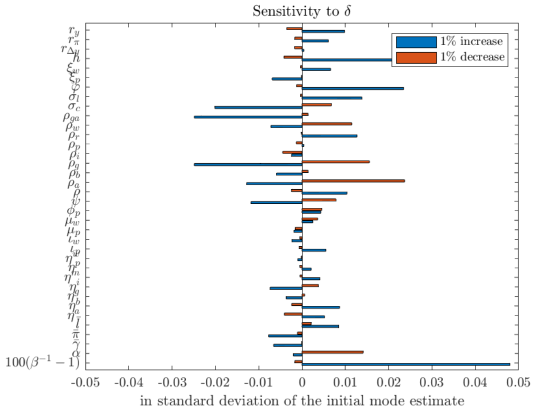
Most results are similar to those obtained with a $\pm 1\%$ deviation in the calibrated values. There are however some differences. For most estimates, the sensitivity is higher. For a few estimates, it is smaller; for instance, the estimate of $\bar{l}$ is more sensitive to a 1% increase than to a 10% increase in the value of λ_w (1.2% versus 0.9%). More surprisingly, for some estimates, the sign of the effect is not the same whether we consider a 1% or a 10% deviation. For instance, the effect of a 1% increase in δ on the estimate of $\bar{l}$ is positive (0.8%), while the effect of a 10% increase is negative (-1.8%). Besides, the relative sensitivity of the estimates is not the same under a 10% and a 1% deviation. For instance, the estimate of the time preference rate ($100(\beta^{-1} - 1)$) is more sensitive to a 1% increase in δ than that of the Taylor rule parameter r_y, while the reverse is true in the case of a 10% increase. Finally, unlike the $\pm 1\%$-deviation case, the pattern of the sign effect of the deviation no longer depends on the



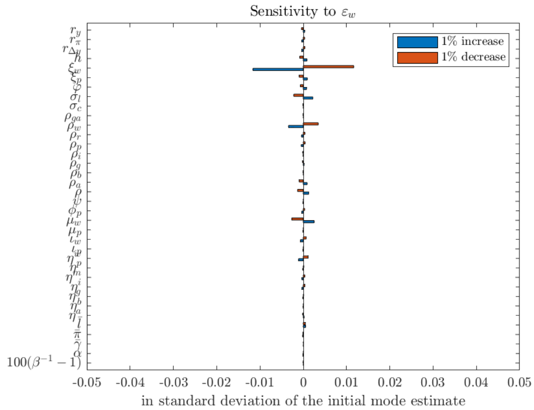
(a) Exogenous spending-GDP ratio (g_y)



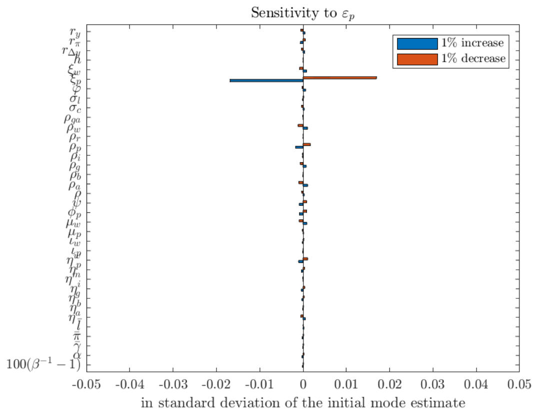
(b) Steady state labor market mark-up (λ_w)



(c) Depreciation rate of capital (δ)



(d) Kimball parameter for wages (ε_w)



(e) Kimball parameter for prices (ε_p)

Figure 2: Changes in the estimated modes of the posterior distributions of the free parameters due to a $\pm 1\%$ deviation on the respective calibrated parameter. Expressed in units of standard deviations of the initial mode estimates.

miscalibrated parameter: the effects of a 10% increase and decrease are now symmetrical, whatever the choice of the miscalibrated parameter.

3.4 Comments on the results

Under both measurement units, our results show that parameter estimates are most sensitive to calibration errors on λ_w and δ. They are less sensitive to a calibration error on g_y, and even less to miscalibrations on ε_p and ε_w. A possible explanation is that the steady-state wage mark-up λ_w and the depreciation rate δ may be much more linked to the structural parameters than are the curvature parameters of the Kimball aggregators in the goods and labor market (ε_p and ε_w). If it is the case, a marginal change in the value of either λ_w or δ marginally affects the estimates of the parameters. This finding implies that much care is required in calibrating λ_w and δ, as these two parameters affect the estimates the most.

Our results also show that the parameters' estimates are not all equally affected by a change in the value of the calibrated parameters. Hence, some estimates are more robust to calibration errors than others. As a consequence, the practitioner has to keep in mind that, in case of a miscalibration, some estimates are more reliable than others. A reason for this result could be that some parameters are more linked to the calibrated parameters than others. Besides, the hierarchy of the estimates' sensitivities depends on the miscalibrated parameter. This finding suggests that, depending on the parameters for which reliable estimates are the most wanted, more care is required in calibrating the values of some parameters than others.

Our results reveal that the magnitude of the effect depends on the miscalibrated parameter. A explanation could be that each structural parameter separately is not equally correlated with each calibrated parameter. Furthermore, the nature of the calibration error (increase or decrease) has an impact on the estimates that differs across the calibrated parameters. In particular, a one-percent increase in either λ_w or δ has much more impact on estimates than a one-percent decrease. This result suggests that it is crucial to set an upper bound on the values of these two calibrated parameters to avoid introducing a large bias in the estimates.

Another important finding is that some effects of calibration errors on the estimates depend on the size of the errors. For some estimates, higher calibration errors do not necessarily result in higher sensitivities, which is counter-intuitive. What is also surprising is that the relative sensitivity of the estimates and the sign of the effect on some estimates depend on the size of the calibration errors.

One should keep in mind that the primary objective of any estimation method is to provide consistent estimates. It is thus interesting to put into perspective the sensitivity of estimates to calibration errors by analyzing the estimation bias. To do so, we compare the parameters' estimates obtained in the control estimation, i.e. the estimation in which the true values of the calibrated parameters are used, with their true values. The results are reported in Figure 3 in Appendix C. For most parameters, the estimate is not bad: the bias is less than 5% of the true value. However, for some parameters, in particular $\bar{l}$, ι_p, ρ_r and the time preference rate, the bias is larger than 10%. These large biases may be explained by two reasons: (*i*) the relatively small sample size of the data used in the estimation and (*ii*) the sensitivity of the estimates to the choice of the prior distributions of the parameters in small samples. This result suggests that, for some parameters, the estimation bias may actually be higher than the sensitivity of estimates to calibration errors. In that case, much more care is required in reducing the estimation bias in a first place than in obtaining good calibrated values, as calibration errors only play a marginal role in the overall bias.

Finally, note that our results are not directly comparable to those of Iskrev (2019) since the author considers perturbations in the calibrated parameters in units of standard deviations instead of percentage points.

4 Additional Remarks

4.1 Estimation based on the Metropolis-Hastings algorithm

So far, we have considered the effects of calibration errors on the estimated posterior modes only. With the Metropolis-Hastings algorithm, we can also estimate the means of the posterior distributions and evaluate the impact of calibration errors on this alternative measure. However, such an extension comes at a heavy computational cost. As the Metropolis-Hastings algorithm significantly increases the execution time of each iteration, we had (*i*) to reduce the number of replications from 250,000 (as initially used by SW) to 10,000 and (*ii*) to consider only 10 simulated datasets for the estimation of the miscalibrated models. Note that as a simplification and to save the computational cost of the tests that would otherwise be required, we have not modified the estimation hyperparameters (e.g., `mh_jscale` or `mh_drop`) set by the authors. The results of this additional experiment are presented in Appendix E.

Considering first changes expressed in percentage of the *control* estimates (Figure 6), we again observe that calibration errors in the depreciation rate of capital, δ, and in the steady state mark-up of the labor market, λ_w, have a larger and broader impact on the estimation of the other parameters. For instance, for both of these fixed parameters, calibration errors can lead to a 4% change (or almost) in the estimation of ρ_r, which corresponds to the persistence of monetary policy shocks. However, the discrepancy with other calibration errors is less clear-cut: calibration errors in the spending-GDP ratio g_y substantially affect the estimation of $\bar{l}$, ρ_r or ι_p and r_y is even quite sensitive to the curvature parameter of the Kimball aggregator for wages. In comparison, the curvature parameter of the Kimball aggregator for prices seems to have a lower effect. Consistently with previous findings, we further observe that the set of parameters that are most affected by calibration errors or the direction of the changes depend on the fixed parameter being miscalibrated. However, overall, the larger magnitude of the changes, the particular case of ι_p whose estimate can vary by up to 5%, and the extreme bias in some of the control estimates (+140% for $\bar{l}$) may question the reliability of these conclusions based on a limited number of estimations and replications of the Metropolis-Hastings algorithm.

Second, we consider the same changes in the estimated parameters (Figure 7), expressed this time in units of standard deviations of the initial estimates. The picture is now quite different: on the one hand, because of the high standard deviation associated to its initial estimate, the extreme changes observed in percentage points for ι_p are now less visible; on the other hand, especially for calibration errors in λ_w and ε_w, the graphs are dominated by large decreases in ρ_w. While it may seem acceptable that such calibration errors, in the two fixed parameters that are directly related to the provision of labour and to the determination of wages in the model, affect the estimation of the persistence of wage mark-up shocks significantly, it is difficult to disentangle this observation from the peculiar impact that one simulated dataset can have on these results (only 10 estimations are performed). This second set of graphs seems however to confirm the idea that calibration errors in the curvature of the Kimball aggregator for prices have a relatively lower impact on the estimation of the free parameters of the model.

4.2 Difficulties associated with the procedure

During the elaboration and the different runs of our code, we encountered some issues that we found interesting to develop here. First, we noticed that our estimates following the calibration tests were identical between different runs, when these were done on the same computer. This is because Dynare sets a default seed of 0, which means that different `stoch_simul` operations always give the same results in this case.

However, what caught our attention was the fact that these estimates, identical between different runs on the same machine, could differ when using different computers. For most of the 100 simulations these differences were minimal, but there was one simulation in particular that gave quite different results and impacted the graphs significantly.

After some research, we realised that this difference did not come from the simulations (because the seed is always the same and is set to 0) but from the estimates. Indeed, these two devices had a different operating system (MacOS and Windows), and therefore numerical approximations that are not exactly the same. This results in the extreme majority of cases in very minimal differences in the estimates, but it can happen (on one problematic simulation in our case) that the estimates differ. As this can significantly affect the final graphs, we thought it would be interesting to explain this finding here.[3]

5 Conclusion

In this project, we studied the impact of calibration errors on the estimation of the parameters in the model developed in SW. As the authors themselves emphasize, the calibrated parameters are so because they are either difficult to estimate or not identified, and not because of strong priors on their value. As these parameters seem for the most part difficult to measure empirically, a miscalibration is quite likely in practice, and it is therefore interesting to evaluate its impact on the estimates.

Using a methodology close to that of Iskrev (2019) applied to simulated versions of SW, we evaluate the sensitivity of estimates to a $\pm 1\%$ deviation of each calibrated parameter separately from their true value. We find that the effect on the estimates ranges from -0.4% to 1.3% for a one-percent increase, and from -0.3% to 0.5% for a one-percent decrease. Estimates are most sensitive to calibration errors in λ_w and δ, less sensitive to a calibration error on g_y, and even less to miscalibrations on ε_p and ε_w. The relative sensitivity of the estimates and the pattern of the sign effect of the calibration error differ across the calibrated parameters. The estimates are not all equally affected by a miscalibration. Most of these results remain valid in the case of a $\pm 10\%$ change in the calibrated values, although the magnitude of the effects, their signs and the relative sensitivities may change. The choice of the measurement unit (in percentage point of the estimate in the control case or in standard deviations of the initial mode estimate) may change the hierarchy of the estimates' sensitivities. For some parameters, the effects of calibration errors are small compared to the estimation bias.

We have identified two directions to further the analysis. First, as suggested by Iskrev (2019), it would be interesting to isolate the sensitivity to calibration errors of each estimate separately. That is, following a deviation in the value of a calibrated parameter, we would measure the change in the estimate of each parameter by holding the other free parameters at their true values. This is different from what is done here as we let *all* estimates adjust simultaneously in response to a deviation in a calibrated parameter. Second, we studied calibration errors on the fixed parameters, which is interesting since these parameters are likely to be miscalibrated from the start as we explained. However, we could also consider the impact of calibration errors on the priors (means and standard errors) of the free parameters, as these errors may also occur.

[3]The benchmark results presented here, as well as those in Appendix D, were obtained on Windows 10. The estimations with the Metropolis-Hastings algorithm (Appendix E) were run under MacOS.

References

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Smets, F. and Wouters, R. (2007). Shocks and frictions in us business cycles: A bayesian dsge approach. *American economic review*, 97(3):586–606.

A Description of the Estimated and Fixed parameters

Table 1: Parameters

Variable	LaTeX	Description
`curvw`	ε_w	Curvature Kimball aggregator wages
`cgy`	ρ_{ga}	Feedback technology on exogenous spending
`curvp`	ε_p	Curvature Kimball aggregator prices
`constelab`	$\bar{l}$	Steady state hours worked
`constepinf`	$\bar{\pi}$	Steady state inflation rate
`constebeta`	$100(\beta^{-1}-1)$	Time preference rate in percent
`cmaw`	μ_w	Coefficient on MA term wage markup
`cmap`	μ_p	Coefficient on MA term price markup
`calfa`	α	Capital share
`czcap`	ψ	Capacity utilization elasticity
`csadjcost`	φ	Investment adjustment cost
`ctou`	δ	Depreciation rate of capital
`csigma`	σ_c	Intertemporal elasticity of substitution
`chabb`	h	Habit parameter
`cfc`	ϕ_p	Share of fixed costs
`cindw`	ι_w	Indexation of wages to past inflation
`cindp`	ι_p	Indexation of prices to past inflation
`cprobw`	ξ_w	Calvo parameter for wages
`cprobp`	ξ_p	Calvo parameter for prices
`csigl`	σ_l	Frisch elasticity of labour supply
`clandaw`	λ_w	Steady state mark-up in the labor market
`crpi`	r_π	Taylor rule inflation feedback
`crdy`	$r_{\Delta y}$	Taylor rule output growth feedback
`cry`	r_y	Taylor rule output level feedback
`crr`	ρ	Interest rate persistence
`crhoa`	ρ_a	Persistence of the productivity shock
`crhob`	ρ_b	Persistence of the risk premium shock
`crhog`	ρ_g	Persistence of the spending shock
`crhoqs`	ρ_i	Persistence of the investment technology shock
`crhoms`	ρ_r	Persistence of the monetary policy shock
`crhopinf`	ρ_p	Persistence of the price markup shock
`crhow`	ρ_w	Persistence of the wage markup shock
`ctrend`	$\bar{\gamma}$	Trend growth rate
`cg`	g_y	Exogenous spending-GDP ratio

Table 2: Exogenous shocks

Variable	**LaTeX**	**Description**
`ea`	η^a	Productivity shock
`eb`	η^b	Risk premium shock
`eg`	η^g	Spending shock
`eqs`	η^i	Investment-specific technology shock
`em`	η^m	Monetary policy shock
`epinf`	η^p	Price markup shock
`ew`	η^w	Wage markup shock

B Initial Estimation on Real Data

Parameter	Posterior mode	Standard deviation at mode	Coefficient of variation (%)
ρ_g	0.98	0.01	0.85
ρ_a	0.96	0.01	1.04
ρ_w	0.97	0.01	1.23
ρ	0.81	0.02	2.96
$\bar{\gamma}$	0.43	0.01	3.29
ϕ_p	1.61	0.08	4.81
ρ_p	0.91	0.05	5.04
μ_w	0.89	0.05	5.71
η^g	0.52	0.03	5.76
h	0.71	0.04	5.93
η^a	0.45	0.03	6.08
η^m	0.24	0.01	6.12
ρ_i	0.7	0.06	8.46
r_π	2.02	0.18	8.76
η^w	0.25	0.02	9.02
ξ_p	0.65	0.06	9.12
α	0.19	0.02	9.14
σ_c	1.42	0.14	9.6
η^b	0.24	0.02	9.64
ξ_w	0.73	0.07	9.73
η^i	0.46	0.05	10.77
μ_p	0.74	0.09	11.67
η^p	0.14	0.02	12.09
$r_{\Delta y}$	0.22	0.03	12.26
$\bar{\pi}$	0.77	0.11	14.48
ρ_{ga}	0.52	0.09	17.03
φ	5.49	1.03	18.81
ψ	0.55	0.12	21.41
ι_w	0.6	0.13	22.16
r_y	0.09	0.02	25.55
σ_l	1.87	0.61	32.56
$100(\beta^{-1}-1)$	0.14	0.06	38.56
ι_p	0.22	0.09	41
ρ_b	0.18	0.08	45.85
ρ_r	0.12	0.06	52.53
$\bar{l}$	0.73	1.07	147.59

Table 3: Estimated modes of the posterior distributions and corresponding standard deviations. Obtained from the initial estimation on real data. The coefficient of variation is defined as the ratio of the standard deviation to the posterior mode.

C Estimation Bias in the Control Estimation

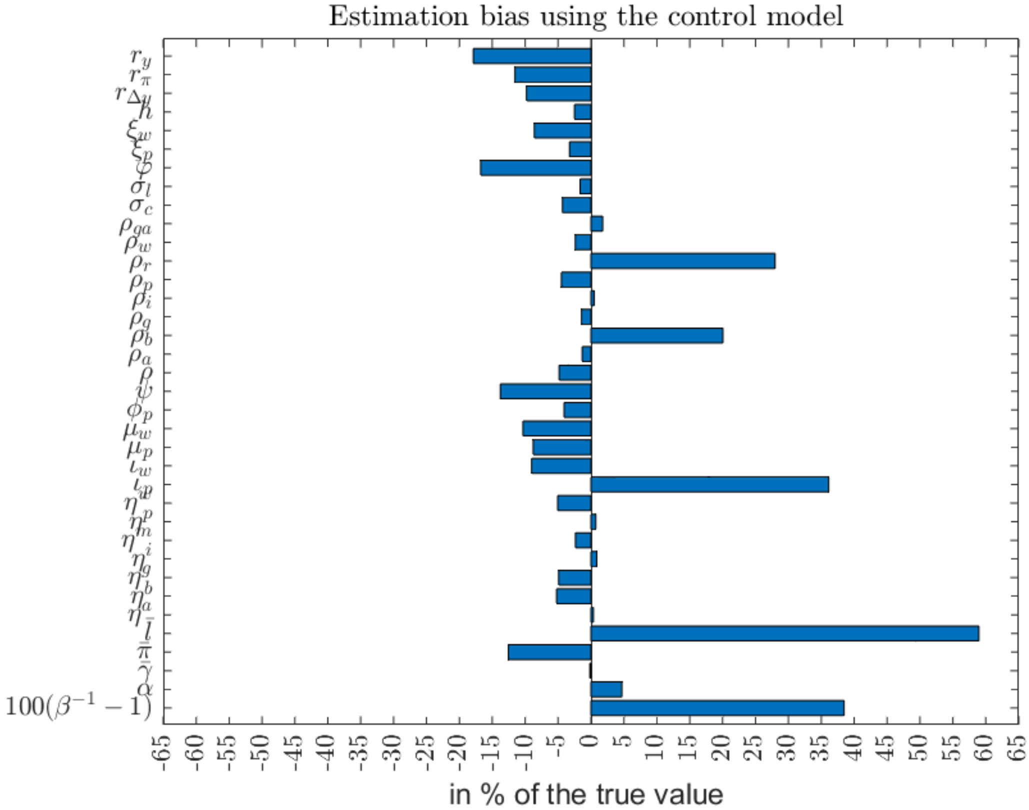
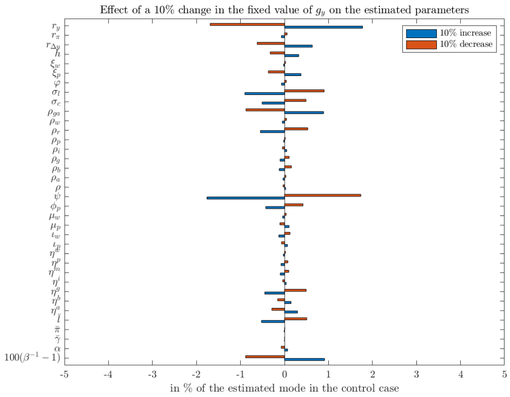


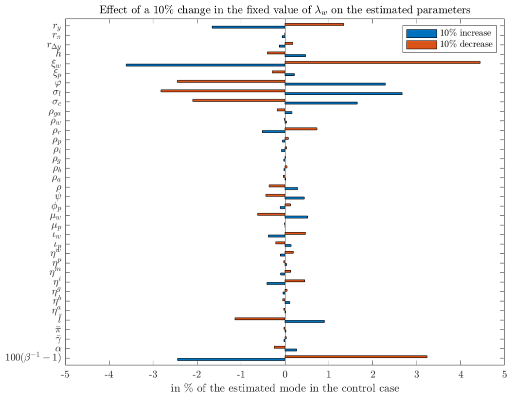
Figure 3: Estimation bias in the control estimation (calibrated parameters all set at their true values)

D Sensitivity to a $\pm 10\%$ Deviation

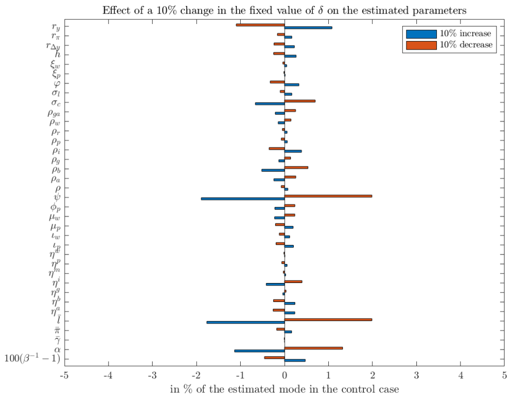
D.1 Effects measured in percentage points



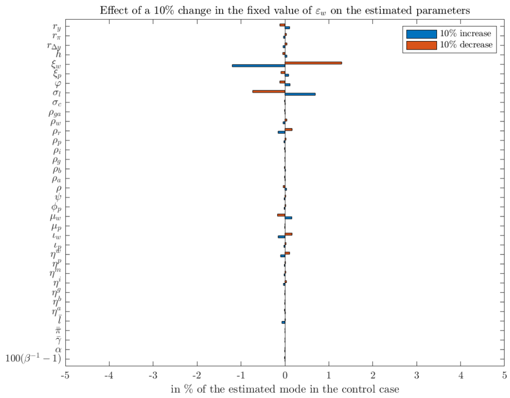
(a) Exogenous spending-GDP ratio (g_y)



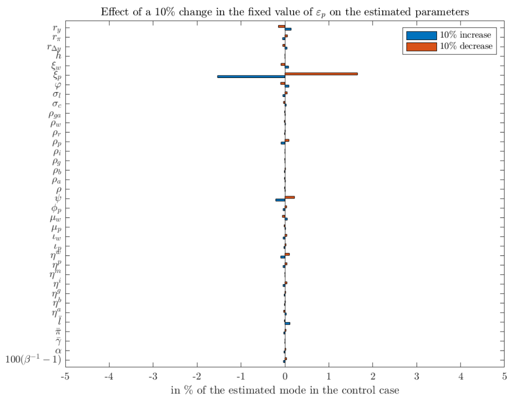
(b) Steady state labor market mark-up (λ_w)



(c) Depreciation rate of capital (δ)



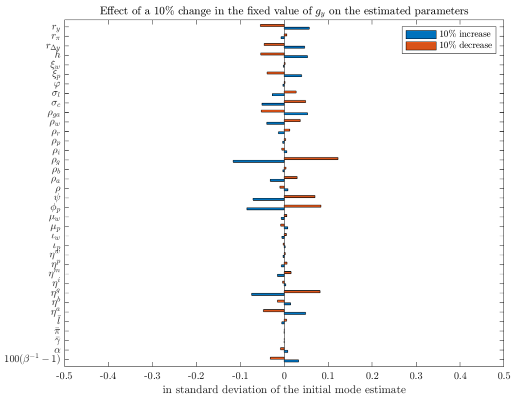
(d) Kimball parameter for wages (ε_w)



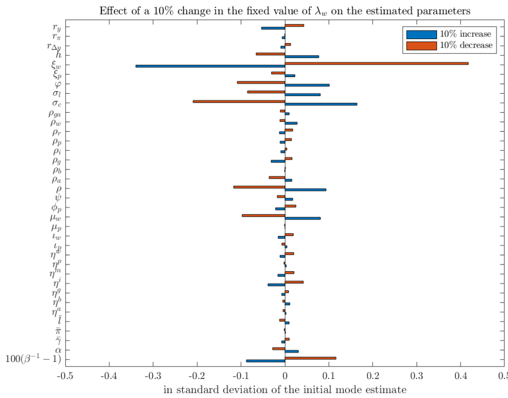
(e) Kimball parameter for prices (ε_p)

Figure 4: Changes in the estimated modes of the posterior distributions of the free parameters due to a $\pm 10\%$ deviation on the respective calibrated parameter. Expressed in % of the estimated modes in the control case.

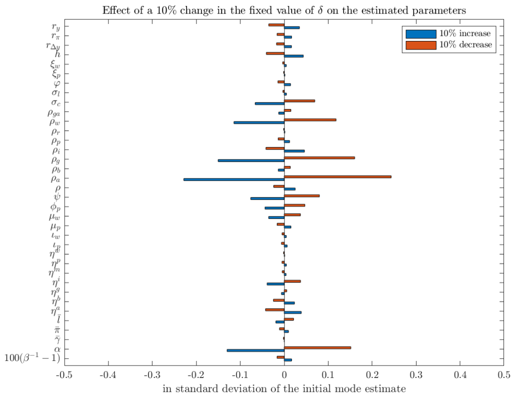
D.2 Effects measured in units of standard deviations



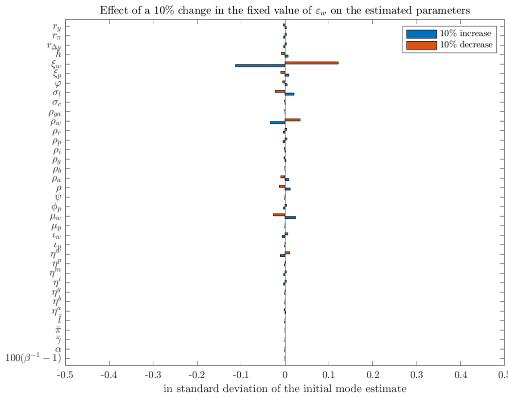
(a) Exogenous spending-GDP ratio (g_y)



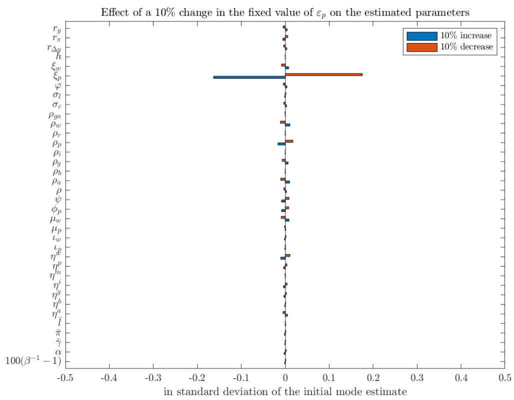
(b) Steady state labor market mark-up (λ_w)



(c) Depreciation rate of capital (δ)



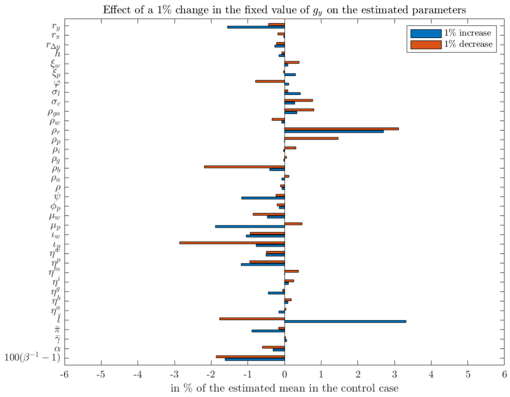
(d) Kimball parameter for wages (ε_w)



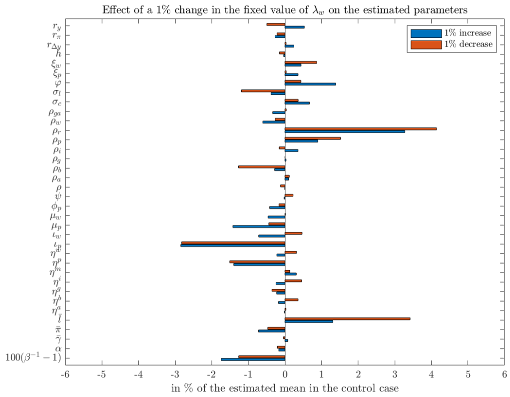
(e) Kimball parameter for prices (ε_p)

Figure 5: Changes in the estimated modes of the posterior distributions of the free parameters due to a ±10% deviation in the respective calibrated parameter. Expressed in units of standard deviations of the initial mode estimates.

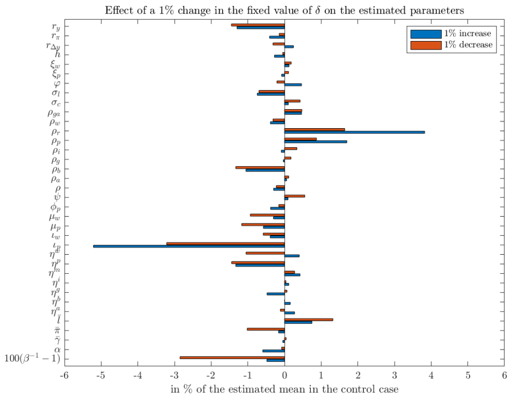
E Results with Metropolis-Hastings Estimation



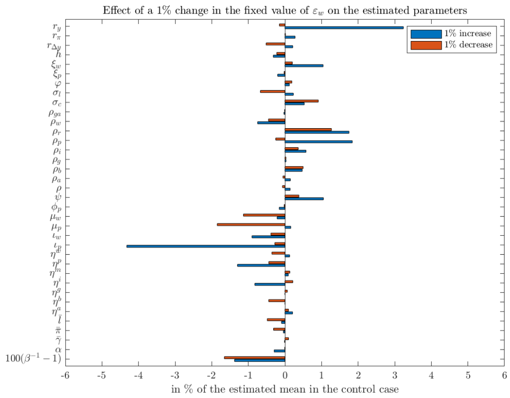
(a) Exogenous spending-GDP ratio (g_y)



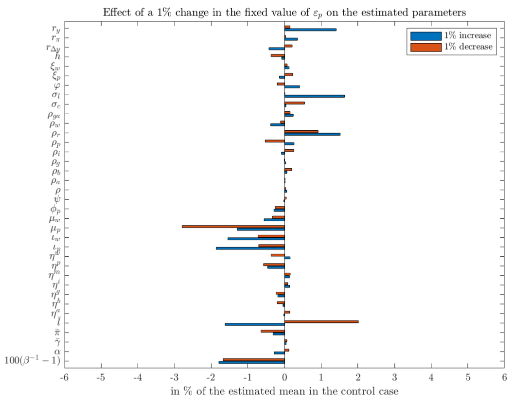
(b) Steady state labor market mark-up (λ_w)



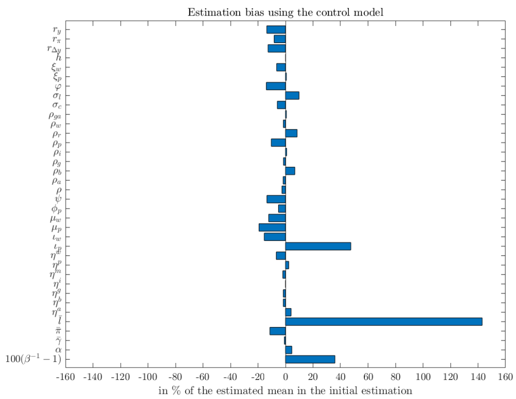
(c) Depreciation rate of capital (δ)



(d) Kimball parameter for wages (ε_w)

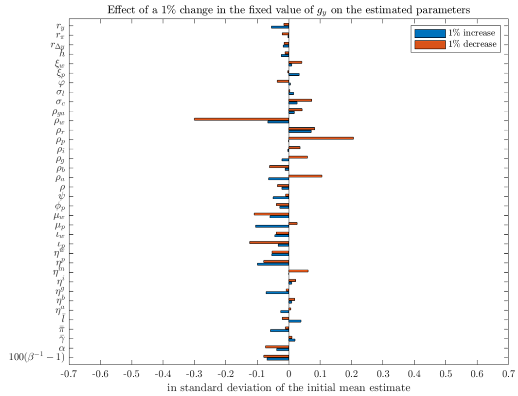


(e) Kimball parameter for prices (ε_p)

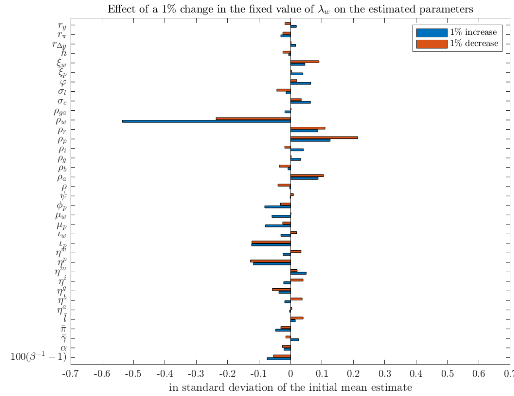


(f) *Control* vs. initial estimates

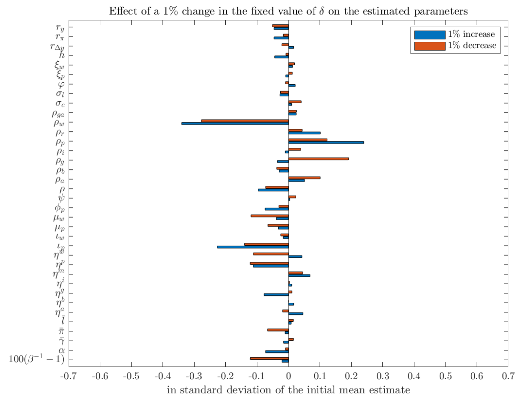
Figure 6: Changes in the estimated means of the posterior distributions of the free parameters due to a ±1% deviation in the respective calibrated parameter. Expressed in % of the estimated means in the control case. Estimation done with the Metropolis-Hastings algorithm.



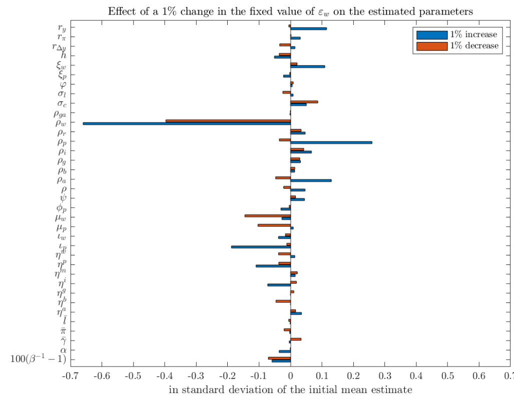
(a) Exogenous spending-GDP ratio (g_y)



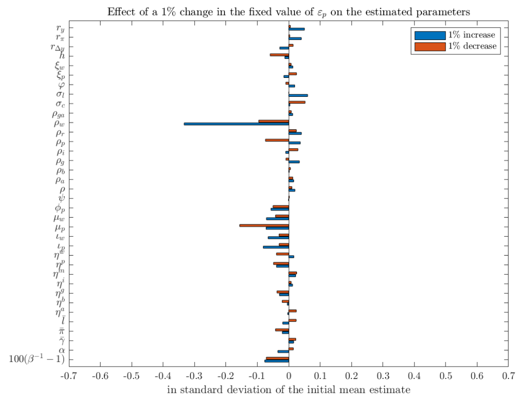
(b) Steady state labor market mark-up (λ_w)



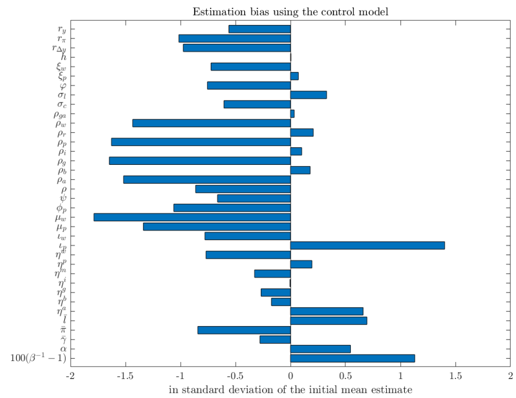
(c) Depreciation rate of capital (δ)



(d) Kimball parameter for wages (ε_w)



(e) Kimball parameter for prices (ε_p)



(f) *Control* vs. initial estimates

Figure 7: Changes in the estimated means of the posterior distributions of the free parameters due to a $\pm 1\%$ deviation in the respective calibrated parameter. Expressed in units of standard deviations of the initial mean estimate. Estimation done with the Metropolis-Hastings algorithm.