

Article

A Comparative Analysis of the Calibrated DSGE Model and SSA Method Results on the Latvian Economy

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Abstract: This article examines the theoretical foundations of economic forecasting based on DSGE models. DSGE models are the main direction of contemporary macroeconomics theory—the inclusion of the stochastic processes and expectations of economic agents in the analysis of economic processes made them one of the best economic forecasting tools. The methodological basis of this paper is two approaches of economic forecasting theory: technical analysis and fundamental analysis. In this article, we have performed the calibration of the DSGE model with investment adjustment costs for the Latvian economy and compared these results with the statistical data filtered with the SSA method. Key results have shown the ability of both approaches to capture the dynamics of the main Latvian macroeconomic indicators.

Keywords: DSGE models; SSA; economic forecasting; Latvian economy

1. Introduction

Nowadays, economic forecasting is a scientific discipline that plays a major role in the planning of economic processes and decision-making. International organisations, governments, and academia conduct economic forecasts for various purposes. The main purpose of using economic forecasting at the level of international organisations and governments is to develop economic policy and analyse the behaviour of the economy in the short-term, medium-term, and long-term. The World Economic Outlook conducted by the International Monetary Fund serves as a prominent example at this level (IMF, 2025). The main use of economic forecasting at the academic level is the theoretical analysis of economic processes—the study of the main interrelations of economic processes.

However, the key point of the forecast application for decision-making or theoretical analysis is related to the use of appropriate forecasting methods. The precision of the forecasts directly influences the decisions implemented and the suitability of the research results. Therefore, the question of how to forecast is relevant.

From the point of view of economic theory, there are two and only two main approaches to the forecasting of economic processes: technical analysis and fundamental analysis. Both approaches are independent and have distinct considerations in the forecasting of economic processes.

The technical analysis (TA) approach to economic forecasting is based on the analysis of past data of an indicator. The principal aim of the TA approach is to recognise patterns in the data that could be used to predict the future state of the indicator. The TA is based solely on quantitative analysis methods, particularly time series, statistical, and numerical analysis methods. The fundamental analysis (FA) approach to economic process



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forecasting is based on the analysis of impact factors. Unlike the TA approach, FA is based not only on quantitative, but also on qualitative data analysis, which includes the analysis of economic reports, news, etc. The main goal of the FA approach is to predict the future values of the economic parameters by analysing impact factors. The fundamental analysis approach is best described by the use of mathematical models to analyse economic processes (Navarro et al., 2023).

Our article examines two main approaches to economic forecasting using the Latvian economy as an example. The main method of fundamental analysis used in the article is the DSGE model (dynamic stochastic general equilibrium), and the main method of technical analysis used in the article is singular spectrum analysis (SSA).

The selection of these analysis methods was based on the following rationale:

- DSGE models are the main direction of modern macroeconomics theory. These models have become a standard tool for economic policy analysis and economic forecasting from the level of international organisations to academia. Especially extensively, they are developed at the level of central banks, for instance, the New Area Wide Model (NAWM) by the European Central Bank and the Norwegian Economy Model (NEMO) by Norges Bank, etc. (Flotho, 2009).
- The SSA method was designed for signal processing—it originated from the Karhunen–Loeve transform (KLT) (Gastpar et al., 2006)—but due to its capabilities, it became the most accurate data filtering and forecasting method.
- In the case of the Latvian academic environment, the analysis based on DSGE models and the SSA method is not widely used.
- The development of DSGE models is one field of activity of the Bank of Latvia, but these models are aimed at specific purposes of the Bank of Latvia, e.g., fiscal policy analysis. As for the consideration of SSA in the Latvian academic environment, the works of (Polukoshko & Hofmanis, 2009; S. Polukoshko et al., 2014) can be mentioned as examples of the various SSA applications; however, these applications of SSA are not always related to economics.

The objectives of our article are the following:

- Perform a comparative analysis of the calibrated DSGE model and the results of the SSA method based on the Latvian economy data.
- Identify the main factors and patterns of the Latvian economy based on the analysis carried out.

Our article addresses the following question: How precisely does the calibrated DSGE model with the investment adjustment costs describe the dynamics of the main Latvian macroeconomic indicators compared to the SSA-filtered data?

The main limitation of this article is the availability of statistical data on the Latvian economy, the time series of which mostly start from the year 1995. Taking into account the historical peculiarities of Latvia's development, the transition to the European statistical system in Latvia began in 1992 (CSB, 2020), and in 1997, the Saeima of Latvia adopted the Official Statistics Law (CSB, 2008). In this article, we use quarterly data from the Latvian economy from 2002Q1 to 2024Q3.

The further organisation of our article is as follows:

- The Literature Review section provides a description of the historical development of the DSGE models and Singular Spectrum Analysis.
- The Methodology section provides a description of the DSGE model with investment adjustment costs and its calibration for the Latvian economy, a description of the basic SSA algorithm, and its application for data preprocessing.

- The Materials and Methods section provides a description of the Latvian economy data acquisition from the Official Statistics Portal and the analysis of these indicators' tendencies with the basic SSA.
- The Results section provides a description of the results obtained by the calibrated DSGE model and SSA.
- The Discussion section provides a detailed analysis of the results obtained and their correspondence with the research purposes and questions.

The conclusions are provided at the end of the article.

2. Literature Review

The development of DSGE models was significant for the development of ideas of the New Classical Economic School of thought in the academic environment of the United States in the 1970s. The ideas of this school were opposed to the Keynesian approach, namely, the microeconomic basis of macroeconomic models, the hypothesis of rational expectations, and perfect competition (Birol, 2015). These ideas formed the basis of DSGE models, but it is necessary to first understand the main stages that preceded the development of DSGE models.

The development of DSGE models was preceded by three main stages: traditional macroeconometric models, projection models, and policy models (Yagihashi, 2020).

The first stage, traditional macroeconometric models, is based on the Keynesian approach to analysis of economic processes, which was the mainstream of macroeconomic theory from 1936 to the early 1970s (De Vroey, 2016). This stage is also marked by the creation of fundamental macroeconometric models and their application in economic policy, for example, the J. Tinbergen model, Klein-Goldberger model, and Brookings model (Ozolins & Pochs, 2013).

The Keynesian approach considered economic processes in the short run and assumed aggregated demand as 'the main driver' of economic growth. Another assumption of the Keynesian approach is price and wage stickiness in the short run (De Vroey, 2016) and consideration of economic processes as discrete-time processes (Valadkhani, 2004).

The Keynesian models gained criticism due to the inability of explaining stagflation in the USA, which was related to the economic policy of the administration of President Richard Nixon, which tried to use the relationship between inflation and unemployment discovered in 1968 (the Phillips curve) to reduce unemployment. Therefore, Keynesian models required further corrections (De Vroey, 2016).

The second stage, projection models, originates from Lucas' Critique that further led to the development of early DSGE models—RBC (real business cycle) and NK (New Keynesian) models (Yagihashi, 2020).

Lucas' Critique is associated with the work of R. Lucas, 'Econometric Policy Evaluation: A Critique' (Lucas, 1976). The core idea of the Lucas Critique can be described by the following points (De Vroey, 2016):

1. Microeconomic foundation of macroeconomic models: this point indicates that economic processes are described by the interactions of rational economic agents who maximise their utility with the resources at their disposal.
2. The assumption of rational expectations (RE) theory: this point indicates that economic agents base their decisions not only on past and present information but also on the future state of the economic processes. In simple terms, this point 'advocates' the use of economic forecasting in macroeconomic models.

It is necessary to emphasise the difference between expectations from the Keynesian approach. In the Keynesian approach, expectations are mainly subjective in nature, in which psychological characteristics, the so-called 'animal spirit' plays a special role (Birol, 2015).

In terms of R. Lucas, only models based on microeconomic foundations and rational expectations are capable of describing ‘the real’ economic situation and are suitable for alternative policy analysis. This means the adaptation of economic agents to changes in economic policy. The Lucas Critique was seen as a significant contribution to macroeconomic theory (De Vroey, 2016).

Second, RBC models were the first models that met the requirements of the Lucas Critique. The first RBC models were proposed at the beginning of the 1980s by F. E. Kydland and E. C. Prescott (Kydland & Prescott, 1982) and J. B. Long and C. I. Plosser (Long & Plosser, 1983). The core idea of RBC models is to perform the analysis of the aggregate business cycle fluctuations. The RBC approach assumes that fluctuations are the responses of economic agents to the exogenous technological shock (Christiano et al., 2018). The main drawbacks of RBC models were related to their main assumptions: consideration of ‘real variables’ as the only cause of business cycle fluctuations and the neutrality of monetary policy in the short run (Slanicay, 2014). These assumptions made the RBC models inefficient for economic policy analysis and further led to the development of NK models (Christiano et al., 2018).

NK models are an extension of RBC models to the monetary policy analysis. In comparison with RBC models, NK models adopt some characteristics of Keynesian models that are assumptions about price and wage rigidities. These assumptions made them ‘more realistic and suitable’ for economic policy analysis (Slanicay, 2014). Typical examples of NK models are the models by G. A. Calvo (Calvo, 1983) and T. Yun (Yun, 1996).

The third stage, policy models, began its active development in the early 2000s and refers to the DSGE models developed by governmental institutions. In general, policy models are developed in the cohesion of both theoretical framework and empirical data. These models are used for two interrelated tasks: economic policy analysis and economic forecasting (Yagihashi, 2020).

After the 2008 global financial crisis, DSGE models have undergone significant transformations. In DSGE models, the participants actively started to include financial frictions and emphasise the role of financial institutions in economic processes (Christiano et al., 2018). Another example is the inclusion of the COVID-19 pandemic shock in the DSGE model, which is described in the work of (Ferroni et al., 2024).

From the above-mentioned, it can be concluded that the development of DSGE models is closely correlated with the development of an economic school of thought and the ‘real-world situation’, which in turn contained an increasingly high degree of uncertainty. DSGE models are excellent at handling tasks such as analysing economic processes under uncertainty, which in turn makes them a standard analysis tool from academia to international organisations.

Another method used in our article is singular spectrum analysis (SSA). SSA is a nonparametric time series analysis method that was originally used for signal processing in the field of natural sciences. The main idea of SSA is to decompose the time series into its principal components—trend, oscillations, and noise (Bógalo et al., 2024).

As mentioned in the Introduction, SSA originated from the Karhunen–Loeve transform (KLT) (Gastpar et al., 2006) that was developed independently by K. Karhunen and M. Loeve in the year 1946 and was based on the principal components analysis technique (Thornton, 2005).

The most widespread recognition of SSA as a method of time series analysis was in 1986, in the works by Broomhead, King, and Fraedrich. These works were related to the field of natural science (Bógalo et al., 2024).

In the year 2001, N. Golyandina, V. Nekrutkin, and A. Zhigljavsky discovered the forecasting abilities of SSA. The SSA forecast is based on a linear recurrent for-

mula, whereby forecasts are expressed as a linear combination of previous elements (Golyandina et al., 2001).

Despite the widespread use and application of SSA in the natural sciences, this method is not so common in economic research. For the analysis of time series in economics, such methods as the moving average, Hodrick–Prescott filter, and Hamilton regression filter, are used (Coussin, 2022).

At present, SSA as a method of time series analysis is undergoing significant development, since there are many variations of SSA, for instance, real-time SSA (Coussin, 2022), generalised SSA (Gu et al., 2024), and multivariant circulant SSA (Bógalo et al., 2024).

Despite belonging to different approaches to the analysis of economic processes, one can notice a common property of DSGE models and SSA—both methods are quite innovative and became the most widespread with the development of technical progress. After the 1980s, the advances in technology made it easier to use complex mathematical methods to model and analyse the impact of uncertainty on economic processes.

In the next section of the article, we consider in detail the methodological basis for our analysis—the DSGE model with investment adjustment costs by (Torres, 2016) and the basic SSA algorithm.

3. Methodology

3.1. DSGE Model with Investment Adjustment Costs

The DSGE model with investment adjustment costs considers the capital accumulation rigidities. Standard DSGE models are based on the assumption that changes in investment lead to simultaneous changes in capital without any additional costs—‘investments simply transform into capital’. However, in the real-world economy, capital has specific characteristics—it cannot accumulate instantaneously because of the costs of investment process. The consideration of investment adjustment costs in the model assumes ‘a capital loss or additional cost in the investment process’ (Torres, 2016).

This model is a closed economy model with only two operating agents—households and firms. It is assumed that households are owners of the production factors—capital and labour. The main goal of households is to maximise their utility (see Equation (1)), which is an intertemporal choice between consumption and leisure. The model does not consider overlapping generations, thus there is an assumption about ‘infinitely lived’ households (Torres, 2016).

$$\sum_{t=0}^{\infty} \beta^t [\gamma \log C_t + (1 - \gamma) \log(1 - L_t)] \quad (1)$$

where:

- t —time period,
- β —discount factor,
- γ —proportion of consumption in total income,
- C —consumption,
- L —labour,
- $1 - L$ —leisure.

The main goal of the firms is to maximise their profit (see Equation (2)) to the values of capital and labour. Firms produce output in accordance with Cobb–Douglas constant return-to-scale technology (Torres, 2016).

$$\max_{(K_t, L_t)} \Pi_t = A_t K_t^\alpha L_t^{1-\alpha} - R_t K_t - W_t L_t \quad (2)$$

where:

- Π —profit,

A —total factor productivity,
 K —capital,
 α —capital elasticity,
 R —rent of capital,
 W —wage.

The optimisation problems of the households and firms are solved with the Lagrange multiplier method—the method derives the first-order conditions of the model (FOCs). The FOCs describe the equilibrium equations of the model. In total, the model consists of 9 equations (Torres, 2016) (see Equations (3)–(11)).

$$(1 - \gamma) \frac{1}{1 - L_t} = \gamma \frac{1}{C_t} W_t \quad (3)$$

$$q_{t-1} = \beta \frac{C_{t-1}}{C_t} [q_t(1 - \delta) + R_t] \quad (4)$$

$$Y_t = C_t + I_t \quad (5)$$

$$Y_t = A_t K_t^\alpha L_t^{1-\alpha} \quad (6)$$

$$K_{t+1} = (1 - \delta)K_t + \left[1 - \frac{\psi}{2} \left(\frac{I_t}{I_{t-1}} \right)^2 \right] I_t \quad (7)$$

$$W_t = (1 - \alpha) A_t K_t^\alpha L_t^{-\alpha} \quad (8)$$

$$R_t = \alpha A_t K_t^{\alpha-1} L_t^{1-\alpha} \quad (9)$$

$$q_t - q_t \frac{\psi}{2} \left(\frac{I_t}{I_{t-1}} - 1 \right)^2 - q_t \psi \left(\frac{I_t}{I_{t-1}} - 1 \right) \frac{I_t}{I_{t-1}} + \beta \frac{C_{t-1}}{C_t} q_{t+1} \psi \left(\frac{I_t}{I_{t-1}} - 1 \right) \left(\frac{I_{t+1}}{I_t} \right)^2 = 1 \quad (10)$$

$$\ln A_t = (1 - \rho_A) \ln \bar{A} + \rho_A \ln A_{t-1} + \varepsilon_t \quad (11)$$

Notes on Equations (3)–(11) (Torres, 2016):

1. Equation (3): Variable q_t refers to the Tobin's Q marginal ratio, which is defined as 'the market value of the total installed capital over the replacement cost of that capital'. In this model, q_t describes the relation between marginal rate of consumption ($\beta \frac{C_{t-1}}{C_t}$) and rate of return on investment ($q_t(1 - \delta) + R_t$).
2. Equation (7): Capital accumulation law. In this model, capital accumulation depends not only on depreciation rate (δ) and investment (I_t), but also on investment adjustment costs ($\frac{I_t}{I_{t-1}}$) and their intensity (ψ).
3. Equation (10): Describes the dependence of the current and expected capital according to the depreciation rate and the expected rate of return on investment. This equation is an equilibrium condition for the investment.
4. Equation (11): Describes the total factor productivity (A_t).

The next step is to calibrate the model and its solution with Dynare. Calibration is a technique to determine the values of the model parameters. The main reason for using calibration is the use of statistically unobservable variables in the models, which complicates their assessment based on statistical data. Most often, the calibration of the parameters is performed based on existing studies (Junior, 2016).

At first, the calibration approach was introduced into the RBC model by Kydland and Prescott, and this approach worked well 'with a few well-identified parameters'. Since DSGE models became more complex, econometric methods such as the maximum likelihood method and Bayesian estimation took over the leading role in identifying the values of the parameters of DSGE models. Basically, the parameters of DSGE models

describe the preferences of the economic agents and the shocks (Fernández-Villaverde & Guerrón-Quintana, 2021), but as mentioned previously, identifying the values of these parameters based on the statistical data may be difficult; therefore, another approach is to ‘mix calibration and estimation’ (Iskrev, 2018).

In our paper, we use literature-based calibration; the model is calibrated based on (Bušs & Grüning, 2023; EM, 2024; Junior, 2016). The main choice of this approach is mainly the analysis of economic processes from an academic point of view. The main interest here is ‘a kind of experiment’ that allows the simulation of the DSGE model to be carried out exclusively on a theoretical basis. The solution of the DSGE model based on calibration is described in the work of Concordia University, but in this work, the calibration is based on a data-driven approach (Gomme & Lkhagvasuren, 2013).

We have performed the parameter calibration in reference with the quarterly data analysis (see Table 1).

Table 1. Calibrated parameters of the DSGE model for the Latvian economy.

Parameter	Notation	Value	Source
Capital elasticity	α	0.40	(Bušs & Grüning, 2023)
Discount factor	β	0.9995	(Bušs & Grüning, 2023)
Depreciation rate	δ	0.0490	(Bušs & Grüning, 2023)
Consumption preference	γ	0.60	(EM, 2024)
Investment adjustment cost	ψ	0.40	(Bušs & Grüning, 2023)
TFP autoregressive parameter	ρ_A	0.85	(Bušs & Grüning, 2023)
TFP standard deviation	σ_A	0.01	(Junior, 2016)

The calibrated parameters lead to the following characteristics of the behaviour of economic agents (Torres, 2016):

1. Households: almost equally value future consumption and current consumption since the discount factor is close to 1 ($\beta = 0.9995$), 60% ($\gamma = 0.60$) of their income is distributed to consumption and 40% to leisure.
2. Firms: labour as a production factor plays a more significant role ($1 - \alpha = 1 - 0.40 = 0.60$) than capital in this model.

The next step after the calibration is the model solution. In our article, for the solution of the model, we use Dynare. Dynare is an open-source software platform that specialises in the solutions of rational expectations models (e.g., RBC, DSGE, NK) and works on MATLAB (v6.3) or Octave platforms. The main characteristics of Dynare can be summarised as follows (Cherrier et al., 2023; Villemot, 2023):

1. The use of Dynare ‘automates’ the solution of rational expectation models; therefore, they have a complex solution algorithm and require an application of specific mathematical techniques, for example, ‘multivariate nonlinear solving and optimisation’.
2. The model is rewritten as on paper in a code file, consisting of several main blocks: variables, parameters, model equations, steady state, and stochastic simulation.
3. The dynamic solution is a numerical approximation and, in general, describes the behaviour of economic processes in the long run.

For a detailed description of the Dynare results, see Section 5.1. Another important step in our analysis is data acquisition and pre-processing. To conduct the comparative analysis with the Dynare results, we acquired data from the Latvian Official Statistics Portal and preprocessed it with the basic SSA.

3.2. Basic Singular Spectrum Analysis

In our article, for we use the basic SSA algorithm for empirical data processing. In particular, we use the ‘Caterpillar–SSA’ approach. The main difference of the ‘Caterpillar–SSA’ approach is that it does not have any assumptions about the time series stationarity (Zhigljavsky, 2010).

The basic SSA algorithm divides the time series into three additive components that are trend, oscillations, and noise. The basic SSA algorithm has four main steps, which are briefly described in the following (Golyandina, 2020; Bógalo et al., 2024):

1. Embedding.

In the first step, the time series is converted into a Hankel matrix (see Equation (12)) by choosing the embedding parameter, windows length (L).

$$X = \begin{pmatrix} x_0 & x_1 & x_2 & \dots & x_{K-1} \\ x_1 & x_2 & x_3 & \dots & x_K \\ x_2 & x_3 & x_4 & \dots & x_{K+1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{L-1} & x_L & x_{L+1} & \dots & x_{N-1} \end{pmatrix} \quad (12)$$

2. Singular Value Decomposition (SVD).

The second step, SVD, performs the decomposition of the trajectory matrix into eigenvectors and eigenvalues. In simple terms, this step is associated with the analysis of principal components. Exactly at this step, the time series is decomposed into trend, oscillations, and noise.

3. Grouping.

Grouping allows us to choose the ‘most relevant components’ for the reconstruction of the time series. In general, eigenvalues and eigenvectors are grouped by their frequencies.

4. Reconstruction.

In the last step, the grouped matrices of eigenvectors and eigenvalues are reconstructed into the original time series by diagonal averaging.

One of the applications of the basic SSA is forecasting. The foundation of SSA-based forecasting is the linear recurrent formula (LRF, see Equation (13)) (Golyandina et al., 2001).

$$f_n = a_1 f_{N-1} + \dots + a_d f_{N-d} \quad (13)$$

The main assumption of LRF is based on ‘the concept of approximate recurrent continuation’, according to which the ‘next element’ is expressed as the linear combination of previous elements. The choosing of the appropriate windows length (see Step 1) plays a crucial role in the accuracy of the SSA-based forecasts (Golyandina et al., 2001).

In our article, we use the basic SSA algorithm for two main purposes—empirical data preprocessing and tendency analysis. The main advantage of SSA is that it is able to analyse both low-frequency and high-frequency fluctuations in time series, unlike methods traditionally used in economic disciplines, such as the Hodrick–Prescott filter (HP filter) (Bógalo et al., 2024).

We performed the log-deviations calculation of the SSA pre-processed empirical data. The log-deviations describe the deviations of the variable of its steady state, which is the core idea of DSGE models. The calculations of the log-deviations were performed with Equation (14), assuming the steady state of the variable (x_t) corresponds to its mean

value ($\bar{x}$) The log-deviations serve as a basis of the empirical data comparison with the Dynare solution.

$$\ln x_t - \ln \bar{x} \quad (14)$$

The data acquisition step and its tendency analysis with the applications of basic SSA is described in the next section of the article.

4. Materials and Methods

Data Acquisition and Tendency Analysis

From the Latvian Official Statistics Portal, we obtained empirical data on the key Latvian macroeconomic indicators—gross domestic product, household consumption expenditures, hours worked, and gross fixed capital formation (see Table 2). At this point, it is important to note that:

- We used quarterly data for our analysis, 2002Q1–2024Q3. This data interval is based on the availability of labour data, the time series of which starts from 2002Q1.
- These four indicators were selected for comparison with Dynare results because they are characterised as the main components of the output (see Equation (6)) and the utility of the household (see Equation (1)). Furthermore, these indicators obtained a strong correlation with the output according to the Dynare results obtained (see Section 5.1).

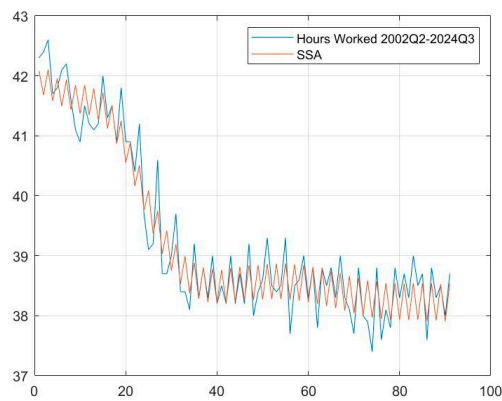
Table 2. Data for the main macroeconomic indicators of the Latvian economy.

Variable in the Model	Empirical Data	Measurement	Data Period	Source
Y (output)	Gross domestic product	thsd. euro, in 2020 prices, seasonally adjusted data	2002Q1–2024Q3	(Official Statistics Portal, 2025a)
C (consumption)	Household final consumption expenditure	thsd. euro, in 2020 prices, seasonally adjusted data	2002Q1–2024Q3	(Official Statistics Portal, 2025a)
K (capital)	Gross fixed capital formation	thsd. euro, in 2020 prices, seasonally adjusted data	2002Q1–2024Q3	(Official Statistics Portal, 2025a)
L (labour)	Hours worked on average per week	Hours worked (total, employees)	2002Q1–2024Q3	(Official Statistics Portal, 2025b)

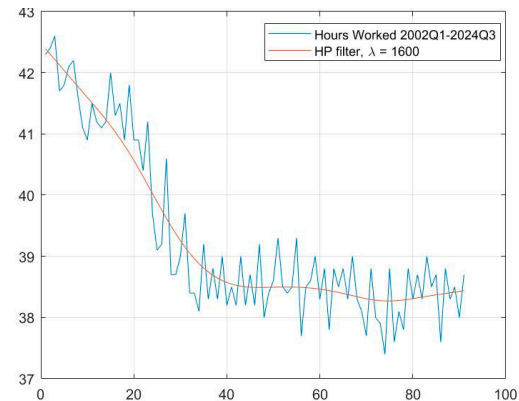
After acquiring the statistical data, we applied the basic SSA algorithm to it for the analysis of the indicators' tendency. The results are described in the following figures.

Figure 1 illustrates the comparative analysis of data smoothing with the basic SSA and Hodrick–Prescott filter on the example of Latvian hours worked quarterly data. Both methods 'identified' the general trend of Latvian hours worked—this indicator is declining over time. However, as a technical analysis method, SSA 'does not explain the causes of this general decline'—it is closely related to demographic processes such as depopulation, population ageing, and migration. Figure 1 shows that the SSA method was able to reconstruct both the general trend and frequent fluctuations in the time series of hours worked, while the HP filter was limited to reconstructing the general trend of this time series.

Figure 2 illustrates the tendencies of the real GDP and gross fixed capital formation of the Latvian economy. Generally, both indicators increase over time; however, the basic SSA 'misspecified' the decline in real GDP during the COVID-19 pandemic, and for both indicators, SSA 'identified' the increase in 2024 Q4; however, the actual data showed a decline. It is also important to note that both indicators experienced rapid growth during the years 2000–2007 that was related to the significant increase in investment; from 2004 to 2007 the investment increased by 81% (EM, 2008).

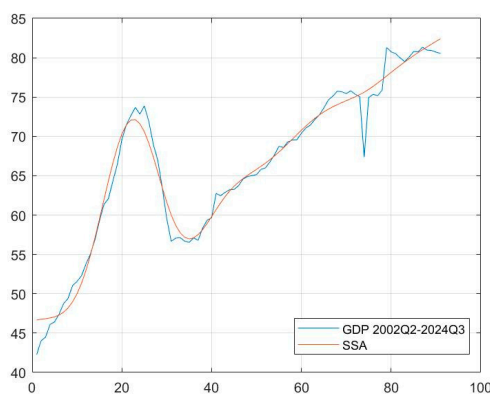


(a) SSA-filtered

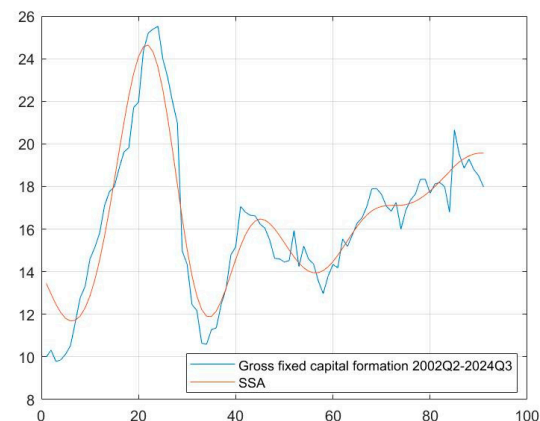


(b) HP-filtered

Figure 1. Hours worked quarterly time series analysis. (a) SSA filtered time series, (b) Hodrick–Prescott filtered time series (note: $\lambda = 1600$ is a smoothing parameter used in the HP filter for quarterly data).



(a) Gross domestic product



(b) Gross fixed capital formation

Figure 2. The analysis of the dynamics of the main Latvian macroeconomic indicators. (a) Gross domestic product, (b) gross fixed capital formation.

Figure 3 illustrates the tendency of the Latvian final consumption expenditure in Latvia. In general, it increases over time. Similarly to the real GDP and gross fixed capital formation, consumption experienced rapid growth during the years 2000–2007 mainly due to a significant wage increase; in 2007 compared to the year 2006, it increased by 32% (EM, 2008). Consumption declined significantly during the COVID-19 pandemic and slightly decreased in 2024 Q4; however, SSA ‘did not notice’.

Overall, the findings illustrated in Figures 1–3 demonstrate the high capability of SSA to filter both high- and low-frequency fluctuations. Despite a decrease in real GDP, household consumption expenditure, and gross fixed capital formation during the COVID-19 pandemic, the SSA method was unable to detect these changes. This result was obtained due to the specificities of SSA; based on the previously ‘captured’ regularities of the time series, SSA ‘continued their growth over time’, regardless of the actual data.

In the next step, we perform the analysis of the Latvian economy based on the calibrated DSGE model with the investment adjustment costs and compare these results with the SSA preprocessed statistical data.

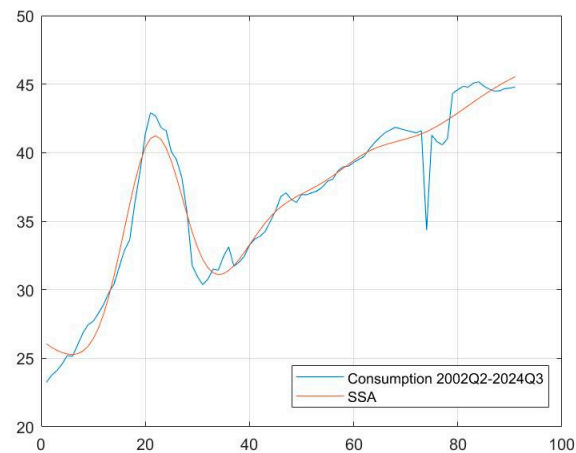


Figure 3. Analysis of the final consumption expenditure of households with SSA.

5. Results

5.1. Dynare Results

Dynare performs the solution of the steady state of the calibrated model. The results are provided to the user as a report with the following information:

1. Solution of the steady state of the model. In general, the steady state describes the behaviour of endogenous variables in the long run. The steady-state values are expressed as log-linear approximations since DSGE models do not have an analytical solution.
2. Theoretical moments (mean, standard deviation, and variance) describe the ‘average level’ of endogenous variables and deviations from it.
3. Correlation matrix.
4. Impulse response function (IRF) plots.

Table 3 contains the results for the steady-state and theoretical moments of the calibrated model. Let us consider these results in detail.

Table 3. Steady-state and theoretical moments of the calibrated DSGE model.

Variable	Steady-State	Mean	STEV	VAR	Volatility	CV
‘Y’	2.4096	2.4096	0.0649	0.0042	1.00	2.69%
‘C’	1.4555	1.4555	0.0257	0.0007	0.40	1.77%
‘I’	0.9541	0.9541	0.0434	0.0019	0.67	4.55%
‘K’	19.4717	19.4717	0.4467	0.1995	6.88	2.29%
‘L’	0.5984	0.5984	0.0033	0	0.05	0.55%
‘W’	2.4161	2.4161	0.0548	0.003	0.84	2.27%
‘R’	0.0495	0.0495	0.001	0	0.02	2.02%
‘q’	1.0000	1.0000	0.0056	0	0.09	0.56%
‘A’	1.0000	1.0000	0.019	0.0004	0.29	1.90%

The steady-state values coincide with the mean values, making the average values the main characteristic of the long-term behaviour of the indicators. However, from the results obtained, the mean value of capital (‘K’) stands out and is disproportionately high compared to other indicators. For example, it is eight times higher than the mean output value (‘Y’). If we look at the empirical data of GDP and capital (see Figure 2), we can see that the gross fixed capital formation significantly exceeds the real GDP. Standard deviation (STDEV) and variance (VAR) values show that there is no significant variability around the mean of endogenous variables. From this result, we can draw a general conclusion that the results of the solution of the calibrated model ‘show’ high stability of the main macroeconomic indicators, with the exception of capital.

By volatility, the relationship between the standard deviations of the endogenous variables and the standard deviation of the output ('Y') is understood. According to the results obtained, capital ('K') is almost seven times more volatile than output. Another calculated volatility metric is the coefficient of variation (CV), which describes the ratio of standard deviation to mean. According to the results obtained, the variability of endogenous variable values around their mean is not high.

The Dynare solution for the steady-state and theoretical moments of the calibrated model showed that capital has the greatest steady-state value and the greatest volatility among all the indicators. The highest volatility could state 'the greater role' of capital in the role of the Latvian GDP and investment dynamics. According to the study of the Bank for International Settlements, advanced industrialised economies have a lower degree of volatility than emerging economies (Becker & Noone, 2008). In the case of the Latvian economy, it is important to take into consideration the transition to the marked-orientated economy and joining the European Union in the year 2004. In 2004, the investment increased almost by 15 percent (Bitāns & Purviņš, 2012).

Table 4 describes the correlation matrix of the endogenous variables obtained by Dynare. According to these results, a very high correlation was obtained between the following variables:

1. Output ('Y') and investment ('I'): 0.9650;
2. Output ('Y') and wage ('W'): 0.9904;
3. TFP ('A') and output ('Y'): 0.9592;
4. TFP ('A') and investment ('I'): 0.9816.

Table 4. Correlation matrix of the calibrated DSGE model.

	'Y'	'C'	'I'	'K'	'L'	'W'	'R'	'q'	'A'
'Y'	1	-	-	-	-	-	-	-	-
'C'	0.8966	1	-	-	-	-	-	-	-
'I'	0.9650	0.7491	1	-	-	-	-	-	-
'K'	0.7205	0.9070	0.5407	1	-	-	-	-	-
'L'	0.8179	0.4785	0.9401	0.2501	1	-	-	-	-
'W'	0.9904	0.9492	0.9195	0.7951	0.7304	1	-	-	-
'R'	0.5650	0.1924	0.7312	−0.1651	0.8702	0.4614	1	-	-
'q'	0.5076	0.4437	0.4966	0.0359	0.4300	0.4991	0.6680	1	-
'A'	0.9592	0.7655	0.9816	0.4974	0.9073	0.9204	0.7715	0.6523	1

The weak negative correlation (−0.1651) was obtained between capital rent ('R') and capital ('K').

According to these results, both the total factor productivity (TFP) and the investment have a significant impact on the output. Another variable that significantly impacts output is wage; however, labour ('L') had a lower correlation with output (0.8179) than wage. The least significant impact on production was obtained between capital rent ('R', 0.5650) and the Tobin marginal Q ratio ('q', 0.5076).

Overall, the correlation matrix obtained from the calibrated model for the Latvian economy showed a strong correlation between output, total factor productivity, investment, and wage. Following from this conclusion, the calibrated model 'predicts' that in the context of the Latvian economy, the GDP dynamics will be most strongly influenced by these indicators—total factor productivity, investment, and wage.

In Figure 4, the impulse response function (IRF) plots are depicted. The IRF plots describe the response of the endogenous variables to the shock with a given standard deviation; these plots are the visualisation of the stochastic simulation performed by

Dynare, and it allows one to analyse the dynamics of the endogenous variables after the occurrence of the shock. In our case, the IRF plots obtained describe the dynamic of output ('Y'), consumption ('C'), investment ('I'), capital ('K'), labour ('L'), wage ('W'), capital rent ('R'), Tobin's marginal Q ratio ('q'), and total factor productivity ('A') to the shock of TFP with a standard deviation of 1% over 20 time periods (time periods are assumed to be quarters, e.g., 5 years).

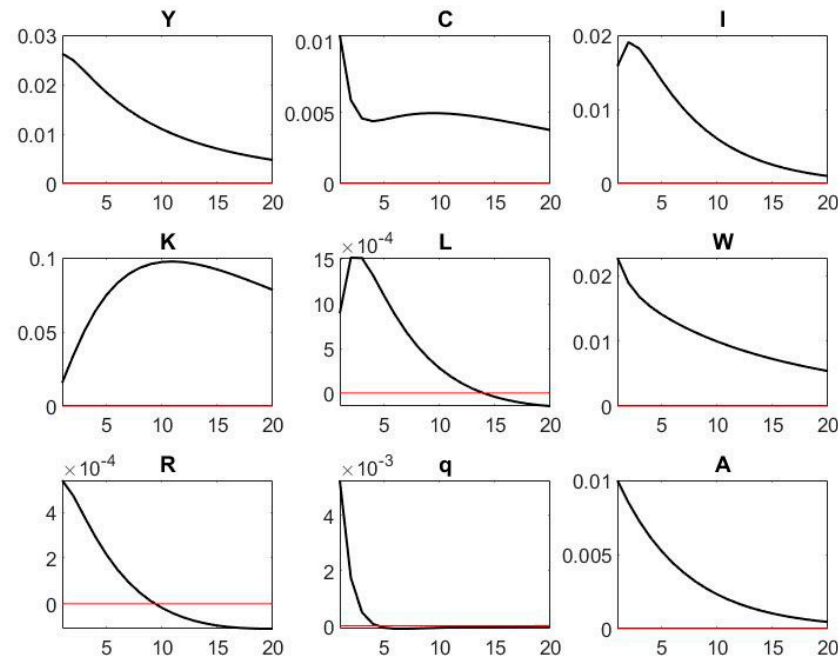


Figure 4. IRF plots of the calibrated DSGE model. Note: with the red is marked the steady-state and with black—deviations from the steady-state.

The 'response' is expressed as a percentage deviation from the steady state of the endogenous variable. The results in Figure 4 show that output, consumption, wage, capital rent, wage, Tobin's marginal Q ratio, and TFP have an immediate response to the TFP shock; however, the TFP shock has the least significant impact on capital rent and Tobin's marginal Q ratio. Investment ('I'), capital ('K'), and labour ('L') have a graduate response to the TFP shock, but it is most clearly expressed in the case of capital. By quarter 10 (in 2.5 years), capital increases to 0.1% in response to TFP shock with a 1% standard deviation.

In general, the TFP shock with a 1% standard deviation does not have a significant impact on the endogenous variables of the calibrated DSGE model with investment adjustment costs.

In the next step, the results of the SSA-filtered data are compared with the results of Dynare.

5.2. SSA-Filtered Data Results

The calculated log-deviation of the SSA-filtered real GDP, consumption, capital, and labour were taken as a basis for the comparative analysis with the Dynare results. The comparison was made in two stages, namely, a comparison of the theoretical moments and a comparison of the correlation coefficients.

Table 5 presents the theoretical moment comparison of the Dynare solution with the log data. At first glance, Dynare results are excessively higher than log-data results. These state the 'more optimistic view of economic processes' of the Dynare solution compared to the real data. However, the mean value of the capital in the log data is the highest, which

in order corresponds to the Dynare results. Both the Dynare and log-data results do not have high variability around their mean.

Table 5. The comparison of Dynare and log-data data theoretical moments.

Variable	Notation	Calibrated Model (Dynare)			Log-Data (SSA)		
		Mean	STDEV	VAR	Mean	STDEV	VAR
GDP	Y	2.4096	0.0649	0.0042	−0.0119	0.1583	0.0251
Consumption	C	1.4555	0.0257	0.0007	0.5813	0.1583	0.0251
Capital	K	19.4717	0.4467	0.1995	1.3846	0.1583	0.0251
Labour	L	0.5984	0.0033	0	−0.0006	0.0336	0.0011

If we consider the ‘volatility metrics’ (see Table 3) in the case of the logarithmic data, GDP, consumption, and capital have the same standard deviation that states the ‘same volatility.’ It basically means that the dynamics of these variables coincide over time and have a ‘higher sensitivity to uncertainty’ (Kehrig et al., 2014).

Table 6 contains the comparison of the correlation coefficients of the results of Dynare, logarithmic data, and empirical data. The analysis was based on the classification of correlation coefficients described in (Hinkle et al., 2003). The results obtained have shown greater precision in one case: the correlation between GDP (‘Y’) and consumption (‘C’) for the three data types.

Table 6. Comparison of Dynare and log-data correlation coefficients.

Variables	Correlation Coefficients			Correlation Strength
	Dynare	Log-Data SSA	Empirical Data	
Y and L	0.8179	−0.7074	−0.64085	Dynare: high negative Log-data: high negative Empirical data: moderate negative
Y and C	0.8966	1	0.986729	Dynare: very high Log-data: absolute Empirical data: very high
C and L	0.4785	−0.7074	−0.60826	Dynare: low positive Log-data: high negative Empirical data: moderate negative
K and L	0.2501	−0.7074	−0.07629	Dynare: low positive Log-data: high negative Empirical data: negligible
K and C	0.9070	1	0.656115	Dynare: very high positive Log-data: absolute Empirical data: moderate
K and Y	0.7205	1	0.643251	Dynare: high positive Log-data: absolute Empirical data: moderate

Note: empirical data refer to the statistical data (not log deviations and not SSA-filtered).

In summary, the comparison of the calibrated model solution with the SSA-filtered data has shown that the parameter values based entirely on the calibration are able to detect some of the key features of economic processes. In our case, it was the dynamics of consumption and capital.

In the next step of the analysis, we perform the forecasts. In the case of calibrated DSGE models, we use the specific feature of Dynare, which is the forecast command, and

in the case of SSA, we apply it to real GDP, consumption, capital, and labour time series forecasts (for data, see Table 2).

5.3. Forecasts

First, let us consider the DSGE model-based forecasts calibrated on the literature-based approach. These forecasts were obtained using the Dynare command ‘forecast’. The ‘forecast’ command is implemented directly in the calibrated model since we do not use the estimation of the parameters (Bayesian estimation or the maximum likelihood method). In its basic terms, this command performs forecasts of steady-state values of endogenous variables (Dynare, 2017). The main mathematical methods behind this command are Kalman smoother and Monte Carlo simulation (Adjemian, 2018).

In Figure 5, you can see the simplest representation of the forecasts of the DSGE models. The ‘middle line’ represents the steady state of the variable, and ‘the side lines’ are the upper and lower bounds of the highest posterior density of 90%, respectively (Dynare, 2017). By default, this command performs the forecast for the five time periods (in our interpretation, this is equivalent to five quarters). The general conclusion of Figure 5 is that these forecasts do not have a high variability from the steady-state values of the variables (output Y, consumption C, investment I, capital K, labour L, wage W, capital rent R, Tobin’s Q ratio q, and total factor productivity A).

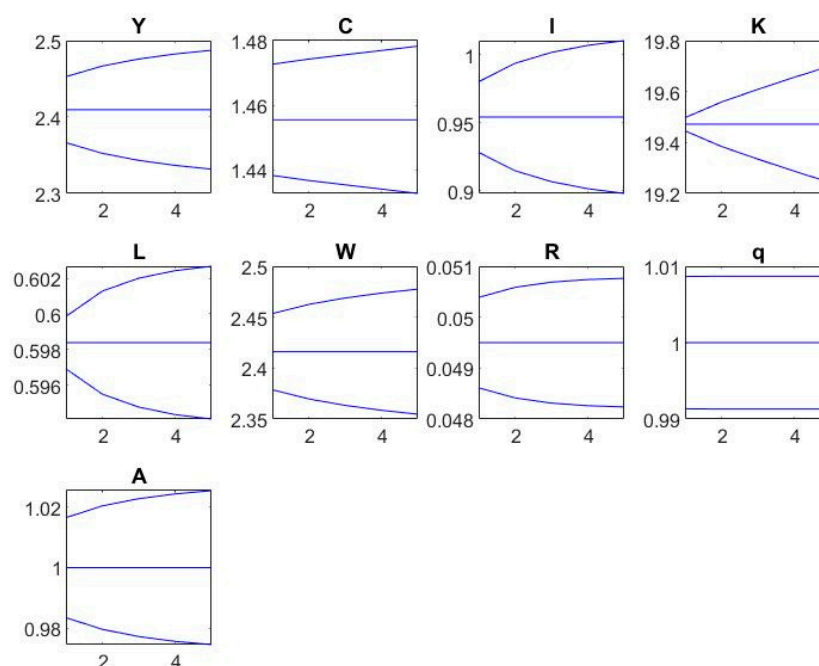


Figure 5. Dynare forecasts of the endogenous variables of the calibrated DSGE model.

However, the main specifics related to the forecasting of DSGE models is that these models are not deterministic models but stochastic models. This states the inclusion of random process analysis, which in the case of DSGE models is described by shocks (external stochastic disturbances). In general, DSGE forecasting is based on Bayesian statistics and has a complex mechanism (Ferroni et al., 2015). In the most detailed form, the DSGE-based forecasting is described in the work of Del Negro and Schorfheide ‘DSGE model-based forecasting’ (Del Negro & Schorfheide, 2013). In the paper of E. Herbst, DSGE model-based forecasting is described as not inferior to the VAR models that are traditionally used in economics theory (Herbst, 2024).

As for the results obtained in Figure 5, they can mainly serve the ‘story telling’ purposes that state that in the 5 quarters, the behaviour of the endogenous variables will be approximately around their steady state.

Next, we have performed the forecasts of the real GDP, consumption, gross fixed capital formation, and working hours of the Latvian economy with SSA. SSA was applied by the following principle: The time series were divided into the optimisation interval (2002Q1–2016Q3), which is the input data for the forecast, and the testing interval (2016Q4–2024Q3), which is the forecast in terms of SSA. The precision of these forecasts was evaluated by calculating the MAPE (mean absolute percentage error) of the forecasts obtained on the testing interval with the actual data of the same interval.

The results of SSA in-sample forecasts are described in Figure 6 (for a description of the main tendencies, see Section Data Acquisition and Tendency Analysis). Regarding the calculated MAPE, the following results were obtained for the test interval (2016Q4–2024Q3):

1. Labour: 0.74%.
2. GDP: 1.46%.
3. Consumption: 2.35%.
4. Capital: 3.56%.

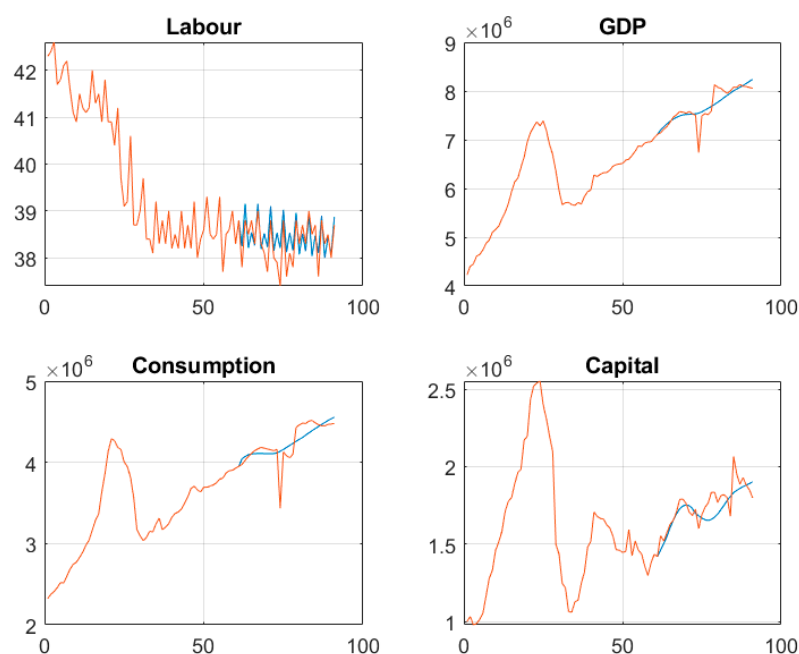


Figure 6. SSA in-sample forecasts of Latvian economic indicators. Note: with the orange is marked the “input data” and with blue—SSA in-sample forecasts.

In general, the MAPE did not exceed five percentage points and was higher only in the case of capital (3.56%). In-sample forecasts approved a high prediction accuracy of the basic SSA approach.

On the basis of the above-mentioned data, we performed out-of-sample forecasts with the basic SSA. The forecasts were performed five steps ahead, respectively, for 2024Q4–2025Q4. The results are depicted in Figure 7 (the forecasts are marked in blue).

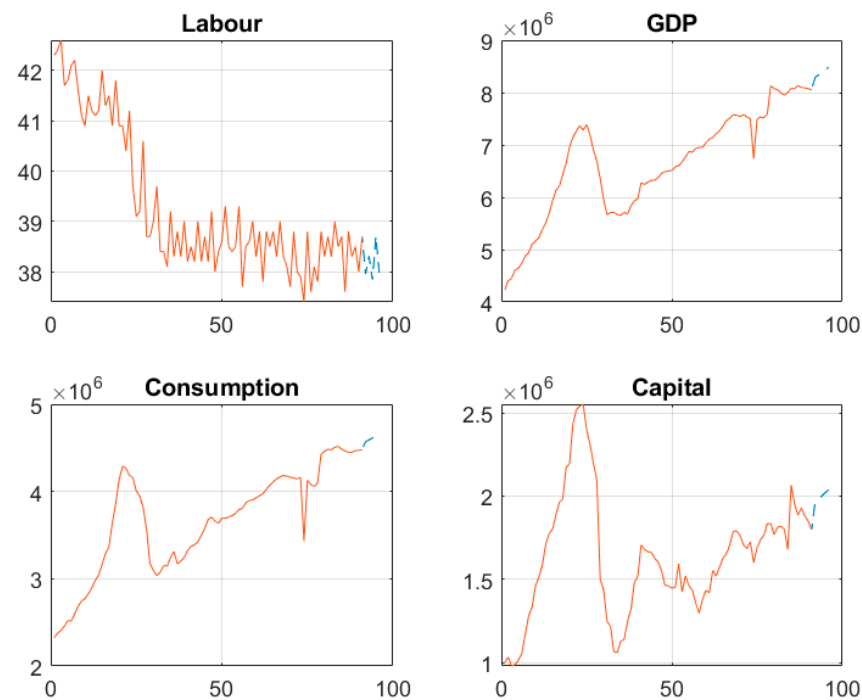


Figure 7. SSA out-of-sample forecasts of Latvian economic indicators. Note: with the orange is marked the “input data” and with blue—SSA out-of-sample forecasts.

As is obvious from Figure 7, SSA replicates the general patterns of the time series. SSA replicates the fluctuations of the labour, and in general, predicts the growth of the real GDP, consumption, and capital. Furthermore, the statistical data of these indicators were updated at the end of February 2025, thus providing us with the opportunity to compare the SSA forecast with the actual data for 2024Q4 ([Official Statistics Portal, 2025a, 2025b](#)). These results are described in Table 7.

Table 7. Comparison of statistical data of Latvian macroeconomic indicators with SSA.

Indicator	Official Statistics Portal	SSA Forecast	Absolute Percentage Error
	2024Q4	2024Q4	
Gross domestic product	8,148,036	8,287,853	1.72%
Household final consumption expenditure	4,483,697	4,571,203	1.96%
Gross fixed capital formation	1,758,754	1,962,917	11.61%
Hours worked on average per week	38.3	37.96	0.89%

The results in Table 7 show that SSA in general ‘predicted’ higher values for the indicators, but the absolute percentage errors, except for the gross fixed capital formation, do not exceed 2 percent, which ‘again proved’ the high accuracy of the SSA forecasting algorithm.

To briefly summarise the forecasting results of both the calibrated DSGE model and SSA, it can be concluded that both approaches did not predict the high volatilities of the indicators, and the SSA-based forecasts showed great accuracy based on the calculated mean percentage errors and absolute percentage errors. A more comprehensive view of the results obtained is provided in the Discussion section.

6. Discussion

We have performed the analysis of the Latvian economic processes using two methods: the calibrated DSGE model with investment adjustment costs and basic SSA. The calibration of the model was based solely on previous studies and economic reports. Furthermore,

the calibrated model was solved with Dynare, and its performance was compared with the SSA-filtered statistical data. On the other hand, we have applied both methods for forecasting purposes.

First, let us consider the comparative analysis of the calibrated DSGE model and SSA-filtered data. These results provided us with an idea of our secondary research objective, ‘identifying the main factors and patterns of the Latvian economy based on the analysis carried out’. In general, the results of the Dynare solution and its comparison with SSA-filtered data demonstrated the ability of the calibrated model to capture the dynamics of capital and consumption. From this, we can conclude that consumption and capital are among the main factors influencing Latvian economic processes.

If we consider the macroeconomic review of Latvia, then private consumption was 59% of the GDP and the gross fixed capital formation was 25% of the GDP in the year 2023 (EM, 2024). According to Trading Economics data, growth rates in Q3 2024 were the following: gross fixed capital formation–14.1%, consumer spending–5.5%, GDP at constant prices (in 2020 prices)–2% (Trading Economics, 2025c, 2025b, 2025a). On the basis of these data, preliminary conclusions can be drawn that the growth of capital and consumption is outpacing the growth of real GDP.

In terms of the stochastic simulation performed by Dynare, the total factor productivity shock did not have a significant impact on the endogenous variables of the calibrated model. The most detailed description of the current situation of the productivity dynamics of the Latvian total factor is provided in the ‘Latvia Productivity Report 2023’ by the Productivity Research Institute of the Faculty of Business, Management and Economics of the University of Latvia, the ‘University of Latvia Think Tank LV PEAK’. According to the report, although the overall productivity of the total factor in Latvia is on an upward trend, it is still below the EU average. The authors of the report note that rising labour costs and insufficient funding for research and development from the private sector are the main problems in increasing productivity (LVPEAK, 2024).

However, the assumptions of the model overestimate the situation regarding labour. It is obvious from the statistical data (see Figure 1) that the working hours (labour) indicator of the Latvian economy has a downward trend. The demographic processes mentioned above influencing the dynamics of labour can also be supplemented by the other factors—the decrease in the working age population, uneven unemployment in the regions of Latvia, skills and qualification of the population (EM, 2024).

The SSA approach also provided us an insight to the main tendencies of the real GDP, consumption, capital, and labour. In general, consumption, capital, and real GDP have an upward trend, while labour has a downward trend, and SSA was able to ‘capture’ the fluctuations of the labour data. Due to its specifics, SSA was ‘not able to foresee’ the COVID-19 pandemic that had a significant impact on all the indicators mentioned above. If we consider the macroeconomic reports and surveys of Latvia, then they also indicate a high susceptibility to geopolitical instability (OECD, 2024; EM, 2024). The OECD economic survey of Latvia also emphasised the increase in private consumption in 2024 and 2025 (OECD, 2024), which also corresponds to the SSA-obtained forecasts.

As for the research question, it can be said that the DSGE model with investment adjustment costs, the parameters of which were calibrated exclusively on previous studies, was able to most accurately reproduce the dynamics of only two indicators—capital and consumption. The analysis of statistical data of these indicators actually showed that both capital and consumption have a higher growth rate compared to the real GDP of Latvia.

Regarding the obtained forecasts, the calibrated DSGE model forecasts can be interpreted as a kind of ‘story telling’ of the Latvian economy in the long run. These forecasts represented the forecasts of the steady state of the endogenous variables of the model and, in general, did not have a high variability over it. This can also be interpreted as a ‘kind of macroeconomic stability’. The SSA-based forecasts were performed on the statistical data of the real GDP, consumption, capital, and labour and showed high accuracy based on the calculated mean percentage error and absolute percentage error.

The conclusions are provided at the end of the article.

7. Conclusions

In our paper, we have applied both fundamental and technical analysis approaches to the analysis of the Latvian economy. Fundamental analysis was considered on the DSGE model with investment adjustment costs, and technical analysis was considered on the basis of SSA. Regarding the results obtained, the following directions for future research can be identified.

The first direction might be increasing the precision of the identification of the values of the DSGE model parameters. In our article, the model was ‘only calibrated in the literature’, and the results of its solution provided only a preliminary idea of the dynamics of the main macroeconomic indicators. Also, this model by (Torres, 2016) can be expanded to include other shocks, such as the cost-push shock that is more specific to the Latvian economy.

Second, the results obtained showed the specifics of the Latvian labour market, and further research could expand to the development of the ‘tailored’ DSGE model to the Latvian labour market, particularly focussing on the role of supply-side factors and human capital. In 2017, G. Buss developed the DSGE model regarding the Latvian labour market, but this model was developed according to the goals of the Bank of Latvia. In general, this model includes such aspects as fiscal policy, Nash bargaining power, and analyses the minimum wage (Buss, 2017).

The third direction might be based purely on the technical analysis approach, such as the comparative analysis of the basic SSA and its variations on the example of Latvian macroeconomic indicators data. This analysis might provide information on the general trends of the main economic indicators of Latvia.

The fourth direction might be a more detailed study of productivity and a comparison of this indicator with the Baltic States and the EU member countries. According to the results, the calibrated model showed a high correlation between output and productivity, but the stochastic simulation showed a not very high impact of the productivity shock on the dynamics of the model indicators. Also, referring to the previously mentioned ‘Latvia productivity report’, the analysis of productivity affects both the analysis of the labour market and technological development. This direction can also complement the analysis with an expanded application of econometric methods, such as regression analysis of GDP, productivity, and wage.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations were used in the article:

CV	Coefficient of variation
DSGE	Dynamic Stochastic General Equilibrium
EU	European Union
Eq	Equation
FA	Fundamental Analysis
HP filter	Hodrick–Prescott filter
IRF	Impulse Response Function
GDP	Gross Domestic Product
KLT	Karhunen–Loeve transform
LV	Latvia
Log	Logarithmic
MAPE	Mean Absolute Percentage Error
NK	New Keynesian
Q	Quarter
RBC	Real Business Cycle
RE	Rational Expectations
thsd.	Thousand
TA	Technical Analysis
TFP	Total Factor Productivity
STDEV	Standard Deviation
SSA	Singular Spectrum Analysis
VAR	Variance

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