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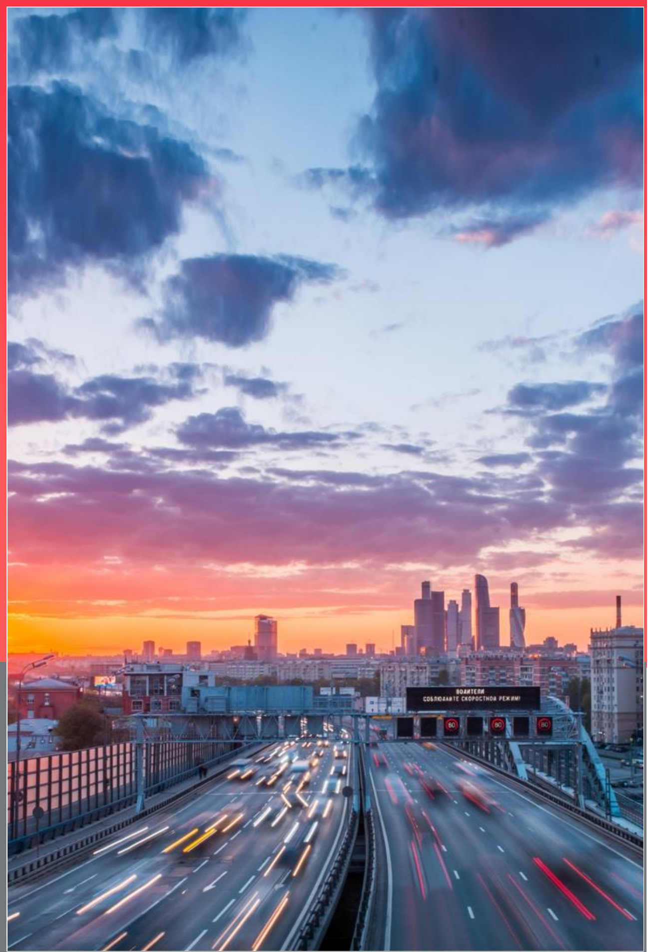

STRUCTURAL SEASONALITY

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Sergey Ivashchenko

Sergey Ivashchenko

Bank of Russia, The North-Western Main Branch

Email: sergey.ivashchenko.ru@gmail.com

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Address: 12 Neglinnaya Street, Moscow, 107016
Tel: +7 (495) 771-91-00
Website: www.cbr.ru

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ABSTRACT

The conventional practice in estimating DSGE models is to rely on seasonally adjusted data. While convenient, this approach distorts the microeconomic foundations of the model. An alternative is to model seasonality explicitly, but this often introduces severe misspecification. This paper proposes a middle ground: using year-over-year growth rates instead of quarter-over-quarter growth rates, which allows the model to endogenously determine the seasonal adjustment. This approach greatly improves forecast accuracy by more than 20% while keeping the internal consistency of the model. Moreover, we show that model misspecification and seasonal adjustment can offset each other, implying that seasonality should be treated as model-specific rather than imposed exogenously. Empirical results for U.S. and Russian data confirm that structural seasonality improves forecasting performance, and model fit relative to conventional seasonal adjustment methods.

Keywords: DSGE; seasonality; structural modeling.
JEL-classification: C13, C32, E32, E52.

INTRODUCTION

It is standard practice in macroeconomics to apply seasonal adjustment procedures—such as X-13 ARIMA-SEATS or TRAMO/SEATS [Gomez and Maravall (1996)]—before using data in empirical analysis. These methods are widely employed by statistical agencies and are based on a univariate approach, extracting seasonal patterns variable by variable without considering cross-variable consistency.

This paper highlights a fundamental tension that arises when seasonally adjusted data are used in a structural DSGE model. Denote an unadjusted (raw) log variable by x_t, its seasonally adjusted counterpart by $x_{sa,t}$, and the seasonal factor by $x_{sf,t}$, so that $x_t = x_{sa,t} + x_{sf,t.}$

Two transparent examples make the problem immediate. First, consider the Euler equation (without habit) written in terms of unadjusted consumption and inflation (equation (1) below). After substituting $c_t=c_{sa,t}+c_{sf,t}$ and $p_t=p_{sa,t}+p_{sf,t}$, the Euler equation reduces to its seasonally adjusted form (denoted (1SA)) only under the restrictive condition that the expected change in the seasonal factor of log-consumption equals the seasonal factor in inflation:

$$
\begin{aligned}
0 &= E_t\beta \frac{C_t}{C_{t+1}} R_t \frac{P_t}{P_{t+1}} - 1 = \\
&= E_t\beta \exp\left(-\left(c_{t+1}-c_t\right)+r_t-p_{t+1}-z_{t+1}\right)-1= \qquad (1)^{1} \\
&= E_t\beta \exp\left(-\left(c_{sa,t+1}+c_{sf,t+1}-c_{sa,t}-c_{sf,t}\right)+r_t-p_{sa,t+1}-p_{sf,t+1}-z_{t+1}\right)-1
\end{aligned}
$$

$$0 = E_t\beta \exp\left(-\left(c_{sa,t+1}-c_{sa,t}\right)+r_t-p_{sa,t+1}-z_{t+1}\right)-1 \qquad (1SA)$$

Second, consider a Cobb–Douglas production function with TFP $z_{y,t}$ (2).

$$
\begin{aligned}
&Y_t = Z_{y,t}\left(Z_t L_t\right)^{1-\alpha_K} K_{t-1}^{\alpha_K} \\
&\exp\left(y_t\right)=\exp\left(y_{sa,t}+y_{sf,t}\right)=\exp\left(z_{y,t}+(1-\alpha_K)l_t+\alpha_K\left(k_{t-1}-z_t\right)\right)= \qquad (2)^{2} \\
&=\exp\left(z_{y,t}+(1-\alpha_K)(l_{sa,t}+l_{sf,t})+\alpha_K\left((k_{sa,t-1}+k_{sf,t-1})-z_t\right)\right)
\end{aligned}
$$

Writing each argument as the sum of its seasonally adjusted component and seasonal factor, the production relation is consistent with its seasonally adjusted counterpart (call it (2SA)) only if the seasonal factor of output $y_{sf,t}$ equals the weighted combination of the capital and labor seasonal factors:

$$\exp\left(y_{sa,t}\right)=\exp\left(z_{y,t}+(1-\alpha_K)l_{sa,t}+\alpha_K\left(k_{sa,t-1}-z_t\right)\right) \qquad (2SA)$$

where α_K (and $1-\alpha_K$) are model parameters (weights). Both equivalence conditions are highly restrictive and unlikely to hold in practice.

These discrepancies are not minor: for U.S. GDP, seasonally adjusted q/q growth rates retain only 61.9% of the variance of their unadjusted counterparts (80% for PCE inflation), and the average difference between y/y growth rates of SA and NSA GDP is 0.4% (RMSE). In other words, seasonal adjustment removes a large share of the underlying variability that the model is meant to explain.

These observations echo earlier discussions in the literature. [Ghysels (1988)] emphasised that seasonal adjustment may remove useful information; [Sims (1993)] and [Hansen and Sargent (1993)] stressed that, while unadjusted data are preferable in theory, model misspecification can

[1] C_t is consumption at period t, R_t – is gross nominal interest rate, P_t is price level at period t, c_t – is log of consumption divided by TFP level, p_t – is inflation, r_t – is log of R_t, z_t – is growth rate of TFP.
[2] Y_t – is output, L_t – is amount of labor, K_t is capital, Z_t – is unit root TFP, $Z_{y,t}$ – is stationary TFP, yt is log of output divided by TFP level Z_t, lt is log of labor, K_t is log of capital divided by TFP level Z_t, z_t is growth rate of TFP Z_t, $z_{y,t}$ is log of stationary TFP $Z_{y,t}$

make seasonal adjustment the lesser practical evil. [Saijo (2013)] and [Christiano and Todd (2002)] provide related empirical and simulation evidence that the choice between seasonally adjusted and unadjusted data matters for parameter estimates and business-cycle properties.

Traditional approaches to seasonality in macroeconomics can be broadly classified into two categories. The conventional method relies on univariate filters, such as X-13 ARIMA-SEATS, which are simple to implement and allow for time-varying seasonal patterns but distort the microeconomic foundations of structural models by ignoring cross-variable consistency. Alternative strategies incorporate seasonality directly into the model, such as through season-specific parameters [Hansen and Sargent (1993); Saijo (2013)] or seasonal autoregressive processes [Ghysels (1988)]. While these preserve some theoretical structure, they often exacerbate model misspecification by imposing rigid forms of seasonality (e.g., fixed patterns in season-specific parameters), requiring more complex estimation techniques.

Building on these insights, this paper proposes a compromise that keeps the microeconomic structure of the model intact while reducing misspecification introduced by an exogenous seasonal pre-filter. The key idea is to treat year-over-year (y/y) growth rates as observed and to leave quarter-to-quarter (q/q) seasonal dynamics as unobserved — that is, to let the model endogenously determine the short-run seasonal pattern consistent with its structural equations. In practice, we treat $x_{yy,t}$ (log y/y growth) as the measurement variable and allow the model to infer the implied q/q seasonal adjustments via the state-space representation; measurement errors capture time-variation in empirical seasonal patterns when needed.

I show that this approach helps maintain the model's microeconomic foundations (i.e., it avoids imposing cross-variable restrictions on seasonal components that are not implied by the theory) while improving forecasting performance in both point and density metrics. Empirical exercises on U.S. and Russian datasets — together with simulation and robustness checks — demonstrate that letting the model chooses the seasonal adjustment leads to materially different parameter estimates and, in many cases, substantially better short- and medium-run forecasts than conventional seasonally adjusted data.

The remainder of the paper is organized as follows. Section 2 presents the DSGE model, data and the experimental design. Section 3 reports estimation results and a detailed comparison of forecasting performance under alternative treatments of seasonality. Section 4 contains robustness checks, including simulated data and an application to Russian data. Section 5 concludes and discusses practical implications for applied DSGE work.

1. MODEL, EXPERIMENT

The key argument against structural seasonality (and usage of unadjusted data) is misspecification. For tractability, we employ a simple DSGE model with a conventional Taylor-type rule. The baseline model is the simple DSGE with conventional Taylor rule from [Ivashchenko (2025)] presented in the appendix. It will be called AR0. The model includes some key features such as price rigidity, fiscal policy, and monetary policy rule.

Few modifications of the model are considered. The original version assumes that all exogenous processes are AR0 (3). Alternative is AR1 (4) and ARSA (5)-(7). ARSA version is more conventional approach of modeling seasonality within DSGE model. It implies that seasonality comes from seasonal shocks.

$$z_{*,t} = \eta_{0,*} + \varepsilon_{*,t} \tag{3}$$

$$z_{*,t} = \eta_{1,*} z_{*,t-1} + (1-\eta_{1,*})\eta_{0,*} + \varepsilon_{*,t} \tag{4}$$

$$z_{*,t} = z_{*,SA,t} + z_{*,SF,t} \tag{5}$$

$$z_{*,SA,t} = \eta_{1,*} z_{*,SA,t-1} + (1-\eta_{1,*})\eta_{0,*} + \varepsilon_{*,SA,t} \tag{6}$$

$$z_{*,SF,t} = \eta_{4,*} z_{*,SF,t-4} + \varepsilon_{*,SF,t} \tag{7}$$

The key idea of the proposed structural seasonal adjustment is to use observed variables. Year-over-year growth rates are unaffected by seasonal factors. So, if q/q growth rates are unobserved than structural model chooses seasonality on the basis of observed y/y growth rates. It should be noted that y/y growth rates are observed with measurement errors. This corresponds to a fixed seasonal pattern without measurement errors, similar to the approach in [Saijo (2013)]. However, conventional seasonality is changing over time. So, measurement errors would capture these changes if it is needed (standard deviation of measurement errors is part of parameters).

The model would be estimated on dataset for USA from 2003q1 till 2024q4. GDP log-growth rate y/y NSA and personal consumption expenditure deflator y/y NSA are used. Growth rates of BIS nominal and real exchange rates average in quarter (q/q). And shadow rate is used as interest rate [Wu and Xia (2016)]. The estimation with additional (q/q) time-series would be done for investigation differences between conventional and structural seasonality. This implies the use of q/q seasonally adjusted GDP log-growth and PCE deflator. The version with (3)-(5) shocks would use another q/q growth rates (without seasonal adjustment). It will show how good direct modeling of seasonal factors is. All priors are presented at appendix.

Differences in estimated parameters highlight the importance of structural seasonality. Difference in seasonally adjusted growth rates q/q would be additional view. The most important view is forecasting ability of models with conventional seasonality vs structural seasonality.

Further experiments use simulated data (from model with ARSA shocks) and comparison results on it. And some robustness test on Russian data.

2. RESULTS

2.1 Estimated values of parameters

The model is estimated with and without q/q growth rates. Table 1 reports estimated values, which differ substantially across key parameters. The inclusion of q/q data alters parameter estimates, as does the choice of shock specification. It illustrates importance of seasonal adjustment to parameters (and model dynamic). Other parameters also differ substantially, but reporting an extended table would not alter the main conclusions.

Table 1. Posterior modes for some parameters in different version

Parameter	AR0	AR0 with q/q	AR1	AR1 with q/q	ARSA	ARSA with q/q
α_K	5.93E-01	4.83E-01	4.90E-01	4.45E-01	4.86E-01	4.45E-01
log(β)	-3.70E-03	-4.39E-03	-4.38E-03	-4.61E-03	-4.39E-03	-4.62E-03
γ_r	6.00E-01	6.00E-01	6.00E-01	6.00E-01	6.00E-01	6.00E-01
γ_{rp}	1.40E+00	1.49E+00	2.15E+00	2.85E+00	1.10E+00	2.63E+00
γ_{ry}	1.00E+00	8.06E-01	7.81E-01	9.05E-01	8.02E-01	9.05E-01
γ_{exp}	6.82E-02	2.20E-01	6.25E-01	7.44E-01	4.67E-01	5.95E-01
h	9.99E-01	8.67E-01	8.75E-01	9.93E-01	8.66E-01	9.93E-01
$\eta_{0,R}$	1.33E-02	1.39E-02	1.49E-02	1.67E-02	1.64E-02	1.67E-02
$\eta_{0,trY}$	3.80E-03	2.74E-03	4.82E-03	4.98E-03	4.88E-03	5.21E-03
Tax	4.00E-01	2.90E-01	2.95E-01	4.08E-01	2.93E-01	4.08E-01
θ_C	1.20E+01	1.05E+01	1.05E+01	1.20E+01	1.08E+01	1.20E+01

The substantial differences in posterior modes across model versions stem from how seasonality affects misspecification. This aligns with [Sims (1993) and Hansen and Sargent (1993)]. Exogenous seasonal adjustment of q/q data introduces inconsistencies with microfoundations. The model compensates by altering estimates. In contrast, unobserved q/q lets the model infer seasonality endogenously. This uses measurement errors. It reduces distortions. Estimates then align better with structural equations.

Consider habit persistence h. In AR1 without q/q, consumption series seem less persistent. Adding q/q makes them more persistent. This raises h (from 0.875 to 0.993). In AR0, other factors dominate. The model has few state variables. It overstates persistence to fit all data. Structural seasonality reproduces data with high persistence from habit. Adding q/q decreases flexibility of the model. It moves h to lower values.

Next, look at γ_{rp}, the policy response to inflation. It rises with q/q in AR0 and AR1 (e.g., from 1.40 to 1.49 in AR0, 2.15 to 2.85 in AR1). Observed inflation becomes less volatile in SA data. The Taylor rule needs a stronger response to explain interest rates. Relatedly, γ_{exp} increases. This shifts weight to shorter-term inflation expectations. Shorter-term inflation is more volatile. The model compensates for lower data volatility. It boosts sensitivity and volatility via expectations.

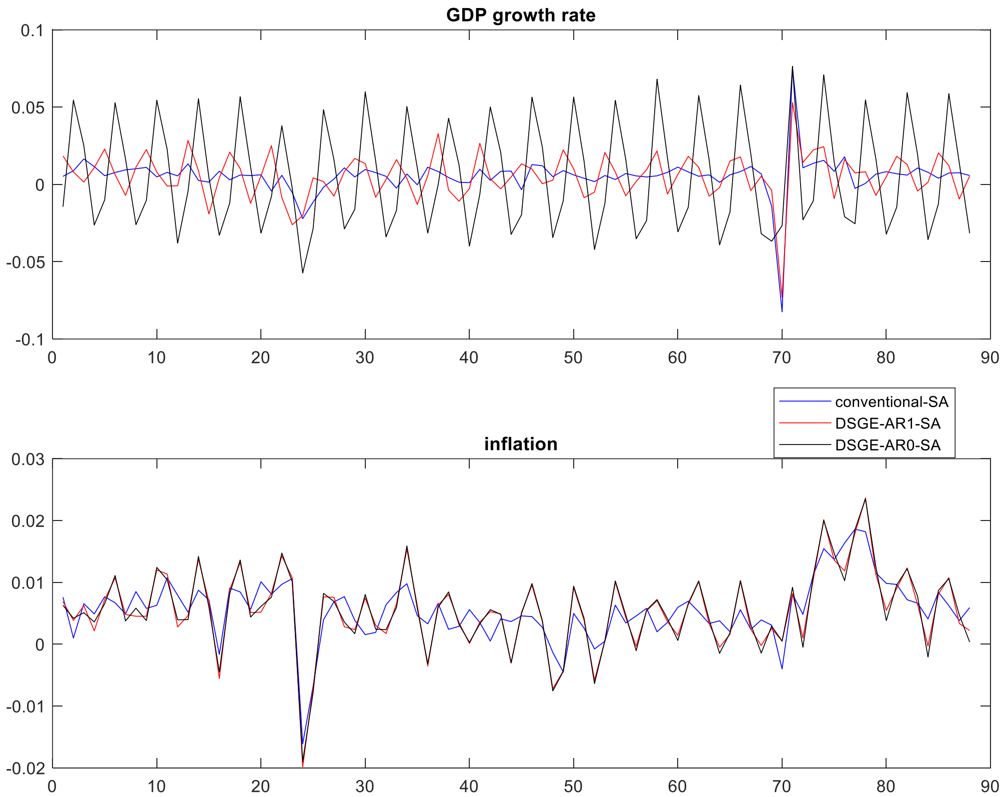
For capital share α_K, it falls with q/q in AR0 and AR1 (e.g., from 0.593 to 0.483 in AR0, 0.490 to 0.445 in AR1). Lower α_K strengthens labor-output links. Labor demand becomes more elastic to output. This enhances firm-household interactions. It alters the marginal cost gap-output relation. In turn, this affects output-inflation via the New Keynesian Phillips curve. While this logic may be tentative, it highlights seasonality's role in propagation mechanisms.

Other parameters like tax follow similar patterns. This may offset fiscal distortions from SA. Changes seem chaotic due to parameter interdependence. Yet, the pattern shows reduced misspecification in structural versions. Unobserved q/q yields more consistent estimates. This improves forecasting (Table 2). It also produces distinct seasonal patterns (Figures 1–2). Extended parameter reports confirm this. They do not change main conclusions. Instead, they stress seasonality's impact on DSGE inference.

2.2 Seasonal adjustment

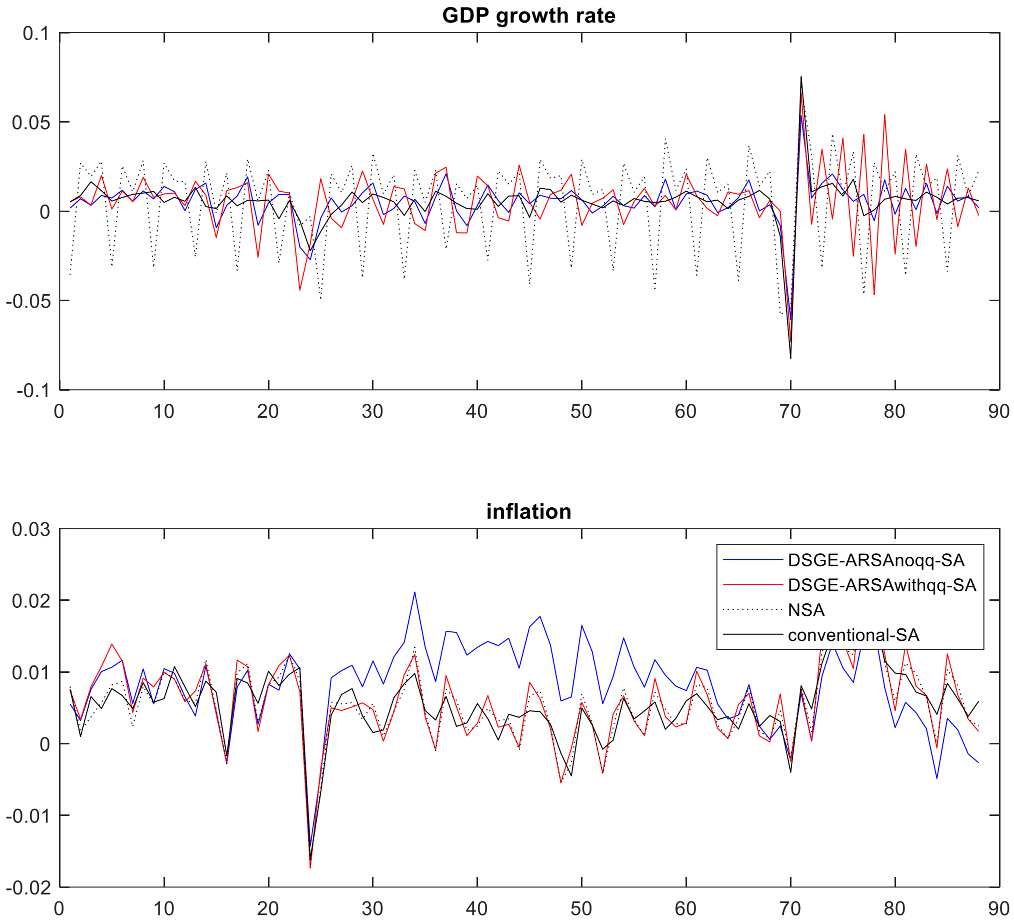
The model with unobserved q/q growth rates produces corresponding smoothed time series that means expectation of q/q growth rate conditional on all dataset (including y/y growth rate). It is presented at figures 1. Figure 1 shows that the DSGE-implied seasonally adjusted data differ substantially from conventional seasonally adjusted data. The resulting time series exhibit clear seasonal patterns. In addition, there is large difference between seasonally adjusted for different versions of model.

Figure 1. Different structured seasonality



The model with ARSA shocks has seasonal shocks. It means that seasonally adjusted series are received after elimination effects of seasonal shocks and initial state (see fig.2). It is interesting that model with unobserved q/q growth rates produces larger inflation for few years. It is related to equation (5) that suggests zero mean for seasonal factor. Zero mean and persistent exogenous process may deviate from zero for a long period. Nevertheless, model with seasonality

Figure 2. Modeled structured seasonality



2.3 Forecasting

We have seen that DSGE based seasonal adjustment is different from conventional one and it has a huge influence on parameters estimation. We next compare in-sample forecasting performance to assess which specification performs better. Table 2 demonstrates forecasting quality of model with and without q/q growth rate. There is huge improvement in terms of RMSE if q/q growth rates are unobserved. Improvement is concentrated in a few variables (mainly output or inflation and interest rates). It is related to different forecasting horizons (except the longest one). Each model version exhibits improvements. It means the following: if model chooses the seasonal adjustment than misspecification becames smaller.

Using seasonally adjusted data distorts the model's microeconomic foundations. It is the first type of misspecification. If nature of seasonality is described than it is imperfect. It is second type of misspecification. And there are other misspecifications. The second type of misspecification is usually larger than the first one [Sims (1993) and Hansen and Sargent (1993)]. However, if we try to minimize "variance of misspecification" for each type of misspecification it would not lead to minimization of "variance of misspecification" for all types together. If the model chooses seasonality, then it is able to "transfer" part of the third type of misspecification to the seasonality. This mechanism appears to be the main source of the substantial forecasting gains observed in the AR0 and AR1 specifications.

The model with ARSA shocks demonstrates the same improvement if q/q data is unobserved. It means that seasonality is not well described by seasonal-shocks in the model. So, it is hard for model to reproduce nsa q/q data. However, if the model chooses seasonality (only y/y data is observed) than model describes data much better.

Table 2 log(RMSE/RMSEqq)

		1	2	4	6	12
	inflation y/y	-11.27%	-34.84%	-62.34%	-50.56%	26.76%
	GDP growth y/y	-35.29%	-12.30%	-6.00%	-1.61%	0.44%
	Growth of nominal exch.	0.46%	-5.45%	-10.67%	-4.47%	-0.88%
	Growth of real exch.	1.02%	1.44%	0.70%	-0.03%	1.12%
ARSA	Interest rate	-8.54%	-9.59%	-6.59%	-3.29%	0.11%
	inflation y/y	9.60%	-13.31%	-45.98%	-38.18%	-3.90%
	GDP growth y/y	-22.89%	-7.87%	-23.78%	-3.26%	0.35%
	Growth of nominal exch.	0.76%	-2.15%	-8.24%	-3.09%	-0.56%
	Growth of real exch.	1.23%	1.77%	0.06%	-0.23%	0.06%
AR1	Interest rate	-11.42%	-12.99%	-8.96%	-4.48%	0.04%
	inflation y/y	-3.07%	0.97%	-3.46%	2.94%	-4.65%
	GDP growth y/y	-24.75%	-28.50%	-23.79%	-35.40%	-4.56%
	Growth of nominal exch.	-1.99%	-3.32%	-4.46%	-0.85%	-0.44%
	Growth of real exch.	-0.47%	-3.97%	-1.74%	-0.90%	0.01%
AR0	Interest rate	-20.24%	-14.84%	-5.86%	-1.62%	0.03%

The density forecast[3] improvement is related to all horizons (see Table 3). This indicates that the gains extend beyond point forecasts. Structural seasonal adjustment yields more accurate density forecasts. It allows to have large improvement in LPS for large horizons despite small improvement in point forecasts for 12 quarters case.

Table 3 LPS-LPSqq

		1	2	4	6	12
	inflation y/y	0.08	0.37	0.78	0.59	-0.02
	GDP growth y/y	0.31	0.20	0.19	0.20	0.21
	Growth of nominal exch.	-0.01	0.04	0.08	0.02	-0.02
	Growth of real exch.	-0.02	-0.02	-0.02	-0.01	-0.02
	Interest rate	0.17	0.38	0.82	1.13	1.18
ARSA	5var	0.32	0.40	1.06	1.37	1.37
	inflation y/y	-0.10	0.15	0.61	0.48	0.20
	GDP growth y/y	0.16	0.09	0.20	0.13	0.17
	Growth of nominal exch.	-0.03	-0.01	0.02	-0.01	-0.03
	Growth of real exch.	-0.03	-0.04	-0.03	-0.03	-0.03
	Interest rate	0.11	0.16	0.22	0.23	0.14
AR1	5var	0.57	0.29	0.62	0.79	0.61

[3]The log predictive score is used as a measure of density forecast accuracy. It is the average of the log predictive density evaluated at the actual observed data points.

	inflation y/y	0.04	0.00	0.04	-0.01	0.05
	GDP growth y/y	0.27	0.29	0.29	0.30	0.31
	Growth of nominal exch.	0.03	0.05	0.05	0.05	0.05
	Growth of real exch.	0.02	0.03	0.04	0.04	0.04
	Interest rate	0.20	0.17	0.04	-0.08	-0.14
AR0	5var	0.80	0.56	0.66	0.57	0.41

It should be noted that all tests are conducted with a simple model over a long sample period that includes the 2008–2009 crisis. This is an unfavorable situation that leads to relatively poor quality of forecasting for all versions of model. The relative RMSE is presented at table 4. All numbers are for versions with unobserved q/q data. The performance of the AR1 and ARSA versions is very similar.

Table 4 (RMSE/RMSE-AR)

		1	2	4	6	12
	inflation y/y	**123.66%**	**134.05%**	**148.90%**	**153.37%**	149.31%
	GDP growth y/y	104.70%	106.01%	96.52%	**106.10%**	95.43%
	Growth of nominal exch.	**113.64%**	103.07%	101.16%	**101.54%**	**100.17%**
	Growth of real exch.	**106.27%**	**98.57%**	**98.43%**	99.98%	**100.18%**
	Interest rate	87.60%	102.49%	111.80%	104.95%	83.41%
ARSA	Mean	107.18%	**108.84%**	**111.36%**	**113.19%**	105.70%
	inflation y/y	129.80%	147.11%	160.66%	162.79%	109.42%
	GDP growth y/y	**90.70%**	**99.92%**	**95.02%**	108.25%	**95.10%**
	Growth of nominal exch.	114.58%	**103.02%**	**100.20%**	101.78%	100.57%
	Growth of real exch.	109.89%	102.52%	98.67%	**99.88%**	100.43%
	Interest rate	**85.30%**	**99.30%**	**109.33%**	**103.76%**	**83.35%**
AR1	Mean	**106.05%**	110.38%	112.78%	115.29%	97.78%
	inflation y/y	237.53%	175.30%	192.09%	162.74%	**98.53%**
	GDP growth y/y	1524.32%	865.74%	639.78%	133.86%	100.66%
	Growth of nominal exch.	278.43%	116.85%	102.96%	102.44%	100.57%
	Growth of real exch.	331.05%	126.68%	98.62%	100.43%	100.38%
	Interest rate	147.22%	155.37%	136.67%	113.71%	83.48%
AR0	Mean	503.71%	287.99%	234.02%	122.64%	**96.72%**

3. ROBUSTNESS RESULTS

3.1 Simulated data

One type of robustness check is usage of simulated data with seasonal component similar to [Saijo (2013)]. The ARSA version of model (estimated with q/q NSA data) is used for simulation. The length of time-series is the same (88 quarters). The seasonally adjusted data is generated too. Perfect seasonally adjusted is achieved by setting seasonal shocks equal to 0. All models are estimated on simulated data. Its forecasts are computed. It is repeated 100 times. Corresponding out of sample RMSE are presented at table 5.

Table 5 log(RMSE/RMSEqq) simulated data

		1	2	4	6	12
ARSA	inflation y/y	-120.10%	-60.57%	11.51%	18.75%	15.15%
	GDP growth y/y	-5.15%	3.73%	-7.25%	-3.41%	-0.51%
	Growth of nominal exch.	4.92%	0.83%	1.29%	-2.03%	-2.09%
	Growth of real exch.	-0.82%	0.44%	-0.69%	-1.74%	-3.27%
	Interest rate	1.26%	2.74%	1.65%	-0.52%	0.13%
AR1	inflation y/y	-120.17%	-63.18%	3.36%	4.19%	0.79%
	GDP growth y/y	31.26%	29.63%	9.44%	2.43%	0.22%
	Growth of nominal exch.	2.89%	2.31%	-1.78%	-8.81%	-5.64%
	Growth of real exch.	2.19%	1.27%	0.17%	-2.72%	-0.60%
	Interest rate	3.03%	4.68%	2.54%	-0.55%	0.05%
AR0	inflation y/y	-88.88%	-54.83%	-0.31%	5.67%	4.11%
	GDP growth y/y	-32.32%	-22.54%	-24.65%	-19.73%	-1.08%
	Growth of nominal exch.	-3.42%	3.21%	3.50%	-0.84%	-3.39%
	Growth of real exch.	-7.64%	9.21%	-0.08%	-0.24%	0.00%
	Interest rate	-5.35%	-2.96%	-0.90%	-0.63%	0.06%

The simulated data demonstrates even larger improvement for short run forecasting. It means that usage of q/q growth rates in addition to y/y greatly decrease fit of the model. Moreover, adding q/q NSA growth rates to the ARSA specification reduces short-run forecasting accuracy. Thus, additional information from q/q data is almost useless. There is some improvement in long-term forecasting ability of model with NSA data which may be related to more accurate estimation of parameters (in absence of misspecification).

The models are misspecified. There is influence of prior for estimation results. It means that estimated values of parameters may be biased estimator of parameters that was used for simulation. However, data is generated from the same distribution. It means that estimated values of parameters (for each version of the model) should have the same distribution. So, standard deviation of these estimators can be computed over 100 tries. Corresponding results presented at Table 6.

Table 6 Std modes for some parameters in different version

Parameter	AR0	AR0 with q/q	AR1	AR1 with q/q	ARSA	ARSA with q/q
α_K	5.67E-04	**2.10E-05**	2.06E-04	**2.07E-06**	**5.05E-07**	8.03E-07
$\log(\beta)$	1.23E-04	**1.63E-05**	1.04E-04	**1.88E-06**	5.50E-06	**2.76E-07**
γ_r	1.16E-02	**2.14E-05**	3.62E-04	**2.54E-06**	3.70E-06	**4.39E-07**
γ_{rp}	5.61E-02	**1.95E-05**	1.96E-04	**1.91E-06**	4.17E-06	**1.08E-06**
γ_{ry}	6.23E-03	**1.47E-05**	4.32E-04	**2.71E-06**	2.32E-06	**1.21E-06**
γ_{exp}	1.69E-03	**1.52E-05**	1.97E-04	**2.41E-06**	**6.60E-08**	1.84E-07
h	**4.01E-10**	1.92E-05	2.28E-04	**4.41E-06**	1.09E-06	**5.80E-07**
$\eta_{0,R}$	2.63E-03	**1.99E-05**	2.57E-04	**4.91E-06**	8.37E-07	**2.97E-07**
$\eta_{0,trY}$	2.00E-03	**2.10E-05**	1.45E-04	**3.03E-06**	2.35E-06	**6.57E-07**

Tax	1.62E-03	**1.16E-05**	3.00E-04	**2.53E-06**	**7.36E-07**	1.06E-06
θ_C	1.52E-01	**1.99E-05**	2.18E-04	**3.80E-06**	2.21E-06	**8.12E-07**

It is interesting that in contrast to [Saijo (2013)] standard deviation of model without SA data is larger. Thus, structural seasonal adjustment leads to less accurate estimation of parameters. It is related to different approach for seasonality. Suggested approach gives to the model ability to choose seasonality without data about actual NSA q/q growth rates. Thus, suggested approach has not additional information that may improve accuracy of estimation in contrast to [Saijo (2013)].

3.2 Russian data

The additional check is usage of data from other country. The model would be estimated on dataset for Russia from 2015q1 till 2024q4. GDP log-growth rate y/y NSA and personal consumption expenditure deflator y/y NSA are used. Growth rates of BIS nominal and real exchange rates average in quarter (q/q). And RUONIA is used as interest rate. All exercises are the same as for USA. SA data are constructed with tramo-seats [Gomez and Maravall (1996)].

Seasonal effects are larger for Russian data. Variance of SA q/q growth rates is only 3.5% of NSA q/q growth rates for GDP (58.25% for PCE inflation). Difference of y/y growth rates for SA and NSA data is similar: 0.44% for GDP and 0.55% for PCE inflation. The improvement of forecasting quality due to usage of structural seasonality approach is even larger for Russian data (see table 7). It is interesting that interest rate became variable with large improvement for each version of model.

Table 7 log(RMSE/RMSEqq) with Russian data

		1	2	4	6	12
ARSA	inflation y/y	1.3%	1.3%	0.4%	-0.1%	-0.2%
	GDP growth y/y	0.0%	0.0%	0.0%	0.0%	0.0%
	Growth of nominal exch.	0.0%	0.0%	0.0%	0.1%	0.1%
	Growth of real exch.	12.0%	8.0%	0.6%	-0.8%	-0.1%
	Interest rate	-34.7%	-34.7%	-34.7%	-34.7%	-34.7%
AR1	inflation y/y	-29.1%	-11.9%	-6.9%	3.0%	-6.0%
	GDP growth y/y	-21.7%	-23.2%	-25.6%	-6.3%	0.6%
	Growth of nominal exch.	-3.9%	-5.7%	-1.8%	-1.2%	-1.1%
	Growth of real exch.	-7.1%	-6.5%	-0.7%	-0.4%	-0.5%
	Interest rate	-21.5%	-39.5%	-35.2%	-30.9%	-2.6%
AR0	inflation y/y	-82.0%	-24.4%	-12.6%	-10.0%	-6.1%
	GDP growth y/y	-17.9%	-2.0%	-9.8%	-6.5%	-1.3%
	Growth of nominal exch.	-0.4%	-0.3%	-6.6%	-3.7%	3.1%
	Growth of real exch.	-1.6%	-1.9%	-5.7%	-4.0%	-0.3%
	Interest rate	-44.4%	-16.4%	-14.9%	-7.8%	-5.4%

DISCUSSION

The conventional seasonal adjustment leads to over smoothing of sa-series (compare to structural one). It is in line with literature that talks about over smoothing of seasonal adjustment [Hayat and Bhatti (2013)]. However, the structural seasonality approach leads to few deep changes. First of all seasonality became model specific property instead of data specific. It increases difference between DSGE models and conventional econometric approaches. Implementing structural seasonality is challenging in models that lack a state-space representation. The comparison of forecast for seasonally adjusted data becomes almost non-informative. Thus, all results and forecasts should be expressed in y/y terms, which differs from conventional practice. It is not complicated but requires changes of many routines.

Many routines include important intermediate steps that are important even for policy implication. The identification of the output gap or recession episodes provides examples of such intermediate steps. Their meaning would be changed with model specific seasonality. However, final decisions are based on forecasts. Monetary policy according to Taylor rule is good example. The policy interest rate is determined by expected inflation and its own lag. The rule with output gap can be implemented too. The forecasting quality for interest rates improves with structural seasonality. However, intermediate step analysis (output-gap trajectory) became less informative. It stimulates to re-investigate some variations of intermediate steps that became conventional. For example, expected growth can be tried as alternative to output gap at Taylor-type rules. In case of optimal policy, existence of observed interest rates allows to receive policy recommendations with the structural seasonality too.

Thus, switching from conventional seasonality to structural one would lead to few changes:

- Keeping microeconomic foundation
- Improving models fit and forecasts
- Losing of comparability of conventional intermediate step of analysis and decision making process.
- Keeping of comparability of conventional final step of analysis and decision making process.
- Request for re-investigation of the best practice

CONCLUSIONS

This paper revisits the conventional reliance on seasonally adjusted data in DSGE estimation. While convenient, such pre-filtering imposes unrealistic restrictions across variables and breaks the model's microeconomic foundations. The theoretical examples of the Euler equation and the Cobb–Douglas production function illustrate that equivalence with seasonally adjusted specifications holds only under highly implausible conditions. Empirically, the distortions are substantial: for U.S. GDP, the variance of q/q growth rates falls to 61.9% after seasonal adjustment (80% for PCE inflation), and the average difference between SA and NSA y/y growth rates is 0.4% (RMSE). Seasonal adjustment therefore removes a nontrivial share of the very variability that DSGE models are designed to capture.

As an alternative, I propose to use y/y growth rates as observables, leaving q/q seasonal fluctuations to be chosen by the model itself. This approach makes the seasonal adjustment to become model-specific rather than imposed exogenously, thereby maintaining the model's microeconomic foundations. The empirical exercises on U.S. and Russian data demonstrate that structural seasonality improves forecasting performance, for point forecasts as well as density forecasts.

The implications are twofold. On the one hand, adopting structural seasonality strengthens internal consistency and reduces overall misspecification (by creation of “negative correlation” between misspecification of model and seasonal adjustment), leading to more reliable forecasts. On the other hand, it challenges conventional intermediate steps of applied analysis: concepts such as the output gap or recession dating are less directly comparable across models once seasonality is determined endogenously. Nevertheless, policy-relevant variables such as interest-rate forecasts benefit directly from the improved fit.

Overall, the evidence suggests that conventional seasonal adjustment is not an innocuous preprocessing step. Allowing models to determine their own seasonal adjustment keeps their theoretical structure intact and can materially improve empirical performance. Future work should further explore how model-specific seasonality interacts with policy rules and structural shocks, and whether it can provide a new benchmark for empirical DSGE practice.

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APPENDIX DSGE MODEL

This model is simple small-scale DSGE model of closed economy. Model includes 3 types of agents: households, firms and government.

Households

Households maximize expected utility function (A1) with budget restriction (A2).

$$U_t = E\left(\sum_{s=0}^{\infty}\beta^s\left(\frac{Z_{C,t+s}\left(\left(C_{t+s}/Z_{trY,t+s}\right)/\left(C_{h,t+s-1}/Z_{trY,t+s-1}\right)^h\right)^{1-\omega_c}}{(1-\omega_c)}+\frac{\mu_M\left(M_{t+s}/Z_{trY,t+s}\right)^{1-\omega_M}}{(1-\omega_M)}-\frac{\mu_L\left(L_{t+s}\right)^{1+\omega_l}}{(1+\omega_l)}\right)\right)=$$

$$=\left(\left(\frac{Z_{C,t}\left(\left(C_t/Z_{trY,t}\right)/\left(C_{h,t-1}/Z_{trY,t-1}\right)^h\right)^{1-\omega_c}}{(1-\omega_c)}+\frac{\mu_M\left(M_t/(P_tZ_{trY,t})\right)^{1-\omega_M}}{(1-\omega_M)}-\frac{\mu_L\left(L_t\right)^{1+\omega_l}}{(1+\omega_l)}\right)\right)+E_t\beta U_{t+1}\to\max_{C,L,K} \quad \text{(A1)}$$

$$P_tC_t+M_t+B_{H,t}/R_t+FX_tB_{WH,t}/R_{W,t}=(1-\tau)W_tL_t+M_{t-1}+B_{H,t-1}+FX_tB_{WH,t-1}+T_t \quad \text{(A2)}$$

C_t is consumption, $C_{h,t}$ is habit (that is equal to consumption but it is not controlled by individual households), L_t is labor, M_t is money, W_t is wage, R_t is interest rate in domestic currency, $B_{H,t}$ is bond/deposit savings in domestic currency, $B_{WH,t}$ is bond/deposit savings in foreign currency, $R_{W,t}$ is interest rate in foreign currency, FX_t is exchange rate (units of domestic currency per unit of foreign), T_t is transfers from government, $Z_{trY,t}$ is exogenous process of TFP growth, $Z_{C,t}$ is exogenous demand shock process. The formula (1) uses alternative form of habit. Conventional habit with minus (instead of dividing) leads to possibility of complex values of utility function with normal distribution of variables. Dividing (that makes first summand equal to $exp(z_{c,t}+(1-\omega_c)(c_t-c_{h,t-1}h))/(1-\omega_c)$) has not such disadvantage and produce similar dependence on lag of consumption.

This model uses an unconventional form of habit. This is done to prevent theoretical possibility of complex numbers (situation when current consumption is below habit related level). Such situation could happen with near-zero probability (taking into account approximation errors). Suggested approach produces similar effects to conventional one: dependence on previous period consumption and higher nonlinear effects (but this effect may be much smaller).

Additional detail is existence of stochastic trend with drift in all real variables. It comes from exogenous unit root TFP process. All summands of utility function should be cointegrated. So, it is impossible to have C_t without dividing by $Z_{trY,t}$. Dropping the stochastic trend from the model is poor practice (it would eliminate microeconomic foundation that is one of the main advantages of DSGE models).

Firms

Firms have monopolistic competition and solve problem (A3)-(A6). They maximize expected discounted dividends flow with price rigidity effect in Rotemberg form (A3). The restrictions are following: budget (A4), production function (A5) and demand (A6) that comes from CES-aggregation.

$$E\left(\sum_{t=0}^{\infty}\left(\mathop{\Pi}_{k=0}^{t-1}R_k\right)^{-1}\left(D_{f,t}-e^{\varphi_p}P_{F,t}Y_{D,t}\left(\frac{P_{f,t}}{P_{f,t-1}}-e^{\bar{p}}\right)^2\right)\right)\to\max_{D,L,Y} \quad \text{(A3)}$$

$$D_{f,t}+W_tL_{f,t}=P_{f,t}Y_{f,t}+T_{W,t} \quad \text{(A4)}$$

$$Y_{f,t} = Z_{trY,t} Z_{Y,t} \left(L_{f,t}\right)^{1-\alpha_k} \quad \text{(A5)}$$

$$Y_{f,t} = \left(\frac{P_{f,t}}{P_{F,t}}\right)^{-z_{\theta,t}} Y_{D,t} \quad \text{(A6)}$$

$D_{f,t}$ – is dividends of firm f, $L_{f,t}$ is amount of labor used by firm f, $P_{f,t}$ is price of goods by firm f, $Y_{f,t}$ is output of firm f, $T_{w,t}$ – is transfer with foreign part of the firm, $P_{F,t}$ is price level of domestic firm, $Y_{D,t}$ is demand for domestic firms output, $Z_{Y,t}$ is exogenous stationary TFP process, $Z_{\theta,t}$ is exogenous process of demand elasticity.

There are two important details related to problem of firms. The first is discounting factor. The conventional is usage of stochastic-discount factor that is based on household's Lagrange multiplier of budget restriction. It is equivalent in case of linear approximation and model without financial rigidities. However, it creates problems for generalization of model: whose Lagrange multiplier should be used if heterogeneous agents owns firm. Moreover, firms may be owned by foreign agents or government. The usage of interest rate eliminates these problems. The second detail is Rotemberg rigidity. Many authors use real costs of price change. It produces additional summand in GDP formula that have not analog in national account system. The usage of moral costs solves such problem. These two approaches are equivalent in case of first order approximation.

Government

Government has budget restriction (A7). Monetary policy rule of Taylor type is (A9) and rule for transfers (A8). There are definitions of two variables that are used in the rules. The first is future inflation $p_{EXP,t}$ that is described by rule (A10). This is done for possibility to control which inflation is more important factor for Taylor rule (next period or future one). The next variable is households domestic currency assets $A_{H,t}$ that is described by (A11). It is liabilities of government (minus assets) that effect on its fiscal policy. Such variable allows to decrease number of state variable.

$$B_{t-1} + T_t = D_t + M_t - M_{t-1} + B_t / R_t + \tau(W_t L_t) \quad \text{(A7)}$$

$$T_t / (P_t Z_{trY,t}) = \gamma_{tr} T_{t-1} / (P_{t-1} Z_{trY,t-1}) + (1-\gamma_{tr})(\gamma_{try}(y_{D,t} - \overline{y_D}) + \gamma_{trA}(a_{H,t} - \overline{a_H}) + z_{tr,t}) \quad \text{(A8)}$$

$$r_{H,t} = \gamma_r r_{H,t-1} + (1-\gamma_r)(\gamma_{rp} E_t(p_{EXP,t+1} - \overline{p}) + \gamma_{ry}(y_{D,t} - \overline{y_D}) + z_{r,t}) \quad \text{(A9)}$$

$$p_{EXP,t} = \gamma_{\exp} p_t + (1-\gamma_{\exp}) E_t p_{EXP,t+1} \quad \text{(A10)}$$

$$a_{H,t} = \frac{A_{H,t}}{P_t Z_{trY,t}} = \frac{B_{H,t} + M_{H,t}}{P_t Z_{trY,t}} = b_{H,t} + m_{H,t} \quad \text{(A11)}$$

Small letters are for stationary variables. The transformation depends on variable: real variables (such as $y_{D,t}$) are logs of ratio initial variable to common trend ($Z_{trY,t}$); nominal variables are divided to price level and common trend as at (A11); interest rates (R_t, $R_{W,t}$) that is stationary positive variable are transformed by logs; real exchange rate (fx_t) is log based on ratio of domestic and foreign price levels and so on.

Rule (A8) reflects 3 ideas of fiscal policy. The first one is smoothing that means slowly changes of government transfers (it is controlled by γ_{tr}). The second one is cyclical dependence. Fiscal policy could be pro- or counter-cyclical depending on sign of γ_{try}. The third idea is budget balancing. Higher level of government debts (that is assets of households counting money as part of government debts) should leads to lower government transfers. Negative value of γ_{trA} reflects this mechanics of government assets control. However, there is question how close to zero it can be without explosiveness. Blanchard-Kahn condition is the main restriction for non-explosive trajectory of all variables including government assets.

Rest of the world

The rest of the world has its budget restriction that is usually calls balance of payments (A12).

$$B_{WH,t-1}FX_t + EX_tP_t + T_{W,t} = FX_tB_{WH,t}/R_{W,t} + IM_tP_{im,t} \quad \text{(A12)}$$

The rest of the world is described by exogenous rules. Its inflation described by (A13). Interest rate (for households) is described by (A14). It includes some dependence on foreign bonds position of households. If they try to increase their foreign debts than interest rate would increase. Import prices are described by (A15). If coefficient is equal to one it would means that exogenous prices for import is in foreign currency. However, coefficient can be different that means some mechanics restriction exchange rate pass through import prices. Equation (A16) describes export that depends on real exchange rate. It is suggested that export goods and domestic consumption are the same (so, their prices are the same too). Equation (A17) comes from CES aggregation of import and domestic goods to final one.

$$p_{W,t} = z_{pw,t} \quad \text{(A13)}$$

$$r_{W,t} = \gamma_{rw,bw}\left(b_{WH,t} - \overline{b_{WH}}\right) + z_{rw,t} \quad \text{(A14)}$$

$$p_{IM,t} = \gamma_{pim,fx}\left(fx_t - \overline{fx}\right) + z_{pim,t} \quad \text{(A15)}$$

$$ex_t = \gamma_{ex,fx}\left(fx_t - \overline{fx}\right) + z_{ex,t} \quad \text{(A16)}$$

$$e^{im_t} = (1-w_c)\left(e^{c_t} + e^{ex_t}\right)e^{-\theta_C\left(p_{im,t}-p_{c,t}\right)} \quad \text{(A17)}$$

Balance

There are balance equations. The first of them (A18) describes conventional GDP. The next one (A19) describes demand for intermediate goods that come from the same CES aggregation as import. The price aggregation (A20) describes dependence between domestic firms prices ($p_{F,t}$), import prices ($p_{im,t}$) and aggregate price level (P_t). It comes from the same CES aggregation. The last equation (A21) describes denomination of domestic currency units. The price of final goods basket in term of domestic goods basket is fixed.

$$e^{y_t} = e^{c_t} + e^{ex_t} - e^{im_t} \quad \text{(A18)}$$

$$e^{y_{D,t}} = (w_c)\left(e^{c_t} + e^{ex_t}\right)e^{-\theta_C\left(p_{F,t}-p_{c,t}\right)} \quad \text{(A19)}$$

$$1 = (w_c)e^{(1-\theta_C)\left(p_{F,t}-p_{c,t}\right)} + (1-w_c)e^{(1-\theta_C)\left(p_{IM,t}-p_{c,t}\right)} \quad \text{(A20)}$$

$$p_{c,t} = \overline{p_c} \quad \text{(A21)}$$

The model includes only one source of domestic demand for simplicity. Introduction of investments and government consumption (44% and 35% of consumption at 2019) makes model much more complicated (additional state variable of capital, investment rigidity, increasing importance of financial rigidity, different deflators for different GDP components and so on). Introduction of government consumption only (without investments) creates additional problems of dividing DGP by 2 components of domestic demand. Thus, single source of domestic demand is significant simplification of the model that allows deep focusing on monetary policy.

Priors for estimation presented at table A1. All computations are made with modified dynare [Adjemian et all (2011).].

Table A1 Priors

Parameter	Lower bound	Upper bound	Density	Prior mean	Prior std	Model version
stderr ε_C	0.0003	10	inv_gamma_pdf	0.01	3	All

stderr ε_{ex}	0.0003	10	inv_gamma_pdf	0.01	3	All
stderr ε_{pim}	0.0003	10	inv_gamma_pdf	0.01	3	All
stderr ε_{pw}	0.0003	10	inv_gamma_pdf	0.01	3	All
stderr ε_{R}	0.0003	10	inv_gamma_pdf	0.01	3	All
stderr ε_{rw}	0.0003	10	inv_gamma_pdf	0.01	3	All
stderr $\varepsilon_{\theta F}$	0.0003	10	inv_gamma_pdf	0.01	3	All
stderr ε_{tr}	0.0003	10	inv_gamma_pdf	0.01	3	All
stderr ε_{trW}	0.0003	10	inv_gamma_pdf	0.01	3	All
stderr ε_{trY}	0.0003	10	inv_gamma_pdf	0.01	3	All
stderr ε_{YF}	0.0003	10	inv_gamma_pdf	0.01	3	All
stderr $\varepsilon_{C,SF}$	0.0003	10	inv_gamma_pdf	0.01	3	ARSA
stderr $\varepsilon_{ex,SF}$	0.0003	10	inv_gamma_pdf	0.01	3	ARSA
stderr $\varepsilon_{pim,SF}$	0.0003	10	inv_gamma_pdf	0.01	3	ARSA
stderr $\varepsilon_{pw,SF}$	0.0003	10	inv_gamma_pdf	0.01	3	ARSA
stderr $\varepsilon_{R,SF}$	0.0003	10	inv_gamma_pdf	0.01	3	ARSA
stderr $\varepsilon_{rw,SF}$	0.0003	10	inv_gamma_pdf	0.01	3	ARSA
stderr $\varepsilon_{\theta F,SF}$	0.0003	10	inv_gamma_pdf	0.01	3	ARSA
stderr $\varepsilon_{tr,SF}$	0.0003	10	inv_gamma_pdf	0.01	3	ARSA
stderr $\varepsilon_{trW,SF}$	0.0003	10	inv_gamma_pdf	0.01	3	ARSA
stderr $\varepsilon_{trY,SF}$	0.0003	10	inv_gamma_pdf	0.01	3	ARSA
stderr $\varepsilon_{YF,SF}$	0.0003	10	inv_gamma_pdf	0.01	3	ARSA
stderr $zzobs_{dPyy}$	10^{-9}	$6*10^{-4}$	inv_gamma_pdf	0.001	0.3	All
stderr $zzobs_{dPyy}$	10^{-9}	$4*10^{-3}$	inv_gamma_pdf	0.001	0.3	All

α_K	0.3	0.8	normal_pdf	0.6	0.05	All
$\ln(\beta)$	-0.01	-1.00E-05	normal_pdf	0.005	5.00E-03	All
φ_P	-5	5	normal_pdf	0	10	All
γ_{exp}	0.001	0.999	normal_pdf	0.5	0.25	All
γ_r	0.6	0.999	normal_pdf	0.8	0.15	All
γ_{rp}	1	5	normal_pdf	1.5	0.5	All
γ_{ry}	-1	1	normal_pdf	0	0.15	All
γ_{tr}	0.6	0.999	normal_pdf	0.8	0.15	All
γ_{trA}	-1	0	normal_pdf	-0.1	0.15	All
γ_{try}	-1	1	normal_pdf	0	0.15	All
γ_{exfx}	0	5	normal_pdf	0	1.5	All
γ_{pimfx}	0	2	normal_pdf	1	0.5	All
γ_{rwbw}	-5	0	normal_pdf	0	0.5	All
h	0	0.999	normal_pdf	0.7	0.15	All
μ_L	-5	5	normal_pdf	0	10	All
μ_M	-5	5	normal_pdf	0	10	All
$\eta_{0,C}$	-5	5	normal_pdf	0	2	All
$\eta_{0,ex}$	-5	5	normal_pdf	0	2	All
$\eta_{0,pim}$	-5	5	normal_pdf	0	2	All
$\eta_{0,pw}$	0	0.02	normal_pdf	0.005	0.005	All
$\eta_{0,R}$	0.001	0.03	normal_pdf	0.0015	0.005	All
$\eta_{0,\theta,F}$	4	12	normal_pdf	8	2	All
$\eta_{0,tr}$	-5	5	normal_pdf	0	10	All
$\eta_{0,trW}$	-5	5	normal_pdf	0	2	All
$\eta_{0,trY}$	-0.01	0.02	normal_pdf	0.01	0.01	All
$\eta_{0,YF}$	-10	10	normal_pdf	0	10	All
$\eta_{1,C}$	-0.999	0.999	normal_pdf	0.5	0.1	AR1,ARSA
$\eta_{1,ex}$	-0.999	0.999	normal_pdf	0.5	0.1	AR1,ARSA
$\eta_{1,pim}$	-0.999	0.999	normal_pdf	0.5	0.1	AR1,ARSA
$\eta_{1,pw}$	-0.999	0.999	normal_pdf	0.5	0.1	AR1,ARSA
$\eta_{1,R}$	-0.999	0.999	normal_pdf	0.5	0.1	AR1,ARSA
$\eta_{1,rw}$	-0.999	0.999	normal_pdf	0.5	0.1	AR1,ARSA
$\eta_{1,\theta,F}$	-0.999	0.999	normal_pdf	0.5	0.1	AR1,ARSA
$\eta_{1,tr}$	-0.999	0.999	normal_pdf	0.5	0.1	AR1,ARSA
$\eta_{1,trW}$	-0.999	0.999	normal_pdf	0.5	0.1	AR1,ARSA
$\eta_{1,trY}$	-0.999	0.999	normal_pdf	0.5	0.1	AR1,ARSA
$\eta_{1,YF}$	-0.999	0.999	normal_pdf	0.5	0.1	AR1,ARSA
$\eta_{4,C}$	-0.999	0.999	normal_pdf	0.95	0.01	ARSA
$\eta_{4,ex}$	-0.999	0.999	normal_pdf	0.95	0.01	ARSA
$\eta_{4,pim}$	-0.999	0.999	normal_pdf	0.95	0.01	ARSA
$\eta_{4,pw}$	-0.999	0.999	normal_pdf	0.95	0.01	ARSA
$\eta_{4,R}$	-0.999	0.999	normal_pdf	0.95	0.01	ARSA
$\eta_{4,rw}$	-0.999	0.999	normal_pdf	0.95	0.01	ARSA
$\eta_{4,\theta,F}$	-0.999	0.999	normal_pdf	0.95	0.01	ARSA
$\eta_{4,tr}$	-0.999	0.999	normal_pdf	0.95	0.01	ARSA
$\eta_{4,trW}$	-0.999	0.999	normal_pdf	0.95	0.01	ARSA

$\eta_{4,trY}$	-0.999	0.999	normal_pdf	0.95	0.01	ARSA
$\eta_{4,YF}$	-0.999	0.999	normal_pdf	0.95	0.01	ARSA
ω_C	1	5	normal_pdf	1.5	1.50E-01	All
ω_L	1	5	normal_pdf	1.5	1.50E-01	All
ω_M	1	5	normal_pdf	1.5	1.50E-01	All
T	0	0.8	normal_pdf	0.4	5.00E-02	All
θ_c	4	12	normal_pdf	8	2	All
w_c	0.4	0.9	normal_pdf	0.7	0.1	All
steady(b_{WH})	-5	5	normal_pdf	0	2	All
Steady(c_H)	-5	5	normal_pdf	0	1	All