Estimating business and financial cycles in Slovenia

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Abstract

In this paper we utilize a multivariate STSM model in order to estimate trend and cyclical components on a set of business and financial economic variables for Slovenia. The results show that financial cycles are somewhat longer compared to business cycles. Comparing the standard deviations of financial and business cycles give inconclusive results on average, but excluding particular macroeconomic variables that are by definition more volatile, we see that also standard deviations of financial cycles tend to be larger. From the economic policy implications point of view the results might not come as a surprise, but are utterly important for additionally implementing financial stability goals alongside the monetary policy mandate, as financial cycles seem to be longer and deeper compared to business cycles.

Keywords: Unobserved components models, financial cycles, housing cycles, business cycles, model-based filters

JEL Classification: C32, E32, E44.

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1 Introduction

The global financial crisis from 2008 has led to rethink the roles of different economic policies in many economies worldwide. The global financial crisis has shown that strictly pursuing price stability does not ensure the overall macroeconomic stability. The rapid rise of credit and asset prices led to inefficient compositions of output, which was accompanied by the excessive real estate investments resulting in the intensification of financial market imperfections. Due to the asymmetricity of effects, differences between the characteristics of business and financial cycles occurred.

Based on a set of macroeconomic and financial variables for Slovenia we estimate the trend, cyclical and irregular components of the several time series as we utilize a multivariate multivariate structural time series model (STSM) developed by Rünstler and Vlekke (2018). They follow Harvey and Koopman (1997) STSM model that decomposes a vector of non-stationary time series data into several components that help to explain the main driving forces of a certain time series. The assumption is that the trend component follows a random walk with a time-varying slope. The irregular components are normally and independently distributed with a mean zero, while the cyclical components are driven by independent latent stochastic cycles (Rünstler and Vlekke, 2018).

The results of each estimated components show differences amongst selected variables, suggesting that business and financial cycles are not synchronized and display differences between them. The financial cycles tend to be longer and deeper on average when compared to business cycles. There are also notable differences in crises characteristics. The irregular component was much more expressed with the pandemic outbreak than in the case of a global financial crisis for macroeconomic variables. On the other hand, the irregular component did not play a significant role during the pandemic and the global financial crisis for financial variables, but the cycle component seem to matter more. The multivariate STSM model results were confirmed by utilizing bivariate STSM model on a large set of financial and macroeconomic variable combinations. We also confirm the results on an univariate model setup.

Despite the results are not novice in a general literature, they are, however, extremely important for policy makers as pursuing (national) financial stability together with the macroprudential policy could provide the decisive factor in economic stability as whole alongside the monetary policy mandate.

The paper is organized as follows. Section 2 provides an overview of the relevant literature. Section 3 is focused on the methodology explanation and selection of macroeconomic and financial variables. In section 4 we discuss the obtained results and provide robustness checks with policy implications. In section 5 we conclude.

2 Literature review

The relationship between financial credit, asset prices, and the real economic activity has been one of the most popular research questions in economic science. For example, studies as Goodhart and Hoffman (2008), Schularick and Taylor (2012) and Hubrich et al. (2013) study the general effects of financial shocks to the macroeconomy. Namely, Hubrich et al. (2013) find that financial shocks account for about one third of the variation in GDP on average, but the contribution of financial shocks changes over time. In this respect, Goodhart and Hoffman (2008) find that the effects of shocks to money and credit are found to be stronger when house prices are booming as well as there is a significant multi-directional link between house prices, monetary variables, and the macroeconomy. These results suggest that there might be different driving forces behind business and financial cycles, especially the ones that change over time.[1]

[1]Several other studies try to predict the forecasting power of financial indicators on economic activity and aim at developing leading indicators of financial distress such as Borio and Lowe (2002, 2004), English, Tsatsaronis and Zoli (2005), Gerdesmeier, Reimers and Roffia (2010), Hatzius et al.

A strand of literature studies the estimation of financial cycles in more detail. Drehmann, Borio and Tsatsaronis (2012), and Aikman, Haldane and Nelson (2015) find evidence of large medium-term cycles in loans and housing data by using univariate filtering methods, while Claessens, Kose and Terrones (2012), Huber (2016) and Bartoletto et al. (2017) use turning point analysis to reach similar conclusions. On the other hand, Comin and Gertler (2006) show the presence of important medium-term fluctuations in business cycles, namely the US GDP. Similarly, Christiano and Fitzgerald (2003) use a bandpass filter. Rünstler and Vlekke (2018) point to an important issue related to the real-time estimates of cyclical components. Business cycle component estimates are usually reported based on symmetric two-sided filters that make use of both past and future observations, but policy-makers, can only rely on one-sided filters, thus on past observations only. This makes real-time estimates subject to considerably higher uncertainty. Orphanides and Van Norden (2002) and Edge and Meisenzahl (2011) find real-time output gap estimates from various univariate methods to differ widely and are of limited value for economic policy. On the other hand, studies on the output gap that use multivariate filters to exploit the information in cyclical co-movements report more favourable results (Rünstler, 2002; Watson, 2007; Basistha and Startz, 2008; Trimbur, 2009; and Burlon and D'Imperio, 2020).

Other methods were utilized as well. Breitung and Eickmeier (2016) and Miranda-Agrippino and Rey (2015), for instance, extract the common component in financial cycles. Communale (2015) applies HP filtering and principal component analysis in order to estimate financial cycles on a variety of EU and OECD countries. Schüler, Hiebert and Peltonen (2015, 2017) construct a set of synthetic financial cycle indicators for euro area countries from credit volumes and house, equity and bond prices by applying a spectral analysis. Strohsal, Proaño and Wolters (2015, 2019) assess cyclical properties of financial series by using ARIMA models.

(2010), Alessi and Detken, (2011), and Ng (2011).

Our method of interest applies a structure into time series. Harvey (1989) and Harvey and Koopman (1997) introduced structural time series models. Several other studies apply the same methodology, such as Chen, Kontonikas and Montagnoli (2012), De Bonis and Silvestrini (2013), Galati et al. (2015), de Winter et al. (2017), Melolinna and Tóth (2018) and Bulligan et al. (2019), but provide a more detailed description of the dynamic properties of business, housing and financial cycles in a multivariate model context. Rünstler and Vlekke (2018) extend the standard multivariate STSM model to estimate cyclical fluctuations in real GDP, credit volumes, and real estate prices, while they focus on interactions between the three variables at different frequencies. In a more comprehensive study Rünstler et al. (2018) tackle the relationship links by utilizing several econometric and theoretical methods, but the main model relies on the STSM methodology.

Based on the theoretical background of the above mentioned literature, another strand of literature takes a policy perspective into the matter. Gadanecz and Jayaram (2016) stress the need for a thorough understanding of financial cycles when evaluating the costs and benefits of macroprudential measures. Similarly, Giese et al. (2014) suggest that macroprudential measures, such as regulatory capital requirements, should be based on a wider range of indicators that includes credit and house price gaps as well. In this respect, financial cycle estimates could also be used for the fine-tuning of other policy instruments such as limits on LTV and DSTI ratios (Hanson, Kashyap and Stein, 2011; Cerutti, Claessens and Laeven, 2015; and Hartmann, 2015) or measuring the credit-to-GDP gap (Drehmann and Tsatsaronis, 2014). An important aspect in estimating relationship between the business and financial cycles is also the estimation of the interaction between monetary policy and macro-prudential policy. Monetary policy appears to affect the financial cycle, as indicated by a growing literature including Adrian, Estrella and Shin (2010), Adrian and Shin (2011), Gertler and Karadi (2011), Borio (2012), Schularick and Taylor (2012), Rey (2013), Bruno and Shin (2015), Black and Rosen (2016) and Lenarčič (2019). These relationships suggest that there is scope to incorporate financial stability considerations in monetary policy decisions. In addition, Borio, Lombardi and Zampolli (2016) try to estimate the impact of financial cycles on fiscal stance and offer a new policy tool in order to estimate cyclically adjusted fiscal balances.

3 Methodology and data

3.1 Methodology of the multivariate STSM model

The methodology broadly follows Harvey and Koopman (1997) multivariate structural time series model (STSM) that is utilized for decomposing a vector of non-stationary time series data into trend, cyclical and other, irregular components. Our paper is based on a extended version of the multivariate STSM model introduced by Rünstler (2004) and later on Rünstler and Vlekke (2018) and Rünstler et al. (2018). The idea behind STSM methodology is to decompose a set of time series data into trends and cycles, which implies a filter in order to extract the cyclical component. The key difference between the STSM and the bandpass filter, for example, is that in the case of STSM methodology the trend and cyclical components are explicitly defined as parametric time series models, the parameters of which are estimated. This results in specialized filter for the observed time series allowing for a more precise characterisation of the cyclical dynamics and reducing the possible risk of obtaining spurious cycles, as documented for the case of bandpass filters (Murray, 2003).

As said, the key feature of the STSM model is the decomposition of a time series into several components, i.e. trend, cyclical and irregular components. The trend component follows a random walk with a time-varying slope, while for the irregular components, it is assumed that they are normally and independently distributed with a mean zero. The specification of the cyclical components is a bit more complex. The cyclical components are driven by independent latent stochastic cycles, which are explained in more detail in the Appendix since the model is based on the STSM model developed by Rünstler and Vlekke (2018).

In comparison to the relevant literature, as described in the literature review, we differ from them by applying the multivariate STSM methodology to a large variety of macroeconomic and financial data in order to provide a more extensive and robust estimation of business and financial cycles and their subcomponents. This in turn provides a stronger case for drawing proper economic policy conclusions. In addition, the Rünstler and Vlekke (2018) relies on the maximum likelihood estimation (MLE) due to the luxury of long sample sizes for the parameter inference and cycle extraction. Many smaller EU countries do not possess the luxury of longer sample sizes, i.e. their data time-series are relatively short (Rünstler et al. 2018). One of the solutions for this is the utilization of Bayesian inference that relies on using pre-sample information in the form of parameter priors.

In order to re-implement the STSM model from Rünstler and Vlekke (2018), additional considerations have to be discussed. Informative priors are imposed on the deep stochastic cycle parameters, such are the parameter λ_i that determines the cycle length (in years) via $\frac{\pi}{2\lambda_i}$, the parameter of decay ρ_i and the autoregressive root ϕ_i. We use the non-informative Normal priors for the loading coefficients in A and A^* matrices, apart from the diagonal elements of the matrix A, which are required to be non-negative. For the innovation variables, the Inverse Gamma priors are specified for the irregular component innovation ϵ_t and level innovation η_t, since they exhibit more volatility compared to the slope innovation ζ_t.

3.2 Data

In this section, we describe the main characteristics of data entering the a multivariate STSM model of business and financial cycles in the Slovene economy. We take into account 19 time series that are presented in Table 1. All time series data are subject to different levels of transformation.

The macroeconomic variables that represent the business cycle are transformed more or less similarly. The real GDP, consumption, investment, exports, imports, industrial production, gross value added of manufacturing and gross value added of services (NACE classification of activities sector RSTU denoted as other services) are logarithmically transformed. We also extract the dynamics of a tradable and non-tradable sectors from the NACE classification of activities gross value added data by following the methodology of Lenarčič and Masten (2020). They rely on a strict definition of tradable and non-tradable sectors, meaning that they exclude those NACE sectors from the analysis, that are not distinctively tradable or non-tradable. If their ratio of exports to total production oscillates around the 10 percent threshold too much, the sector is excluded. More precise, a sector is treated as a tradable one if its ratio of exports to production exceeds the 10 percent threshold for at least 75 percent of time using the WIOD data for all 28 European countries and a timespan from 2000 till 2011. This means that manufacturing, mining, quarrying and other industry (NACE classification activities denoted as BCDE), wholesale, retail, transportation, storage, accommodation and food services (NACE classification activities denoted as GHI) are treated as tradable sectors, while construction (NACE classification activities denoted as F), real estate activities (NACE classification activities denoted as L), public administration, defence, education, human health, and social work services (NACE classification activities denoted as OPQ), and other services (NACE classification activities denoted as RSTU) are treated as non-tradable sectors. These separate sectors are weighted by gross value added in order to obtain the tradable and non-tradable sector variables. As others they are transformed logarithmically.

The index of the residential real estate prices is taken from the Statistical Office of Republic of Slovenia (henceforth SORS) and is expressed in nominal terms. As the current official index of the residential real estate prices only dates back to 2007Q1, we extend the series by proxying its dynamics with a SORS index of used flats from 2000Q1 till 2006Q4. To extend the residential real estate series even further back in time (i.e. from 1996Q1 till 1999Q4), we take the dynamics of advertised residential real estate prices from SLONEP database. The reason of the extension of the latter is to overcome the short time series problem with the intention of covering as much information as possible with respect to business and financial cycles in the data. The compounded nominal residential real estate index's reference year is 2015. We transform the nominal compounded residential real estate index into real terms by deflating it with an HICP index and then transform it logarithmically.

Here we discuss the financial cycle variables. We extract total loans to the non-financial private sector, loans to non-financial corporations and loans to households from Bank of Slovenia. Since these three series are expressed in nominal terms, we transform them to real terms by deflating them with the HICP index as well. All three series are then logarithmically transformed. Similar treatment of transformation to loans to households and non-financial corporations is imposed to housing (mortgage) and consumer loans given to households. Nevertheless, due to missing data for consumer and housing (mortgage) loans before the period of 2005Q4, we append the dynamics of short and long-term loans in the missing data period from 1996Q1 on, respectively. We also assume that housing and consumer loans might be subject to different dynamics to a certain degree and thus provide additional information that may not be clearly evident considering only total loans to households. We are also interested in the total activity of the banking sector by taking into account the balance sheets of banks in Slovenia. The value of the balance sheets of banks is expressed in nominal terms. We first deflate the banks' balance sheet time series with the HICP inflation and then logarithmically transform it. The nominal equity index is a compounded index. The period of 2003Q2-2020Q4 is represented by the Slovene stock market index SBITOP[2], while the period of 1995Q1-2003Q2 is proxied by the dynamics of a mutual fund Generali Galileo[3]. The compounded nominal equity index is taken in logs as well. What we are left with, are the nominal long-term rates that determine the term spread. As several others indexes, in order to obtain a longer series, we compound the nominal long-term rate as well. The main period of 2002Q2-2020Q4 is represented by a representative 10 year government bond yield. The period before has to be proxied. The long-term rate dynamics from 1998Q1 till 2002Q1 is proxied by Bank of Slovenia's 270-day Bills rate, while the period 1995Q1-1997Q1 is proxied by the Bank of Slovenia's rate on Lombard loans. The term spread variable is calculated as the difference between the nominal long-term rates of Slovenia and Germany.

[2]SBITOP index is the Slovene blue-chip index. It is a free-float capitalization-weighted index comprising the most liquid shares traded at Ljubljana Stock Exchange (https://ljse.si/).

[3]Generali Galileo mutual fund is a mixed flexible mutual fund (https://www.generali-investments.si/).

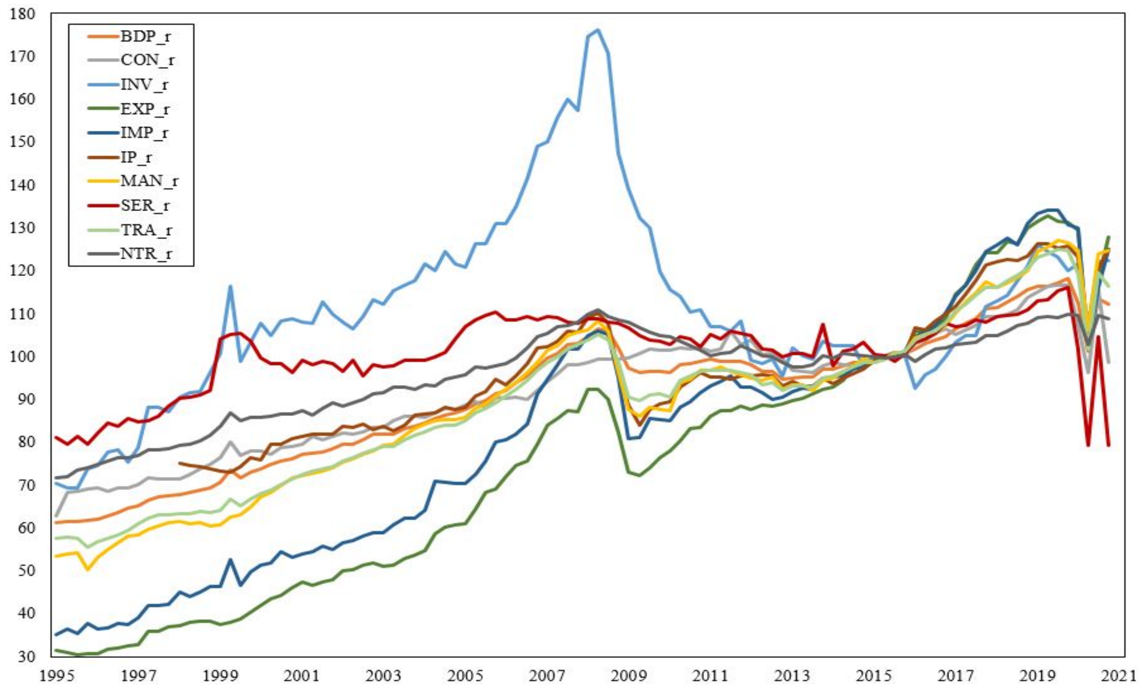
Table 1: Data entering the model

Time-series	**Abbreviations**	**Nominal/real**
Real GDP	GDP_r	R
Real industrial production	IP_r	R
Real consumption	CON_r	R
Real investment	INV_r	R
Real gross value added in manufacturing	MAN_r	R
Real gross value added in services	SER_r	R
Real gross value added in tradable sector	TR_r	R
Real gross value added in non-tradable sector	NTR_r	R
Real exports	EXP_r	R
Real imports	IMP_r	R
Real residential real estate prices	RRE_r	R
Real bank balance sheet size	BAL_r	R
Real total loans to the private non-financial sector	TL_r	R
Real loans to non-financial corporations	$LNFC_r$	R
Real loans to households	LHH_r	R
Real housing (mortgage) loans	$LHHM_r$	R
Real consumer loans	$LHHC_r$	R
Nominal equity price index	EQP_n	N
Term spread	SPR_n	N

Source: SORS, Bank of Slovenia, SLONEP, LJSE, Generali investments, FRED St. Louis, own calculations.

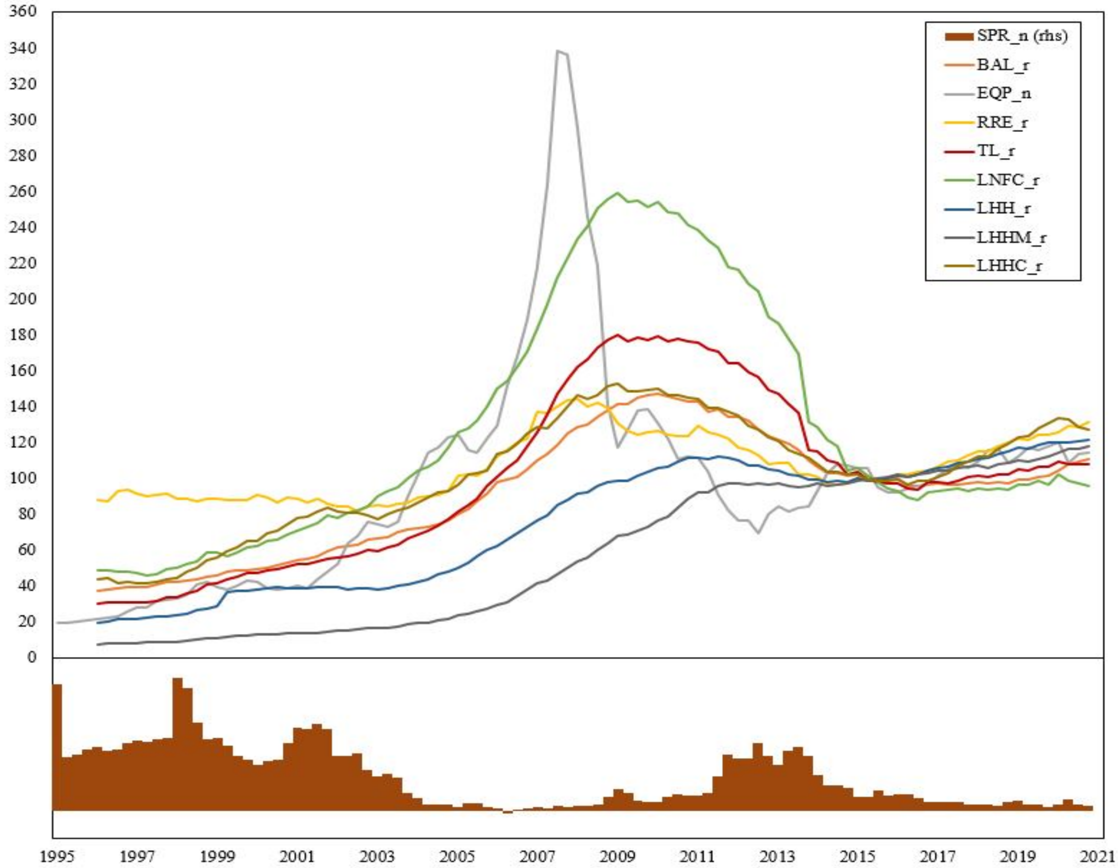
We also present the descriptive statistics of the data as shown in Table 2, while in the Figures 1 and 2 we plot all the macroeconomic and financial time series that enter the model. The number of observations of all variables varies between 92 and 104. The standard deviation of loans variables to non-financial corporations and households is approximately three times larger compared to the standard deviation of the real GDP, the real residential real estate prices and most of the others macroeconomic variables with the exception of exports and imports. Somewhat larger variation compared to the loans variables is observed in nominal equity prices. An even more sizeable variation is observed in housing (mortgage) loans, while consumer loans demonstrate somewhat lower variation expressed in standard deviation terms. The reason behind the higher variation of loans variables are the extremely large growth values of financial variables in general (either in the banking sector or in the stock markets) during the last global financial crisis. What is noteworthy also to mention is that the downturn of the observed economic variables due to the COVID-19 pandemic crisis was relatively limited, especially for the financial sector ones and if we compare the dynamics to the global financial crisis. The most affected were the real GDP, nominal equity prices, loans to the non-financial corporates and to some extent the term spread. Other variables, notably the real residential real estate prices and loans to households seem to be unaffected by the COVID-19 pandemic. A relatively high standard deviation is also reported for the term spread variable. This is mainly the cause of a relatively high inflation during the transition period in the 1990s and to some extent the global financial crisis period in which mostly the peripheral countries experienced high sovereign yields and term spreads with respect to core, less riskier, countries.

Figure 1: Dynamics of the macroeconomic time series data - index 100 = 2015



Source: SORS, own calculations.

Figure 2: Dynamics of the financial time series data - index 100 = 2015 (lhs), in % and p.p. (rhs)



Source: SORS, Bank of Slovenia, SLONEP, LJSE, Generali investments, FRED St. Louis, own calculations.

Table 2: Descriptive statistics of the transformed variables

Variable	Number of observations	Mean	Standard deviation	Minimum	Maximum
$\ln GDP_r$	104	4.49	0.18	4.12	4.77
$\ln IP_r$	92	4.56	0.15	4.29	4.84
$\ln CON_r$	104	4.51	0.15	4.14	4.76
$\ln INV_r$	104	4.69	0.19	4.24	5.17
$\ln MAN_r$	104	4.46	0.24	3.92	4.84
$\ln SER_r$	104	4.61	0.09	4.37	4.76
$\ln TRA_r$	104	4.47	0.22	4.02	4.83
$\ln NTR_r$	104	4.56	0.12	4.27	4.71
$\ln EXP_r$	104	4.23	0.45	3.41	4.89
$\ln IMP_r$	104	4.33	0.39	3.56	4.90
$\ln RRE_r$	100	4.66	0.16	4.41	4.97
$\ln BAL_r$	100	4.45	0.41	3.63	5.00
$\ln TL_r$	100	4.47	0.53	3.42	5.19
$\ln LNFC_r$	100	4.71	0.52	3.84	5.56
$\ln LHH_r$	100	4.19	0.57	2.98	4.80
$\ln LHHM_r$	100	3.71	0.95	2.07	4.77
$\ln LHHC_r$	100	4.57	0.37	3.73	5.03
$\ln EQP_n$	104	4.39	0.65	3.00	5.83
SPR_n	104	2.57	2.32	-0.16	9.98

Source: SORS, Bank of Slovenia, SLONEP, LJSE, Generali investments, FRED St. Louis, own calculations.

4 Results

4.1 Results of the STSM model

Due to the extensive number of macroeconomic and financial variables, we build a matrix of variable combinations that enter the multivariate STSM model. We consider two cases. In the first one, we look at the business and financial cycles relationship pairwise (i.e. bivariate STMS model), as shown in the upper part of the Table 3. In second case, we extend the first case by also including the dynamics of the residential real estate $\ln RRE_r$ variable, thus extending the model into a multivariate one (lower part of the Table 3). The reason to use the real residential real estate price variable $\ln RRE_r$ alongside the business and financial cycles is the link that it provides between the two. A relatively large share of economic research acknowledges the important role of residential real estate prices on boom–bust cycles, especially in loan volume cycles (Mian and Sufi, 2010; Schularick and Taylor, 2012; Jordà, Schularick, and Taylor, 2015, 2016). The residential real estate prices may represent an important mechanism that reinforces the interconnectedness and leverage between the business and financial cycles as an increase in residential real estate prices implies a higher value of collateral used in housing (mortgage) loans (Geanakoplos, 2009). On the other hand, in a bust period a lower value of collateral could significantly affect and constrain balance sheets of banks and dampen credit supply.

Table 3: Matrix of multivariate combinations between macroeconomic and financial variables

Variables	$\ln BAL_r$	$\ln TL_r$	$\ln LNFC_r$	$\ln LHH_r$	$\ln LHHM_r$	$\ln LHHC_r$	$\ln EQP_n$	SPR_n
$\ln GDP_r$	x	x	x	x	x	x	x	x
$\ln IP_r$	x	x	x				x	x
$\ln CON_r$	x	x		x	x	x		
$\ln INV_r$	x	x	x				x	x
$\ln MAN_r$	x	x	x				x	x
$\ln SER_r$	x	x	x				x	x
$\ln TRA_r$	x	x	x				x	x
$\ln NTR_r$	x	x	x				x	x
$\ln EXP_r$	x	x	x				x	x
$\ln IMP_r$	x	x	x				x	x
$\ln GDP_r$ with $\ln RRE_r$		x		x	x			

The first part of the results are presented in Tables 4 and 5, where we show the results from the bivariate STSM model varieties. In this setup we assume a direct connection between the business and financial cycles. For the sake of space we only present the averages of cycle lengths and standard deviations for macroeconomic and financial variables. The diagnostics are shown in figures in the appendix B for more detail. We use a Monte Carlo Metropolis Hastings optimization routine with two chains, while the acceptance ratio per chain for all bivariate STMS models spans within the

17-41% interval.[4] The total number of iteration of each chain is 10,000. We assume a beta shaped distribution of the prior in the case of the parameter of decay ρ and auto-regressive root ϕ as the value of both parameters is bounded between 0 and 1. We select a normal shaped distribution of the prior for the frequency parameter λ. All of the parameters have standard deviation of the prior set at 0.1. With respect to the innovations, the shape of the prior distribution is set to inverse gamma.[5]

Table 4: Estimated cycle lengths in years and standard deviations of business cycles in combinations of bivariate models

Variables	$\ln BAL_r$	$\ln TL_r$	$\ln LNFC_r$	$\ln LHH_r$	$\ln LHHM_r$	$\ln LHHC_r$	$\ln EQP_n$	SPR_n
$\ln GDP_r$	7.7145	7.9135	7.8114	7.8451	7.7823	7.7684	7.4268	7.9981
	(4.20)	(1.39)	(0.54)	(1.63)	(0.68)	(1.03)	(0.94)	(0.65)
$\ln IP_r$	7.7234	7.8759	7.6465	.	.	.	7.8672	7.7491
	(1.09)	(1.19)	(1.43)	.	.	.	(1.33)	(0.54)
$\ln CON_r$	8.0143	7.8025	.	7.5674	7.2089	7.7516	.	.
	(0.76)	(0.86)	.	(1.69)	(0.98)	(0.85)	.	.
$\ln INV_r$	7.8530	7.8729	7.8533	.	.	.	7.7758	7.2317
	(4.63)	(12.67)	(0.77)	.	.	.	(0.98)	(1.09)
$\ln MAN_r$	7.9450	7.8980	8.0367	.	.	.	8.3269	7.5609
	(0.96)	(1.66)	(1.13)	.	.	.	(0.68)	(1.37)
$\ln SER_r$	7.8522	7.5347	8.4091	.	.	.	7.4992	7.4747
	(0.41)	(2.40)	(4.29)	.	.	.	(0.70)	(0.42)
$\ln TRA_r$	7.8069	7.8838	7.8613	.	.	.	7.3717	7.7673
	(3.33)	(0.49)	(1.09)	.	.	.	(0.83)	(0.16)
$\ln NTR_r$	7.7441	8.5141	7.8165	.	.	.	8.0120	8.0099
	(0.64)	(1.96)	(0.89)	.	.	.	(0.64)	(3.94)
$\ln EXP_r$	7.8744	7.8326	7.7333	.	.	.	8.1530	8.2422
	(0.91)	(0.83)	(0.87)	.	.	.	(0.66)	(0.33)
$\ln IMP_r$	7.8563	7.6214	7.9005	.	.	.	7.7060	6.8394
	(0.95)	(1.40)	(0.94)	.	.	.	(0.80)	(2.73)

Note: The estimates show the annual length of the cyclical components and are calculated by the term $2\pi/4\lambda^G$. The values in brackets depict the standard deviation of the cyclical components and are denoted as σ^C (multiplied by 100).

[4] The optimal value of the acceptance ratio is around one quarter.

[5] For the decay ρ and auto-regressive root ϕ the prior mean is to 0.75, while for the frequency parameter λ the prior mean is 0.2. The values of the prior means of the innovations are more heterogeneous since the number of pairs between macroeconomic and financial variables is large. Nevertheless, the value of prior means in these cases do not exceed 0.005.

Table 5: Estimated cycle lengths in years and standard deviations of financial cycles in combinations of bivariate models

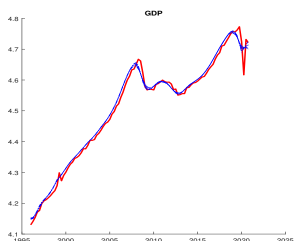
Variables	$\ln GDP_r$	$\ln IP_r$	$\ln CON_r$	$\ln INV_r$	$\ln MAN_r$	$\ln SER_r$	$\ln TRA_r$	$\ln NTR_r$	$\ln EXP_r$	$\ln IMP_r$
$\ln BAL_r$	7.5918	7.9776	7.7891	7.8242	7.8097	7.8607	7.9551	7.9380	7.8232	7.7346
	(1.55)	(0.87)	(0.86)	(1.55)	(0.40)	(1.40)	(1.59)	(0.42)	(1.32)	(2.13)
$\ln TL_r$	7.9550	7.8657	7.8529	7.8606	7.6614	8.0743	7.9135	8.1506	7.8489	7.6501
	(1.45)	(1.26)	(0.73)	(1.24)	(0.72)	(4.00)	(1.24)	(1.01)	(1.30)	(1.50)
$\ln LNFC_r$	7.8489	7.8269	.	7.8538	7.8271	8.2111	7.8483	7.7979	7.6840	7.8834
	(0.37)	(0.51)	.	(0.74)	(4.66)	(4.87)	(0.47)	(1.01)	(0.91)	(0.73)
$\ln LHH_r$	7.8408	.	7.4047	.	.	.	.	.	.	.
	(1.35)	.	(1.25)	.	.	.	.	.	.	.
$\ln LHHM_r$	7.8811	.	8.1572	.	.	.	.	.	.	.
	(0.72)	.	(1.07)	.	.	.	.	.	.	.
$\ln LHHC_r$	7.7808	.	7.9098	.	.	.	.	.	.	.
	(1.14)	.	(1.14)	.	.	.	.	.	.	.
$\ln EQP_n$	7.4987	7.9355	.	8.0106	8.2785	7.6916	7.4941	8.0037	8.2712	8.1665
	(1.64)	(1.23)	.	(1.21)	(1.15)	(1.05)	(2.14)	(0.68)	(0.72)	(1.05)
SPR_n	7.6491	7.9311	.	6.9915	8.1972	7.9542	7.6187	8.1319	8.0303	9.5535
	(0.41)	(1.77)	.	(0.98)	(1.07)	(0.22)	(1.26)	(2.17)	(0.20)	(0.66)

Note: The estimates show the annual length of the cyclical components and are calculated by the term $2\pi/4\lambda^G$. The values in brackets depict the standard deviation of the cyclical components and are denoted as σ^C (multiplied by 100).

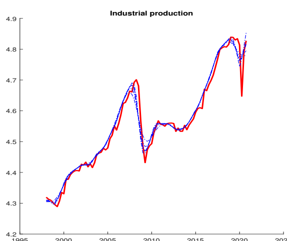
Figures 3-7 graphically sum up the results from Tables 4 and 5 and show the actual data line of each variable (solid red line) and their smoothed counterparts (dashed blue lines) from all of the bivariate STSM model varieties. The deviations from the actual data line and the smoothed lines are caused by the cycle and irregular components in the data.

Figure 3: Smoothed variables of GDP, industrial production, consumption and investment

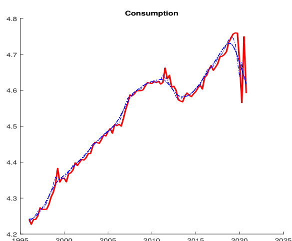
(a) $\ln GDP_r$



(b) $\ln IP_r$



(c) $\ln CON_r$



(d) $\ln INV_r$

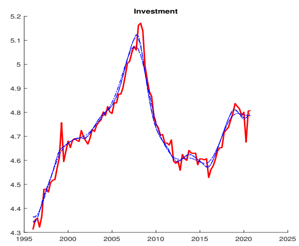
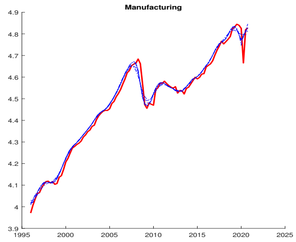
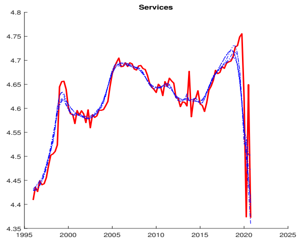


Figure 4: Smoothed variables of manufacturing, services, tradable and non-tradable output

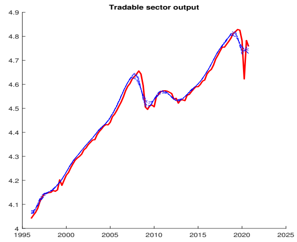
(a) $\ln MAN_r$



(b) $\ln SER_r$



(c) $\ln TRA_r$



(d) $\ln NTR_r$

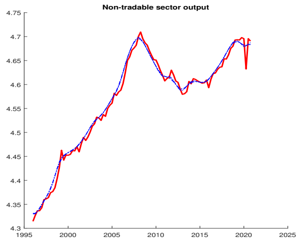
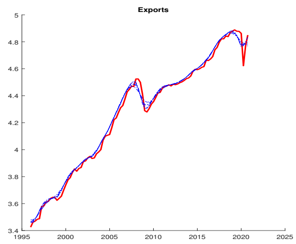


Figure 5: Smoothed variables of exports and imports

(a) $\ln EXP_r$



(b) $\ln IMP_r$

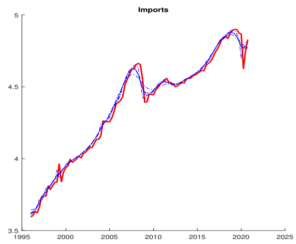
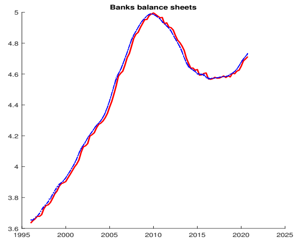
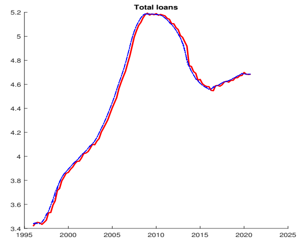


Figure 6: Smoothed variables of banks' balance sheets, total loans, loans to NFC and HH

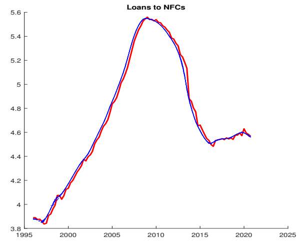
(a) $\ln BAL_r$



(b) $\ln TL_r$



(c) $\ln LNFC_r$



(d) $\ln LHH_r$

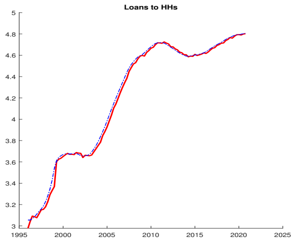
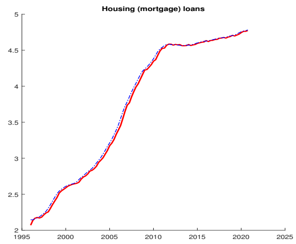
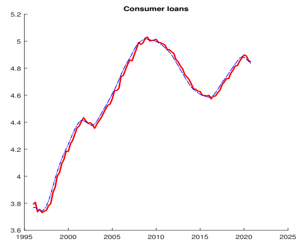


Figure 7: Smoothed variables of housing (mortgage) loans, consumer loans, equity prices and term spread

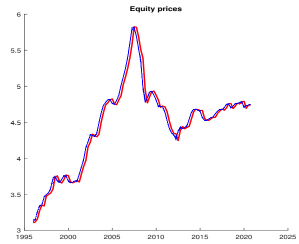
(a) $\ln LHHM_r$



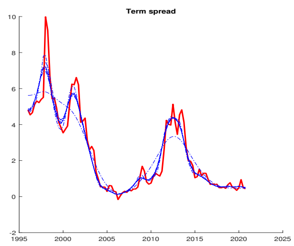
(b) $\ln LHHC_r$



(c) $\ln EQP_n$



(d) SPR



The following Table 6 sums up the latter two tables by averaging the estimated cycle lengths and standard deviations of variables that are applied in the bivariate STSM model setups. Based on these results, it seems that financial cycle variables are slightly longer lasting with an average of 7.9 years, while the business cycle variables last for 7.8 years on average. If we do not consider the investment and the services variables (i.e. $\ln SER_r$ and $\ln NTR_r$) which are significantly more volatile, the financial cycle variables also experience higher volatility on average compared to business cycle variables.

Table 6: The averages of cycle length and standard deviation of variables applied in the bivariate STSM models

Variable	Average cycle length	Average std. dev.
$\ln GDP_r$	7.78	1.38
$\ln IP_r$	7.77	1.12
$\ln CON_r$	7.67	1.03
$\ln INV_r$	7.72	4.03
$\ln MAN_r$	7.95	1.16
$\ln SER_r$	7.75	1.64
$\ln TRA_r$	7.74	1.18
$\ln NTR_r$	8.02	1.61
$\ln EXP_r$	7.97	0.72
$\ln IMP_r$	7.58	1.36
$\ln BAL_r$	7.83	1.21
$\ln TL_r$	7.88	1.45
$\ln LNFC_r$	7.86	1.59
$\ln LHH_r$	7.62	1.30
$\ln LHHM_r$	8.02	0.90
$\ln LHHC_r$	7.85	1.14
$\ln EQP_n$	7.93	1.21
SPR_n	8.01	0.97

Now we move to the second case, where we consider the effects of the residential real estate variable in a multivariate STMS model. In Table 7, we present the parameter estimates from the three-variable multivariate STSM model varieties. For the computation of the posterior means we select a Monte Carlo Metropolis Hastings optimization routine with two chains as well. The acceptance ratio per chain for all three models hovers within the 26-34% interval, while the total number of iteration of each chain is 10,000. Regardless of the multivariate STSM model variety, for the parameter of decay ρ and auto-regressive root ϕ we select a beta shaped distribution of the prior, since the value of the parameters are bounded between 0 and 1. For both the decay ρ and auto-regressive root ϕ we set the prior mean to 0.75. We choose a normal shaped distribution of the prior for the frequency parameter λ with a prior mean of 0.2. All of the parameters have standard deviation of the prior set at 0.1. With respect to the innovations, the shapes of the prior distribution are set to inverse gamma. Prior means for innovations are set differently, depending on the variables. For the irregular innovations σ_ϵ, the prior mean is set to 0.05 for all three types of variables entering the multivariate STSM model. The prior mean for the level innovations σ_ν is set to 0.001 for the macroeconomic variable, 0.004 for the financial variable and 0.005 for the residential real estate variable. The prior mean for the slope innovations σ_ζ are set 0.001 for both the financial and residential real estate variables, while it is set to 0.00005 for the macroeconomic variable.

Table 7: Parameter estimates of the multivariate STSM model varieties

	Parameters						**Innovations**					
	ϕ		ρ		λ		σ_ϵ		σ_ν		σ_ζ	
	prior mean	post. mean	prior mean	post. mean	prior mean	post. mean	prior mean	post. mean	prior mean	post. mean	prior mean	post. mean
Model 1												
$\psi_{1,t}$	0.750	0.7682	0.750	0.7813	0.200	0.1925	0.005	0.0126	0.001	0.0009	0.000	0.0017
$\psi_{2,t}$	0.750	0.7569	0.750	0.7616	0.200	0.1768	0.005	0.0118	0.004	0.0029	0.001	0.0082
$\psi_{3,t}$	0.750	0.7590	0.750	0.7187	0.200	0.1941	0.005	0.0103	0.005	0.0087	0.001	0.0023
Model 2												
$\psi_{1,t}$	0.750	0.7602	0.750	0.7406	0.200	0.1889	0.005	0.0127	0.001	0.0024	0.000	0.0016
$\psi_{2,t}$	0.750	0.7463	0.750	0.7309	0.200	0.2040	0.005	0.0117	0.004	0.0037	0.001	0.0094
$\psi_{3,t}$	0.750	0.7578	0.750	0.7468	0.200	0.1858	0.005	0.0113	0.005	0.0092	0.001	0.0039
Model 3												
$\psi_{1,t}$	0.750	0.7499	0.750	0.7456	0.200	0.1761	0.005	0.0125	0.001	0.0010	0.000	0.0019
$\psi_{2,t}$	0.750	0.7394	0.750	0.7696	0.200	0.2024	0.005	0.0034	0.004	0.0038	0.001	0.0072
$\psi_{3,t}$	0.750	0.7412	0.750	0.7366	0.200	0.2045	0.005	0.0099	0.005	0.0099	0.001	0.0035

The results of the three-variable multivariate STSM model also show, that the shape of financial cycles are different than business cycles in Slovenia, but there are also substantial differences between variables. The cycle lengths of business cycles (GDP variable) range from 8.2 to 8.9 years (based on the values of the parameter

$2\pi/4\lambda^G$ in Table 8), while the length of financial cycles depends on the financial variable we consider. The length of the cycle for the total loans $\ln TL_r$ lasts approximately for 8.9 years, while the average length of loans to households $\ln LHH_r$ and housing (mortgage) loans $\ln LHHM_r$ are somewhat shorter, 7.7 and 7.8 years, respectively. They are also more in line with the bivariate STSM model results. On the other hand, standard deviations of financial variables (depicted by the parameter σ^C) are larger than the standard deviation of the business cycle variable, suggesting that financial cycles could be deeper in crisis times.

Table 8: Properties of cyclical components of the multivariate STSM model results

Variable	**Properties**						
	Cycle length	Std. dev.				Phase	
					GDP^C	TL^C	RRE^C
$\ln GDP_r$	8.161	3.560		GDP^C		-0.129	-0.627
$\ln TL_r$	8.887	5.703	Coh	TL^C	0.812		-0.116
$\ln RRE_r$	8.093	2.534		RRE^C	0.530	0.793	
					GDP^C	LHH^C	RRE^C
$\ln GDP_r$	8.313	3.272		GDP^C		-0.080	0.808
$\ln LHH_r$	7.700	3.330	Coh	LHH^C	0.836		0.981
$\ln RRE_r$	8.456	5.321		RRE^C	0.579	0.517	
					GDP^C	$LHHM^C$	RRE^C
$\ln GDP_r$	8.920	3.493		GDP^C		0.813	-4.697
$\ln LHHM_r$	7.761	4.539	Coh	$LHHM^C$	0.590		0.356
$\ln RRE_r$	7.682	5.106		RRE^C	0.316	0.801	

Note: The column cycle length is calculated by the term $2\pi/4\lambda^G$ and shows estimates of the annual length of the cyclical components, while the term σ^C represents the standard deviation of the cyclical components (multiplied by 100). We also report matrices with average coherences in the lower left and average phase shifts (in annual terms) in the upper right diagonal of the reported matrix. A positive value of the phase shift means that series row leads series column. All statistics are derived from the spectral generating function described in the appendix.

We plot the components of the three-variable multivariate STSM models in the following set of figures (Figures 8-10). Despite using a different financial variable in all varieties of models, i.e. $\ln TL_r$, $\ln LHH_r$ and $\ln LHHM_r$, we are able to show the stableness of the cycle component of $\ln GDP_r$ that represents the business cycle. What is noteworthy to mention is the differences that arise between two major events in the last 20 years in Slovenia. In all varieties of models the GDP variable exhibits a particularly stronger effect of the cycle component during the global financial crisis than in the latest COVID-19 pandemic. On the other hand, the STSM model puts more emphasis on the irregular component during the pandemic crisis than on the cycle component, thus suggesting that the pandemic period is not treated as a part of a larger business cycle dynamic. If we compare the components of the financial variables, we see that both, the cycle and irregular components, were much more pronounced in the global financial crisis and its immediate aftermath then in the pandemic crisis. We can draw similar conclusions for the residential real estate variable.

Figure 8: Estimated components of GDP, RRE and TL variable multivariate STSM model

(a) $\ln GDP_r$ (b) $\ln TL_r$ (c) $\ln RRE_r$

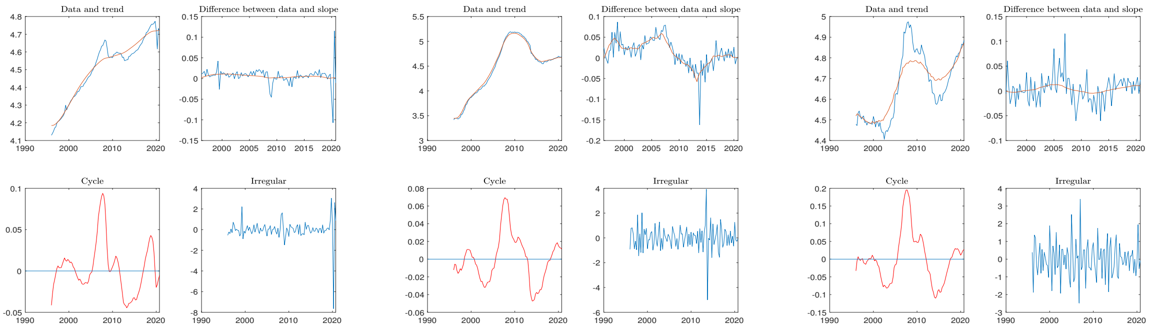


Figure 9: Estimated components of GDP, RRE and LHH variable multivariate STSM model

(a) $\ln GDP_r$ (b) $\ln LHH_r$ (c) $\ln RRE_r$

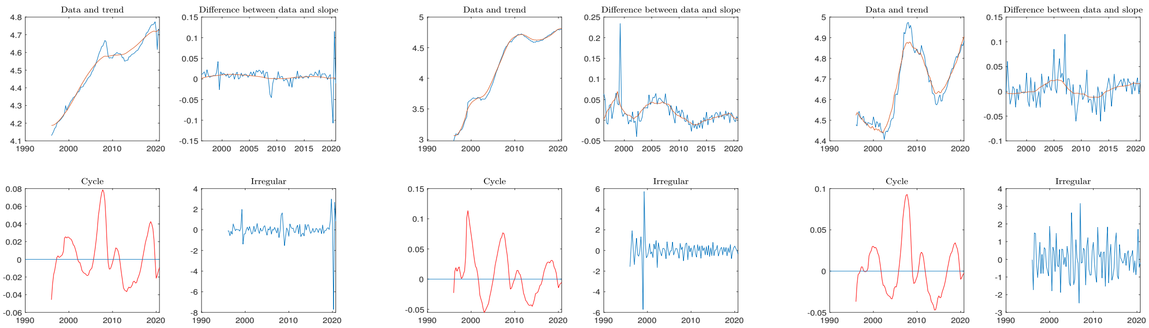
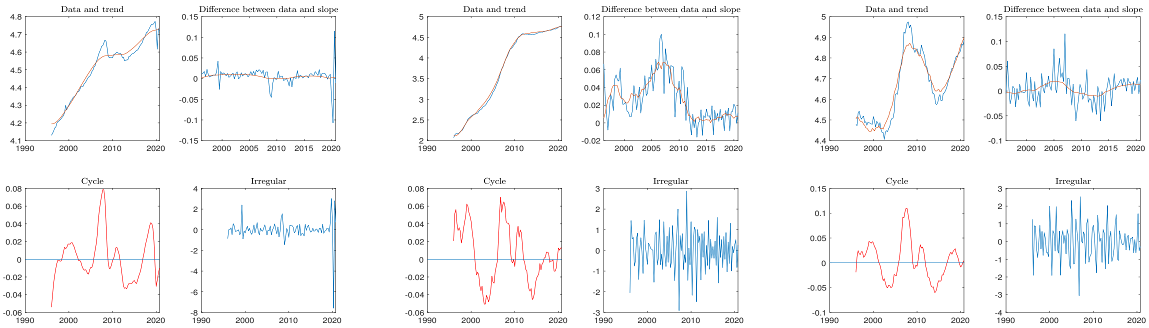


Figure 10: Estimated components of GDP, RRE and LHHM variable multivariate STSM model

(a) $\ln GDP_r$ (b) $\ln LHHM_r$ (c) $\ln RRE_r$



We provided some evidence that there are differences between business and financial cycles in Slovenia to a certain degree. To check whether this is true, we provide variances and coherences of the variables that enter the three-variable multivariate model at different frequency bands in the Table 9. Relatively high coherences between business and financial cycles are mostly a result of the contributions from the medium-term frequencies, while we use different average coherences separately, i.e. frequency bands of 32 to 120 and 8 to 32 quarters.

Table 9: Variance and coherences at different frequency bands

Variable	Model 1	Model 2	Model 3
	Variance 32-120 quarters		
$\ln GDP_r$	0.702	0.679	0.680
$\ln TL_r/\ln LHH_r/\ln LHHM_r$	0.699	0.674	0.679
$\ln RRE_r$	0.698	0.675	0.678
	Coherences 32-120 quarters		
$\ln GDP_r$, $\ln TL_r/\ln LHH_r/\ln LHHM_r$	0.814	0.838	0.588
$\ln GDP_r$, $\ln RRE_r$	0.534	0.576	0.327
$\ln TL_r/\ln LHH_r/\ln LHHM_r$, $\ln RRE_r$	0.744	0.512	0.800
	Coherences 8-32 quarters		
$\ln GDP_r$, $\ln TL_r/\ln LHH_r/\ln LHHM_r$	0.810	0.830	0.645
$\ln GDP_r$, $\ln RRE_r$	0.552	0.634	0.457
$\ln TL_r/\ln LHH_r/\ln LHHM_r$, $\ln RRE_r$	0.750	0.591	0.814

Note: The contribution of the 32-120 band to their overall variance is shown. The coherences between the cyclical components are split at frequency bands of 32-120 and 8-32 quarters.

4.2 Robustness checks and policy implications

We check the robustness of the multivariate versions of the STSM models by studying all the variables univariately. As above, we deploy a Monte Carlo Metropolis Hastings optimization routine with two chains and 10,000 the total number of iteration of each chain. The graphical diagnostics are presented in the Appendix D in more detail, while the estimated cycle length and standard deviation of cycles of each variable estimated in an univariate setting is shown in Table 10. The results confirm the observations made from the multivariate STSM models. It seems that the business cycle that corresponds with the dynamics of macroeconomic variables is, on average, approximately one year shorter in comparison to the financial cycle variables.

Table 10: Estimated cycle length and standard deviation of cycles of variables with an univariate model

Variable	Cycle length	Std. dev.
$\ln GDP_r$	7.8340	2.16
$\ln IP_r$	8.0117	3.20
$\ln CON_r$	8.1269	1.16
$\ln INV_r$	8.6513	5.54
$\ln MAN_r$	8.0152	4.04
$\ln SER_r$	6.9695	3.00
$\ln TRA_r$	8.5471	3.31
$\ln NTR_r$	7.6531	1.12
$\ln EXP_r$	6.6534	5.16
$\ln IMP_r$	7.2163	4.80
$\ln RRE_r$	10.3397	3.27
$\ln BAL_r$	8.3772	1.18
$\ln TL_r$	8.0504	0.72
$\ln LNFC_r$	8.0485	1.15
$\ln LHH_r$	12.9223	4.67
$\ln LHHM_r$	9.8858	2.94
$\ln LHHC_r$	9.4196	2.93
$\ln EQP_n$	10.2729	20.91
SPR_n	8.0679	123.61

Note: The column cycle length is calculated by the term $2\pi/4\lambda^G$ and shows estimates of the annual length of the cyclical components, while the term σ^C represents the standard deviation of the cyclical components (multiplied by 100).

Similarly as in multivariate cases, differences in characteristics between both crises arise in the univariate varieties of the models as well. As already said, during the global financial crisis the significance of the cycle component of most variables was significantly more expressed than during the COVID-19 pandemic period. On the contrary, the irregular components were much more significant during the COVID-19 pandemic.

From the policy implications perspective it is important to understand the results of the STSM model simulations. The divergence between of both cycles, the business and the financial one, suggest that the separate policies have to be in play, in order to achieve the optimal price and/or financial stability. Of course, in search for price stability the monetary policy implies the financial stability to a certain degree, however, if we combine our considerations of cycles divergence with the heterogeneity of financial cycles between euro area countries as in Rünstler et al. (2018), the case for a tailored national macroprudential policy is that much stronger.

5 Conclusions

The main premise of the present paper was to assess the differences in cyclical components between the business and financial cycles for Slovenia based on a set of both macroeconomic and financial type of variables. In this respect we utilize a multivariate variety of a STSM model, proposed by Rünstler and Vlekke (2018). The results show of a bivariate STSM model varieties show that financial cycles are somewhat longer compared to business cycles. Comparing the standard deviations of financial and business cycles give inconclusive results on average, but excluding particular macroeconomic variables that are by definition more volatile, we see that also standard deviations of financial cycles tend to be larger. The differences in between the business and financial cycles are larger when we apply a multivariate form of the STSM model by adding the dynamics of residential real estate prices variable, for which we follow the assumption that residential real estate prices form an indirect link between the two types of cycles. For robustness checks we assume no links between the cycles and estimate cycles for each variable separately by using an univariate version of the STSM model. The results from univariate STSM models confirm our observations from multivariate STSM model results. These results might not come as a surprise in the existing literature, but are utterly important for economic policy makers by additionally implementing financial stability goals on the basis of macroprudential policy (on a national level) alongside the monetary policy mandate, as financial cycles seem to be longer and deeper compared to business cycles.

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Appendix A: The STSM model

The STSM model follows the model specification of Rünstler and Vlekke (2018). We define a vector of n time series $\mathbf{x}'_t = (x_{1,t}, ..., x_{n,t})$ where $t = 1, ..., T$ and T depict the number of observations. The variable $\mathbf{x}_t$ is specified as the sum of a trend variable μ_t, $\mathbf{x}_t^C$ and irregular component ϵ_t, so that

$$\mathbf{x}_t = \mu_t + \mathbf{x}_t^C + \epsilon_t \tag{1}$$

The ϵ_t is a $n \times 1$ vector of irregular components with normal and independent distribution with a zero mean and $n \times n$ covariance matrix $\Sigma_\epsilon, \epsilon_t \sim$ n.i.d. $(0, \Sigma_\epsilon)$. Further on, the μ_t is a $n \times 1$ vector of stochastic trend components that follows a random walk with a time-varying slope β_t. The stochastic trend is therefore defined as

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \nu_t \tag{2}$$

where

$$\beta_t = \beta_{t-1} + \zeta_t \tag{3}$$

Vector β_t of the time-varying slope follows a random walk, while vectors $\nu'_t = (\nu_{1,t}, ..., \nu_{n,t})'$ and $\zeta'_t = (\zeta_{1,t}, ..., \zeta n, t)'$ represent the level and slope innovations with a normal and independent distribution with a zero mean as their $n \times n$ covariance matrices are defined as $\Sigma_\nu, \nu_t \sim$ n.i.d. $(0, \Sigma_\nu)$ and $\Sigma_\zeta, \zeta_t \sim$ n.i.d. $(0, \Sigma_\zeta)$, respectively. The latter specification amounts to a multivariate local linear trend as introduced by Harvey and Koopman (1997).

As in Rünstler (2004) the cyclical components are specified as a vector $\mathbf{x}_t^{C'} = (x_{1,t}^C, ..., x_{n,t}^C)'$ and are linear combinations of n independent stochastic cycles denoted as $\tilde{\mathbf{\Psi}}_{i,t} = (\Psi_{i,t}, \Psi_{i,t}^*)$, where $t = 1, ..., n$. Here we write down extended version of the stochastic cycles definition from Rünstler and Vlekke (2018), where the high persistence of credit and house price cycles is accounted for by adding an autoregressive root $0 < \phi_i < 1$. The dynamics of the stochastic cycles is written down as follows

$$(1 - \phi_i L) \left(I_2 - \rho_i \begin{bmatrix} \cos\lambda_i & \sin\lambda_i \\ -\sin\lambda_i & \cos\lambda_i \end{bmatrix} L \right) \begin{bmatrix} \Psi_{i,t} \\ \Psi_{i,t}^* \end{bmatrix} = \begin{bmatrix} \kappa_{i,t} \\ \kappa_{i,t}^* \end{bmatrix} \tag{4}$$

The term ρ_i represents a decay parameter, where $0 < \rho_i < 1$. The term λ_i is the frequency parameter and takes the values $0 < \lambda_i < \pi$. The term I_2 is a 2×2 identity matrix, while L is the lag operator. The variables $\kappa_{i,t}$ and $\kappa_{i,t}^*$ are the cyclical innovations and are normally and independently distributed, so that $\kappa_{i,t} \sim$ n.i.d. $(0, \sigma^2_{\kappa_i i}, I_2)$ and $\kappa_{i,t}^* \sim$ n.i.d. $(0, \sigma^2_{\kappa_i i}, I_2)$.

Next we define the autocovariance generating function $\tilde{V}_{ii}(s) = \mathbb{E}\left[\tilde{\mathbf{\Psi}}_{i,t}, \tilde{\mathbf{\Psi}}'_{i,t-s}\right]$, for $s = 1, 2, ...$ by dropping cosine and sine functions of period $2\pi/\lambda_i$, so that

$$\tilde{V}_{ii}(s) = \sigma^2_{\kappa_i i} h(s; \rho_i) T^+(s\lambda_i) \tag{5}$$

where

$$T^{+}(s\lambda_i) = \begin{bmatrix} \cos(s\lambda_i) & \sin(s\lambda_i) \\ -\sin(s\lambda_i) & \cos(s\lambda_i) \end{bmatrix} \tag{6}$$

The term $h(s;\rho_i)$ is a scalar function for which it holds $h(s;\rho_i) = (1-\rho_i^2)^{-1}\rho_i^s$. The matrix $T^{+}(s\lambda_i)$ is orthonormal and skew-symmetric.

As the extended specification of the stochastic cycles from Rünstler and Vlekke (2018) amounts to a scalar distributed lag of the stochastic cycles as specified in the Rünstler (2004) model, it maintains many of its properties as long as ϕ_i does not take the value close to one. Then the auto spectra remain hump shaped. Nevertheless, the extended specification implies, that the auto spectra are more dispersed around their peak and skewed towards somewhat higher mass at the lower frequencies. Moreover, the above symmetry properties of the autocovariance generating function of the original stochastic cycles are maintained. This means that autocorrelations of $\Psi_{i,t}$ and $\Psi^*_{i,t}$ are identical, while their cross-correlations are skew symmetric.

The assumption is that vector $\mathbf{x}_t^C$ is driven by n independent latent stochastic cycles. Specifying the elements of $\mathbf{x}_t^C$ as linear combinations of both $\Psi_{i,t}$ and $\Psi^*_{i,t}$ allows modelling cyclical co-movements among the n series in terms of phase-adjusted covariances and phase shifts. For this purpose, we define the $n \times 1$ vectors $\mathbf{\Psi}_t = (\Psi_{1,t}, ..., \Psi_{n,t})'$ and $\mathbf{\Psi}^*_t = (\Psi^*_{1,t}, ..., \Psi^*_{n,t})'$. The $n \times 1$ vectors of innovations $\kappa_{i,t}$ and $\kappa^*_{i,t}$ are defined equivalently. They are assumed to be uncorrelated, so that $\mathbb{E} = [\kappa_t \kappa_t'] = \left[\kappa_t \kappa_t^{*'}\right] = I_n$ and $\mathbb{E} = \left[\kappa_t \kappa_t^{*'}\right] = 0$. Cyclical components $\mathbf{x}_t^C$ are consequently defined by

$$\mathbf{x}_t^C = A\mathbf{\Psi}_t + A^*\mathbf{\Psi}_t^* \tag{7}$$

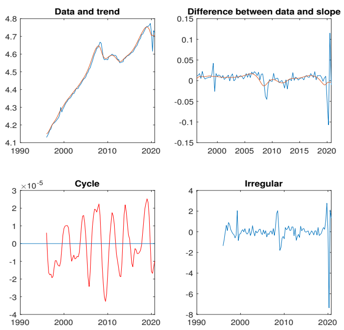
where $A = (a_{ij})$ and $A^* = (a_{ij}^*)$ are general $n \times n$ matrices. For more detail refer to Harvey and Koopman (1997), Rünstler (2004) and Rünstler and Vlekke (2018).

Appendix B: Diagnostics of the bivariate STSM models

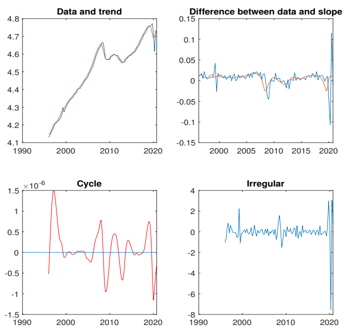
Business cycle variables:

Figure B1: Estimated components of the $\ln GDP$ variable in bivariate STSM model combination with...

(a) ...$\ln BAL$



(b) $\ln TL$



(c) $\ln LNFC$

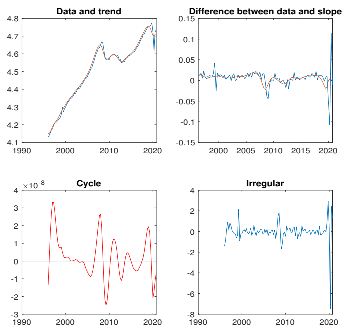
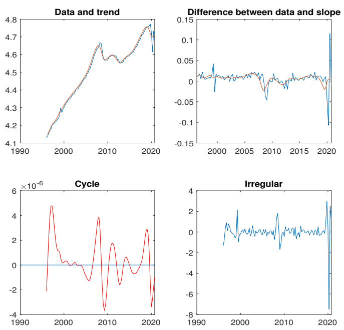
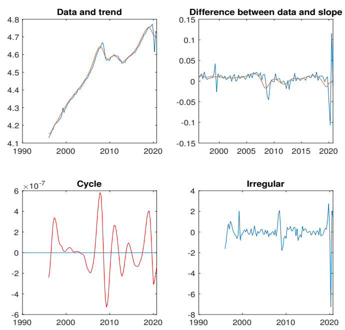


Figure B2: Estimated components of the $\ln GDP$ variable in bivariate STSM model combination with...

(a) ...$\ln LHH$



(b) $\ln LHHM$



(c) $\ln LHHC$

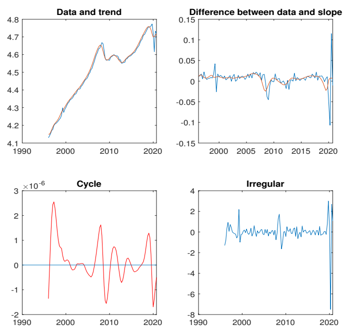
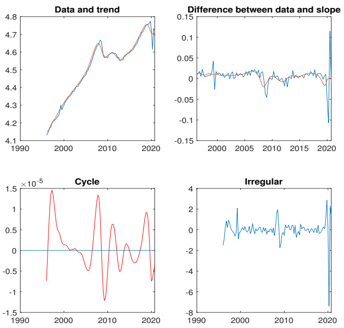


Figure B3: Estimated components of the $\ln GDP$ variable in bivariate STSM model combination with...

(a) ...$\ln EQP$



(b) SPR

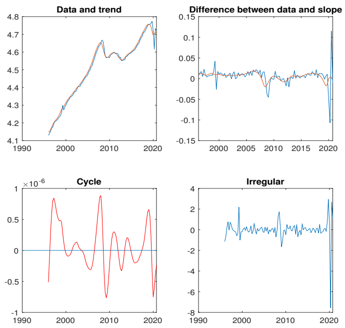
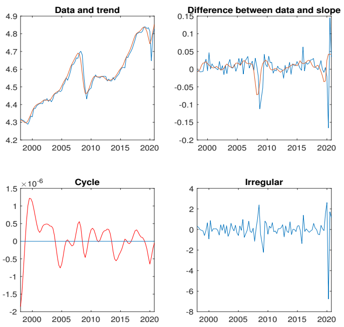
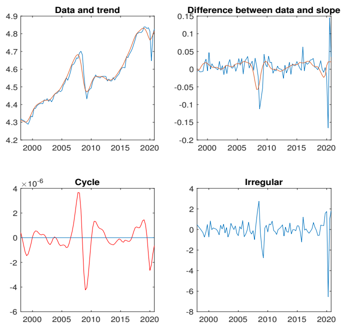


Figure B4: Estimated components of the $\ln IP$ variable in bivariate STSM model combination with...

(a) ...$\ln BAL$



(b) $\ln TL$



(c) $\ln LNFC$

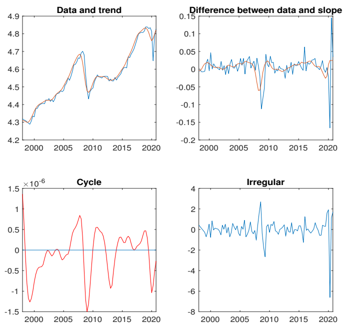
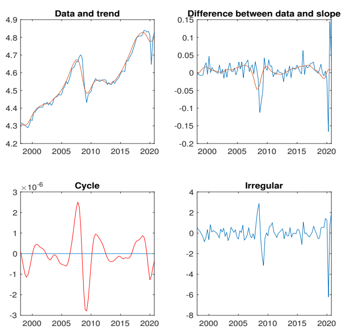


Figure B5: Estimated components of the $\ln IP$ variable in bivariate STSM model combination with...

(a) ...$\ln EQP$



(b) SPR

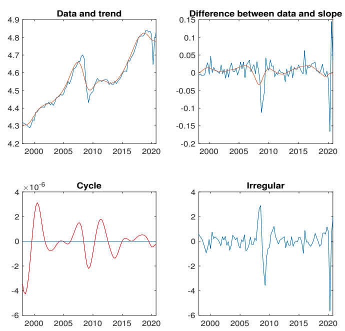
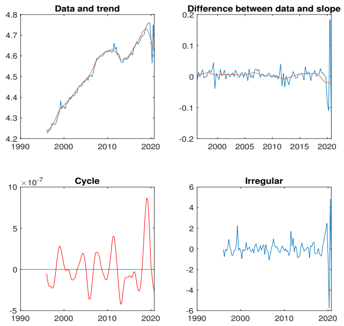
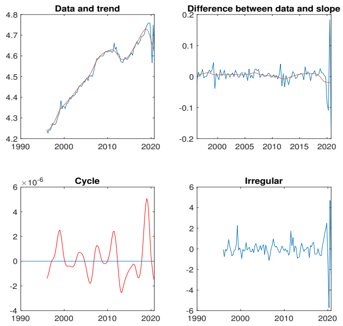


Figure B6: Estimated components of the $\ln CON$ variable in bivariate STSM model combination with...

(a) ...$\ln BAL$



(b) $\ln TL$



(c) $\ln LHH$

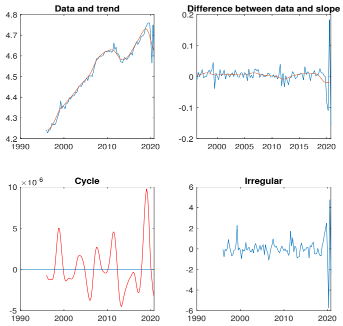
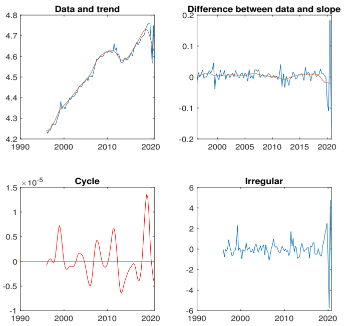


Figure B7: Estimated components of the $\ln CON$ variable in bivariate STSM model combination with...

(a) ...$\ln LHHM$



(b) $\ln LHHc$

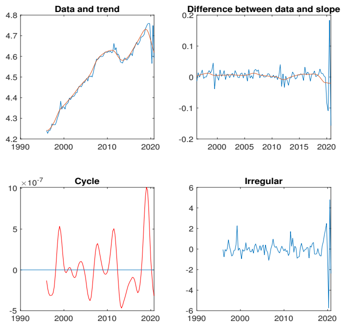
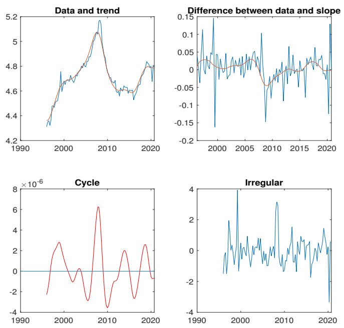
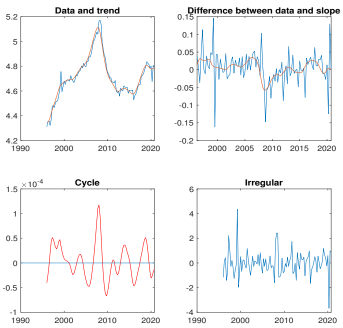


Figure B8: Estimated components of the $\ln INV$ variable in bivariate STSM model combination with...

(a) ...$\ln BAL$



(b) $\ln TL$



(c) $\ln LNFC$

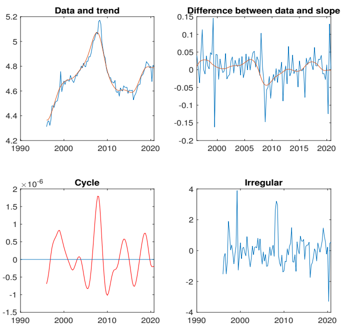
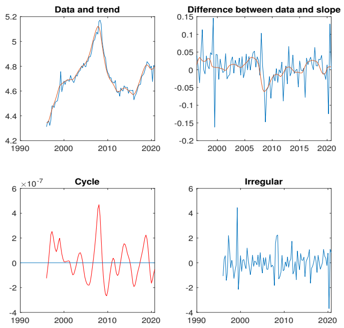


Figure B9: Estimated components of the $\ln INV$ variable in bivariate STSM model combination with...

(a) ...$\ln EQP$



(b) SPR

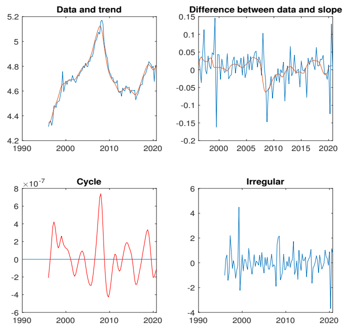
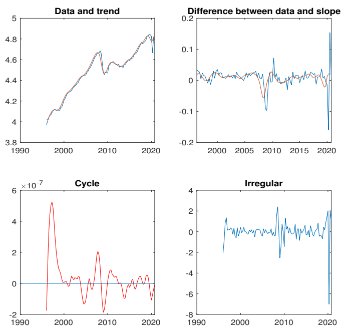
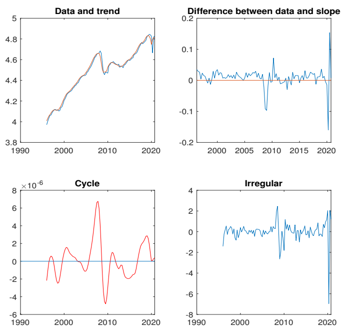


Figure B10: Estimated components of the $\ln MAN$ variable in bivariate STSM model combination with...

(a) ...$\ln BAL$



(b) $\ln TL$



(c) $\ln LNFC$

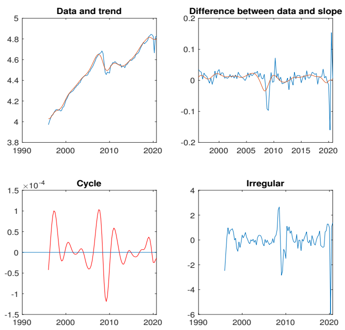
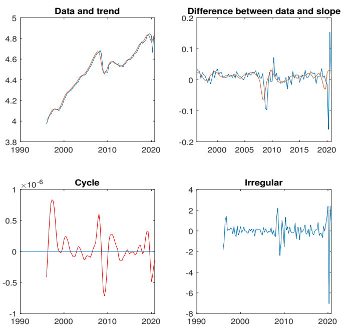


Figure B11: Estimated components of the $\ln MAN$ variable in bivariate STSM model combination with...

(a) ...$\ln EQP$



(b) SPR

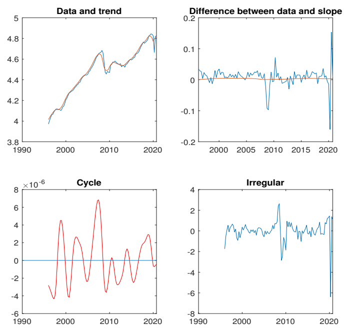
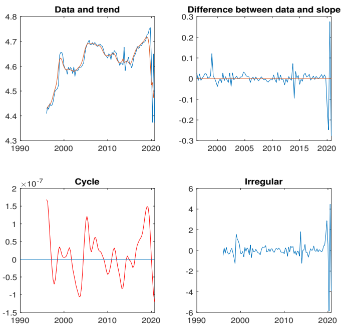
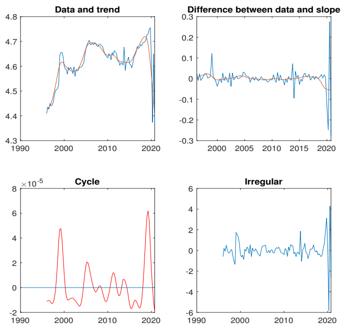


Figure B12: Estimated components of the $\ln SER$ variable in bivariate STSM model combination with...

(a) ...$\ln BAL$



(b) $\ln TL$



(c) $\ln LNFC$

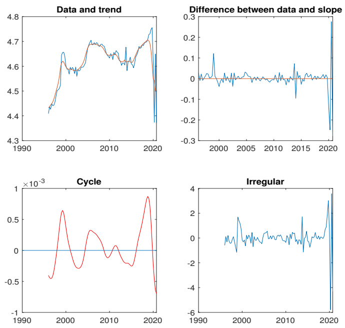
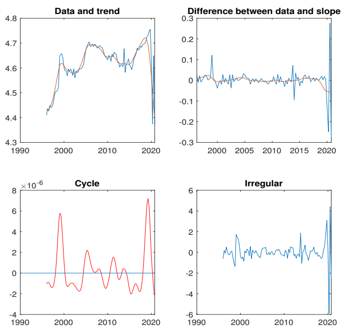


Figure B13: Estimated components of the $\ln SER$ variable in bivariate STSM model combination with...

(a) ...$\ln EQP$



(b) SPR

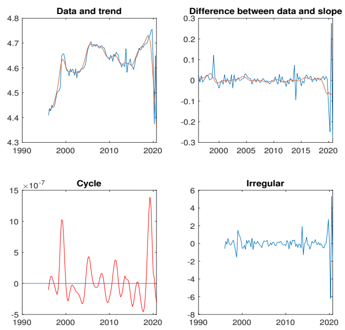
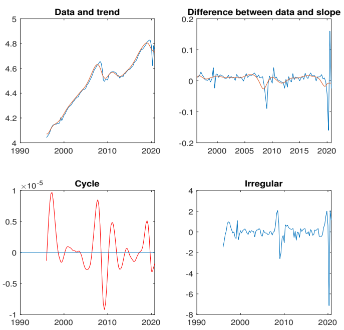
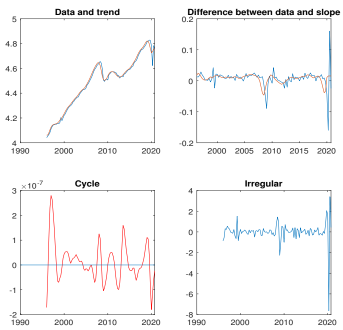


Figure B14: Estimated components of the $\ln TRA$ variable in bivariate STSM model combination with...

(a) ...$\ln BAL$



(b) $\ln TL$



(c) $\ln LNFC$

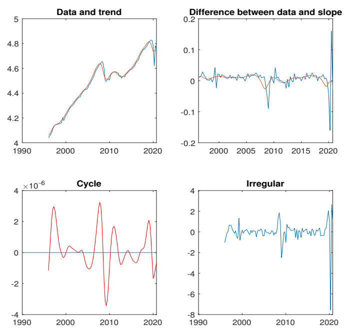
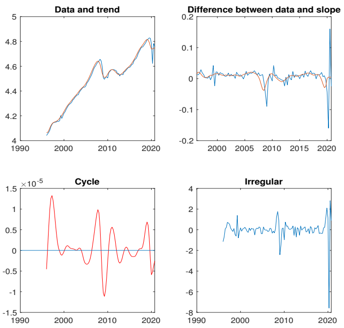


Figure B15: Estimated components of the $\ln TRA$ variable in bivariate STSM model combination with...

(a) ...$\ln EQP$



(b) SPR

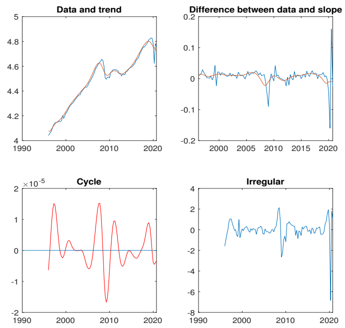
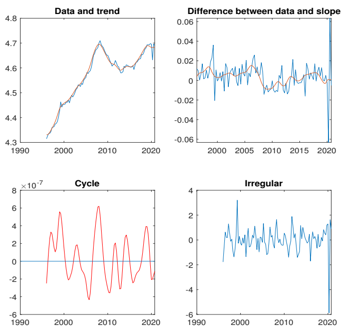
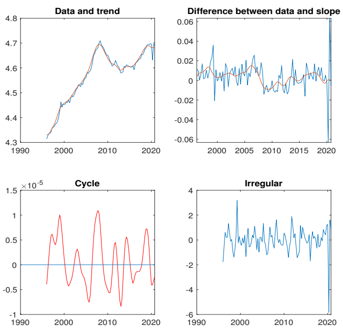


Figure B16: Estimated components of the $\ln NTR$ variable in bivariate STSM model combination with...

(a) ...$\ln BAL$



(b) $\ln TL$



(c) $\ln LNFC$

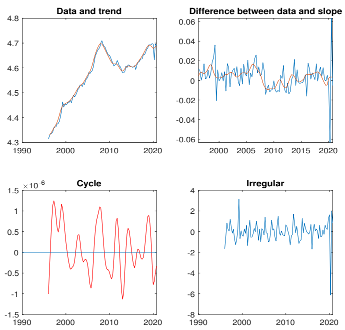
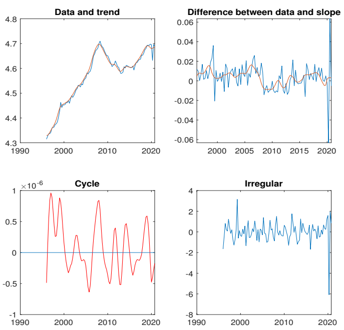


Figure B17: Estimated components of the $\ln NTR$ variable in bivariate STSM model combination with...

(a) ...$\ln EQP$



(b) SPR

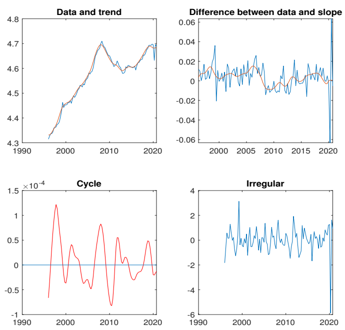
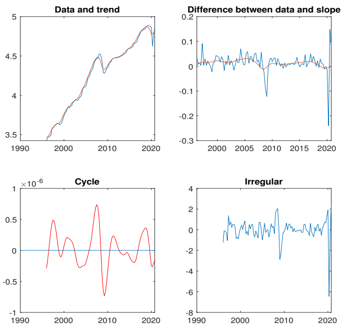
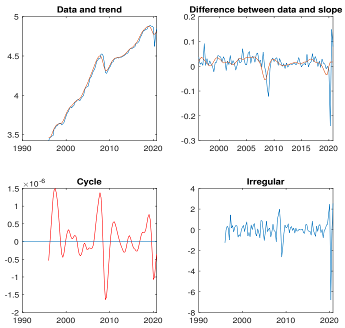


Figure B18: Estimated components of the $\ln EXP$ variable in bivariate STSM model combination with...

(a) ...$\ln BAL$



(b) $\ln TL$



(c) $\ln LNFC$

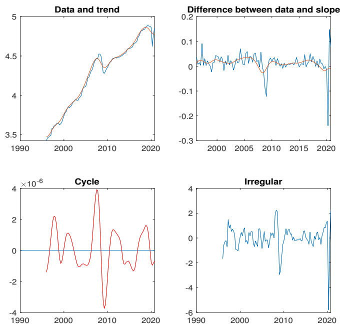
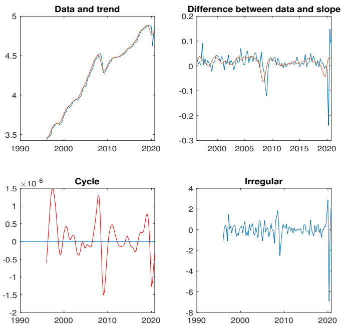


Figure B19: Estimated components of the $\ln EXP$ variable in bivariate STSM model combination with...

(a) ...$\ln EQP$



(b) SPR

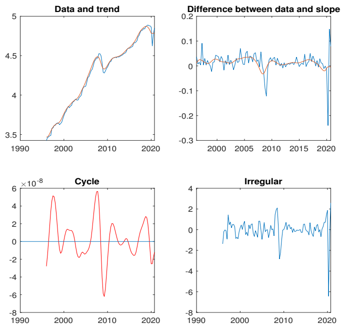
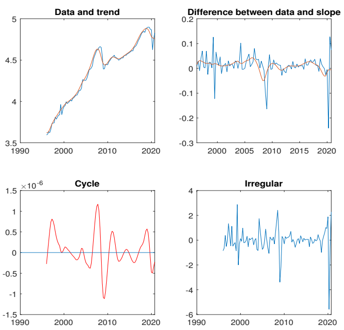
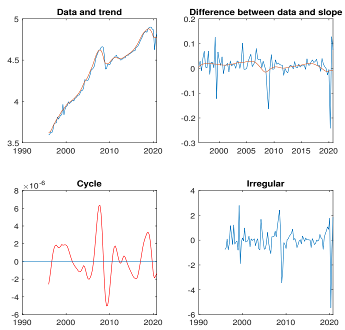


Figure B20: Estimated components of the $\ln IMP$ variable in bivariate STSM model combination with...

(a) ...$\ln BAL$



(b) $\ln TL$



(c) $\ln LNFC$

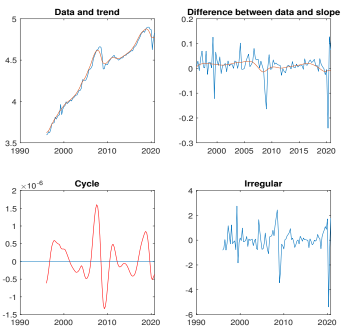
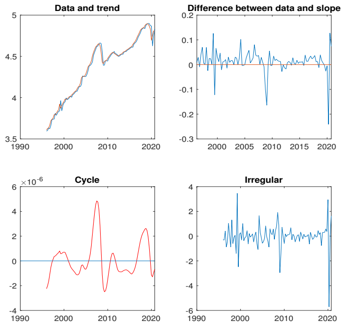
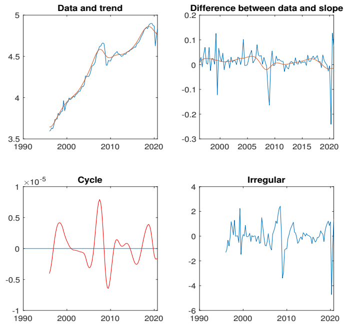


Figure B21: Estimated components of the ln IMP variable in bivariate STSM model combination with...

(a) ...ln EQP



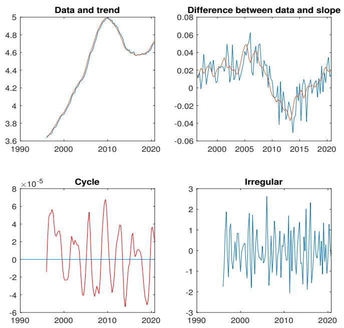
(b) SPR



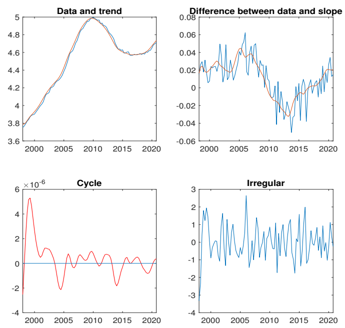
Financial cycle variables:

Figure B22: Estimated components of the ln BAL variable in bivariate STSM model combination with...

(a) ...ln GDP



(b) ln IP



(c) ln CON

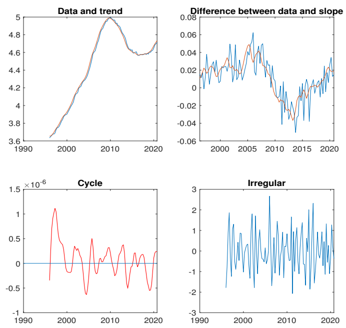
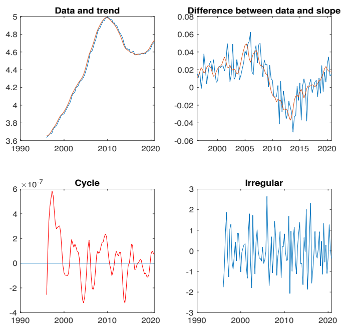
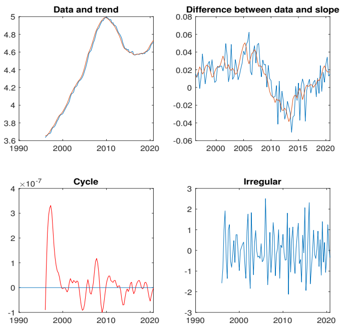


Figure B23: Estimated components of the $\ln BAL$ variable in bivariate STSM model combination with...

(a) ...$\ln INV$



(b) $\ln MAN$



(c) $\ln SER$

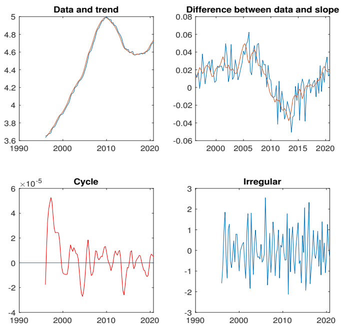
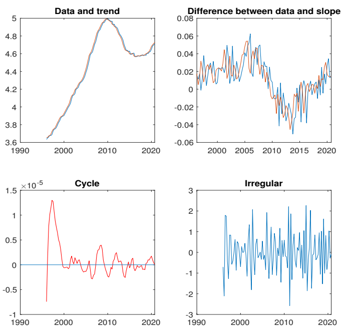
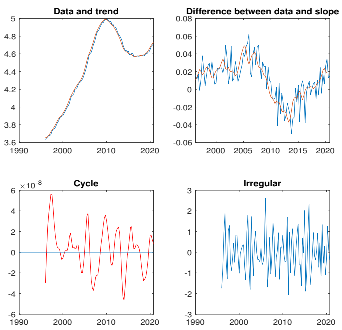


Figure B24: Estimated components of the $\ln BAL$ variable in bivariate STSM model combination with...

(a) ...$\ln TRA$



(b) $\ln NTR$



(c) $\ln EXP$

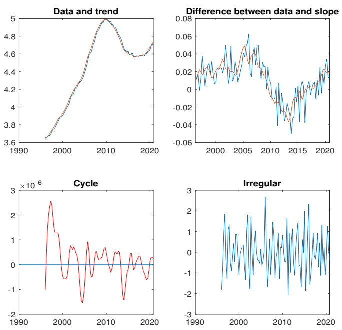


Figure B25: Estimated components of the $\ln BAL$ variable in bivariate STSM model combination with...

(a) ...$\ln IMP$

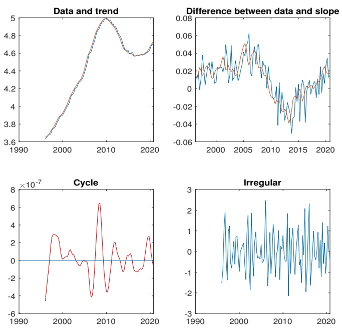
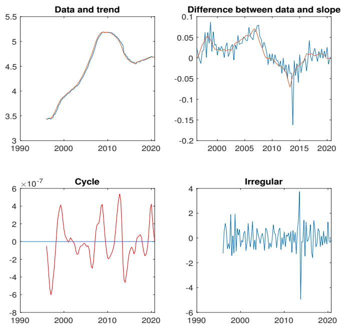
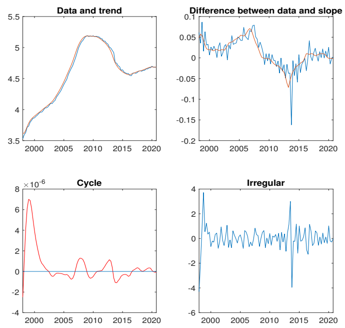


Figure B26: Estimated components of the $\ln TL$ variable in bivariate STSM model combination with...

(a) ...$\ln GDP$



(b) $\ln IP$



(c) $\ln CON$

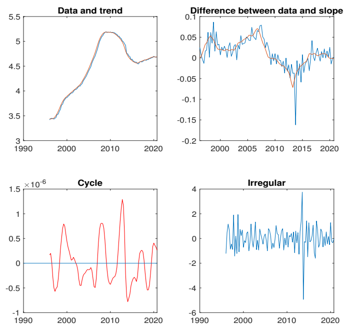
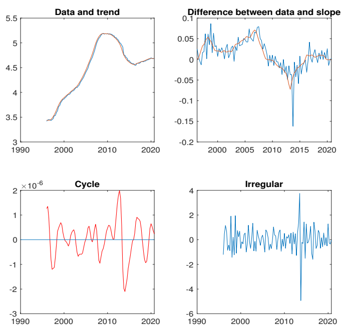
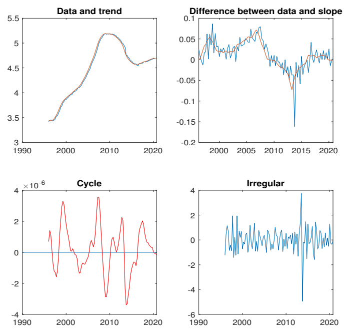


Figure B27: Estimated components of the $\ln TL$ variable in bivariate STSM model combination with...

(a) ...$\ln INV$



(b) $\ln MAN$



(c) $\ln SER$

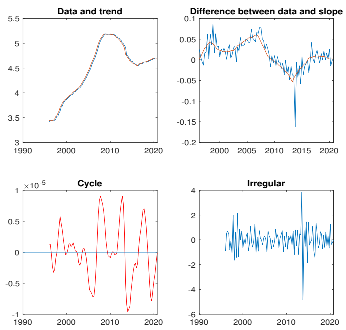
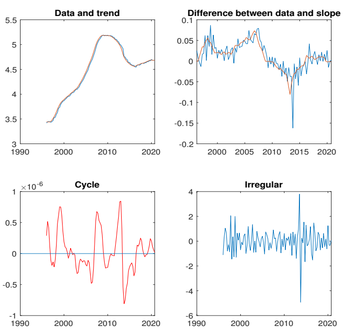
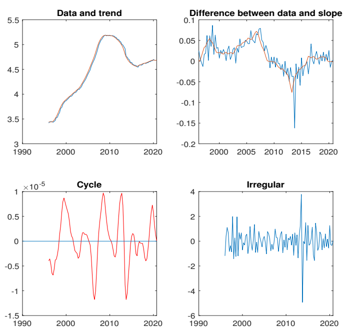


Figure B28: Estimated components of the $\ln TL$ variable in bivariate STSM model combination with...

(a) ...$\ln TRA$



(b) $\ln NTR$



(c) $\ln EXP$

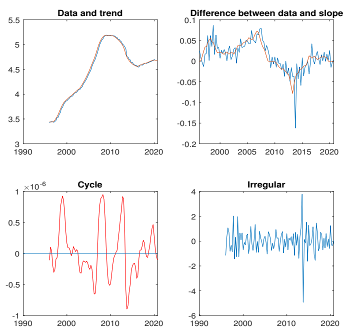


Figure B29: Estimated components of the $\ln TL$ variable in bivariate STSM model combination with...

(a) ...$\ln IMP$

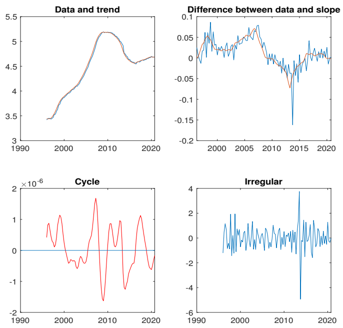
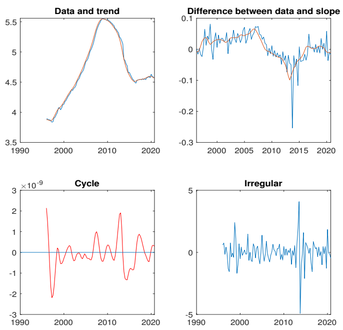
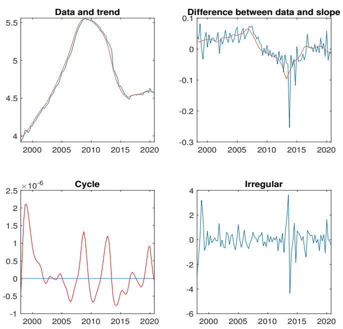


Figure B30: Estimated components of the $\ln LNFC$ variable in bivariate STSM model combination with...

(a) ...$\ln GDP$



(b) $\ln IP$



(c) $\ln INV$

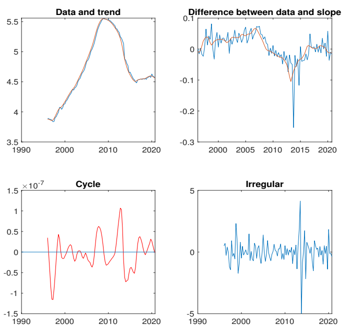
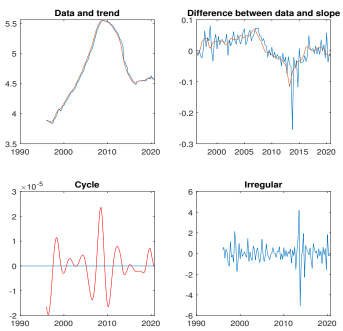
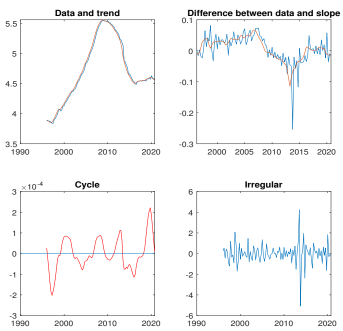


Figure B31: Estimated components of the $\ln LNFC$ variable in bivariate STSM model combination with...

(a) ...$\ln MAN$



(b) $\ln SER$



(c) $\ln TRA$

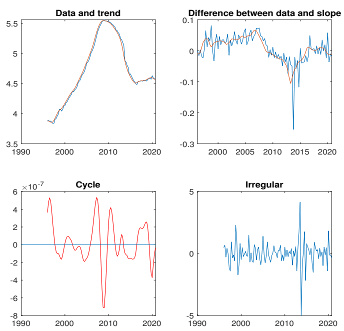
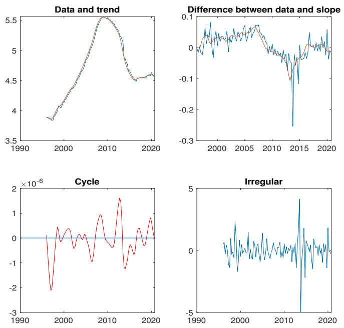
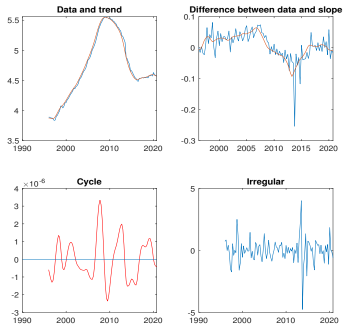


Figure B32: Estimated components of the $\ln LNFC$ variable in bivariate STSM model combination with...

(a) ...$\ln NTR$



(b) $\ln EXP$



(c) $\ln IMP$

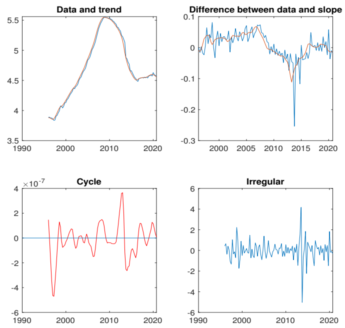
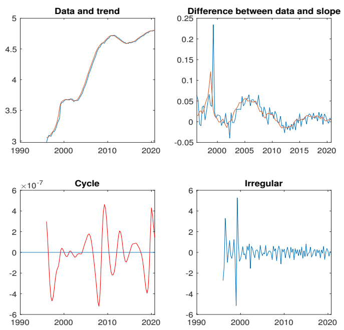


Figure B33: Estimated components of the $\ln LHH$ variable in bivariate STSM model combination with...

(a) ...$\ln GDP$



(b) $\ln CON$

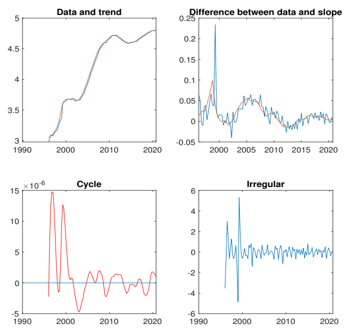
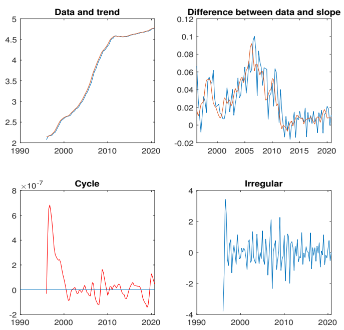


Figure B34: Estimated components of the $\ln LHHM$ variable in bivariate STSM model combination with...

(a) ...$\ln GDP$



(b) $\ln CON$

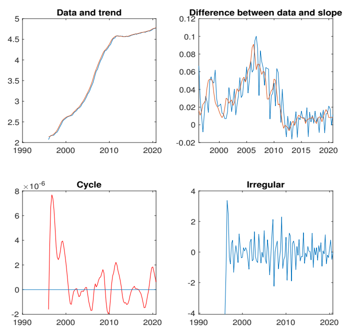
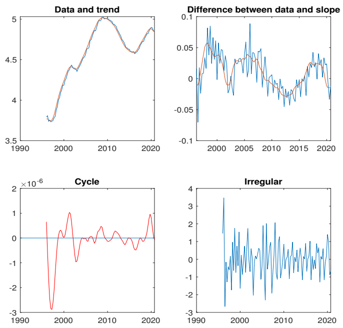


Figure B35: Estimated components of the ln $LHHC$ variable in bivariate STSM model combination with...

(a) ...ln GDP



(b) ln CON

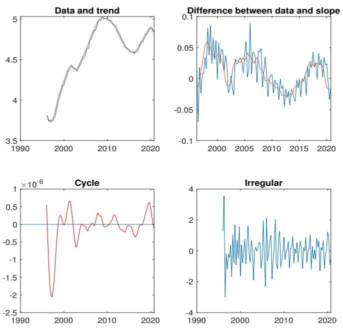
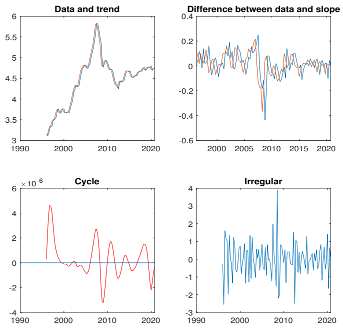
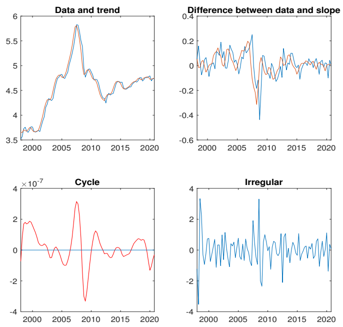


Figure B36: Estimated components of the ln EQP variable in bivariate STSM model combination with...

(a) ...ln GDP



(b) ln IP



(c) ln INV

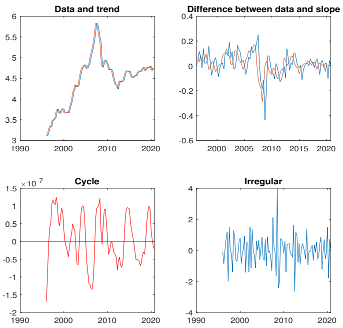
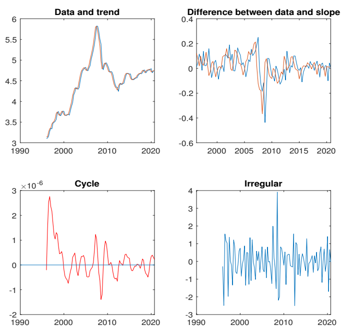
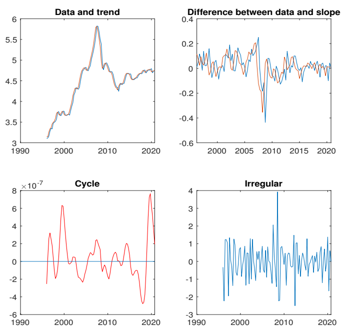


Figure B37: Estimated components of the ln EQP variable in bivariate STSM model combination with...

(a) ...ln MAN



(b) ln SER



(c) ln TRA

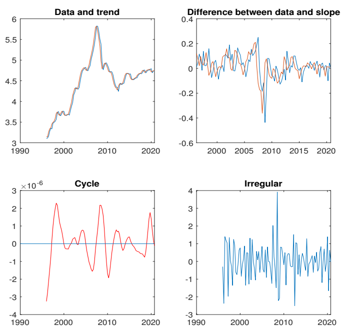
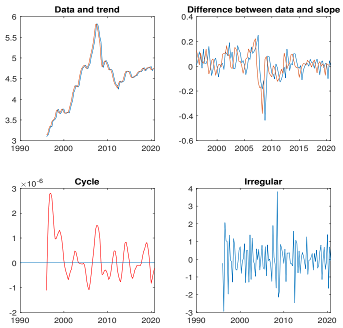
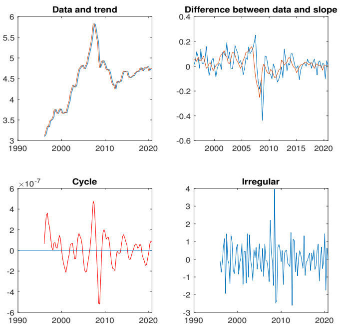


Figure B38: Estimated components of the $\ln EQP$ variable in bivariate STSM model combination with...

(a) ...$\ln NTR$



(b) $\ln EXP$



(c) $\ln IMP$

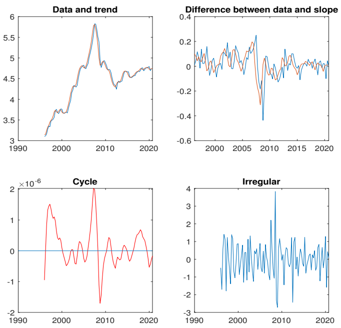
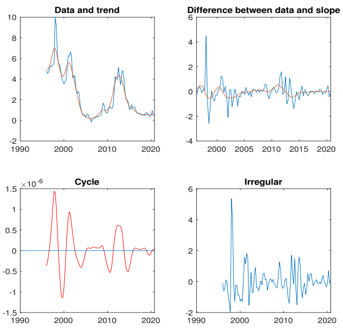
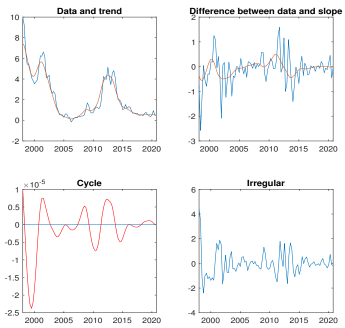


Figure B39: Estimated components of the $\ln SPR$ variable in bivariate STSM model combination with...

(a) ...$\ln GDP$



(b) $\ln IP$



(c) $\ln INV$

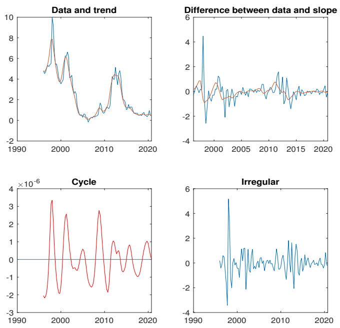
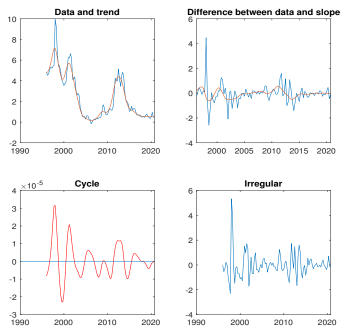
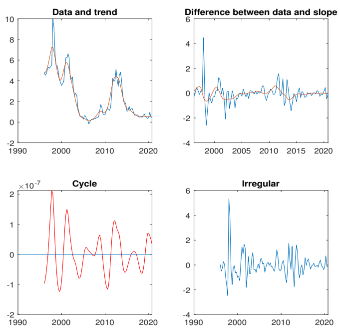


Figure B40: Estimated components of the $\ln SPR$ variable in bivariate STSM model combination with...

(a) ...$\ln MAN$



(b) $\ln SER$



(c) $\ln TRA$

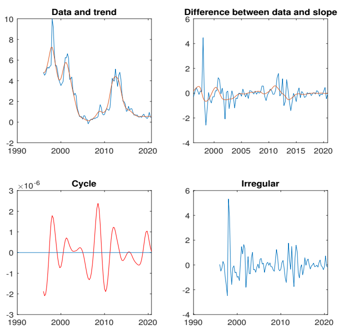
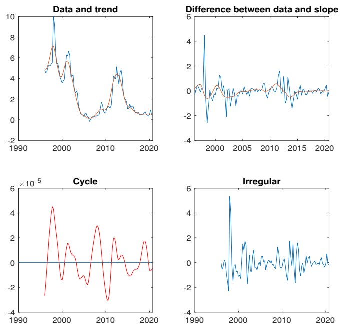
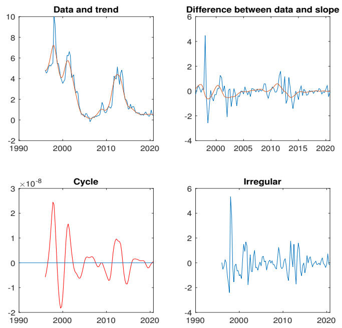


Figure B41: Estimated components of the $\ln SPR$ variable in bivariate STSM model combination with...

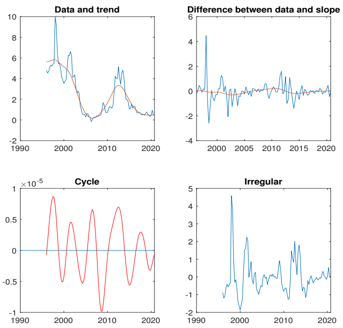
(a) ...$\ln NTR$



(b) $\ln EXP$



(c) $\ln IMP$



Appendix C: Diagnostics of the three-variable multivariate STSM models

STSM model with GDP, total loans and residential real estate variables

Figure C1: Coherences, phases and auto spectra

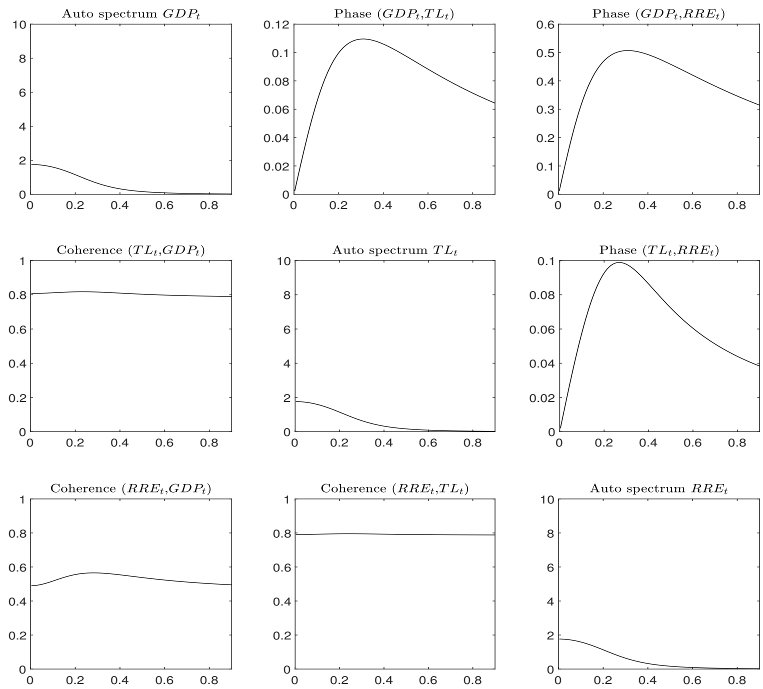
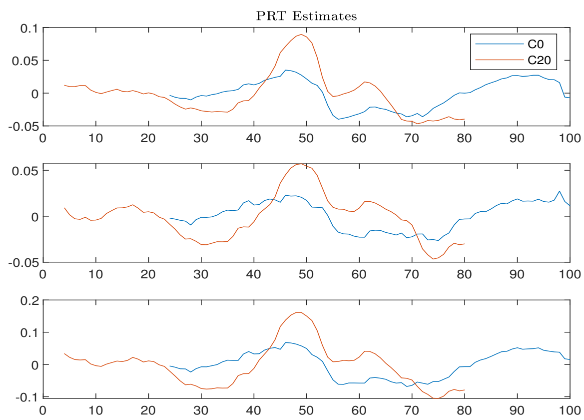


Figure C2: PRT estimates



STSM model with GDP, loans to households and residential real estate variables

Figure C3: Coherences, phases and auto spectra

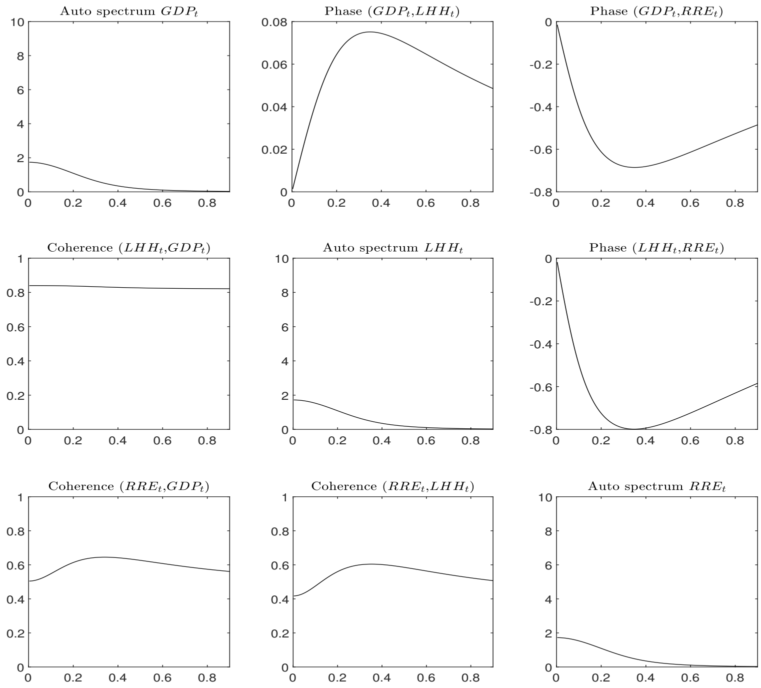
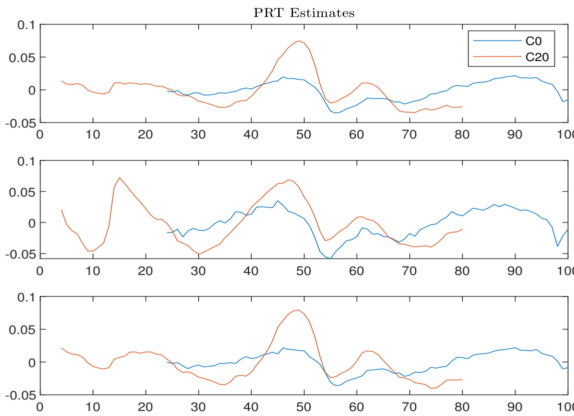


Figure C4: PRT estimates



STSM model with GDP, housing (mortgage) loans and residential real estate variables

Figure C5: Coherences, phases and auto spectra

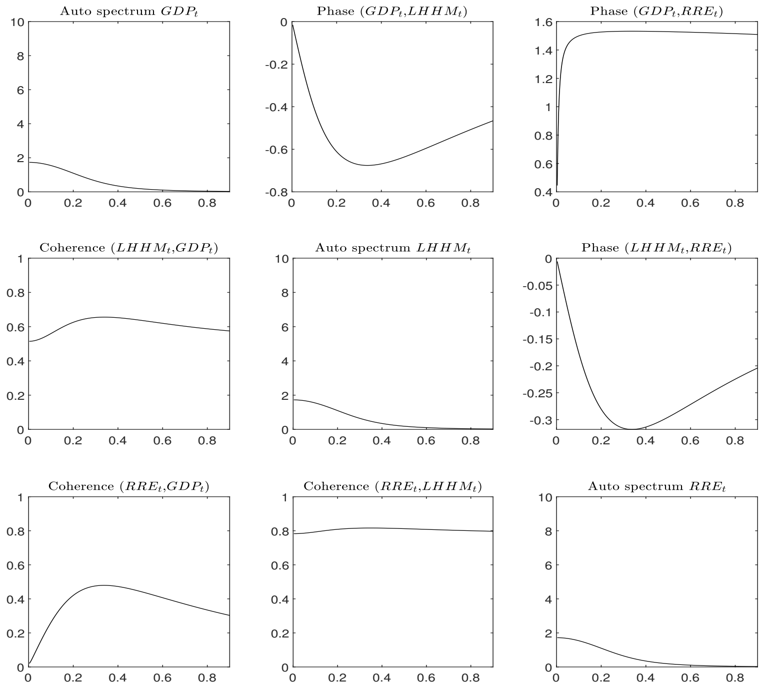
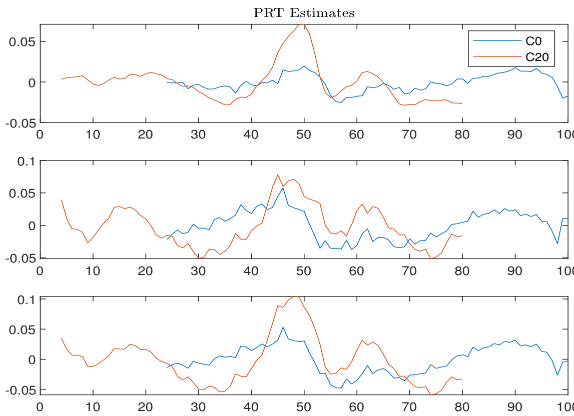


Figure C6: PRT estimates



Appendix D: Diagnostics of the univariate STSM models

Business cycle variables:

Figure D1: Estimated components of GDP variable

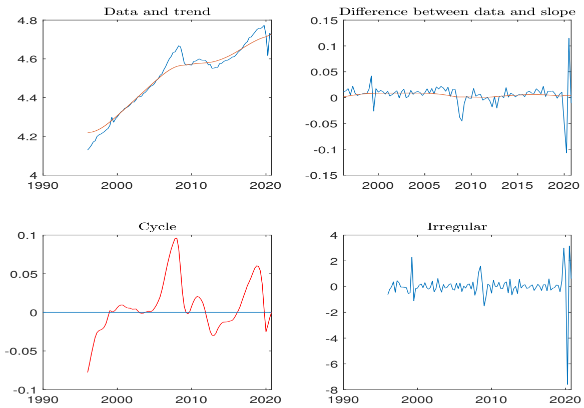


Figure D2: Estimated components of industrial production variable

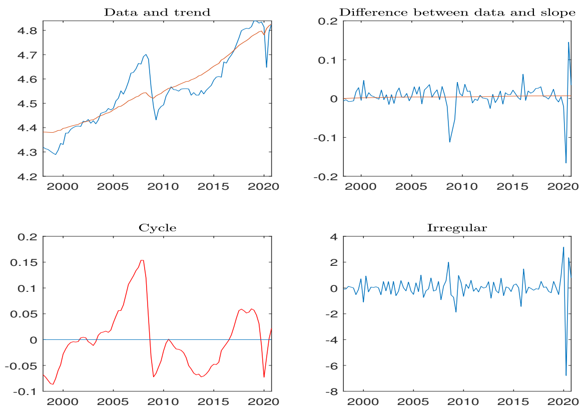


Figure D3: Estimated components of consumption variable

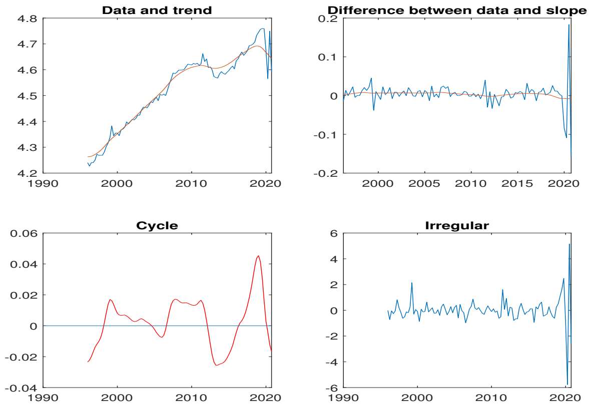


Figure D4: Estimated components of investment variable

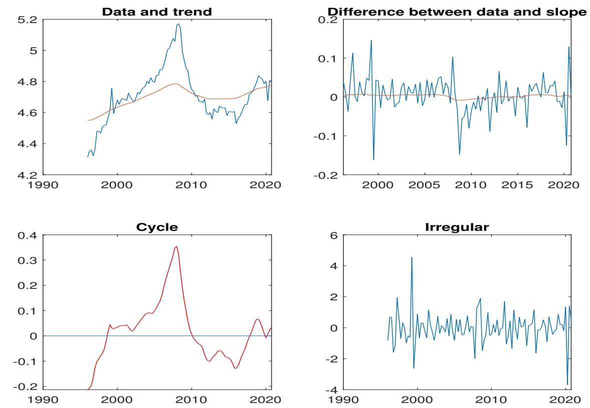


Figure D5: Estimated components of manufacturing sector variable

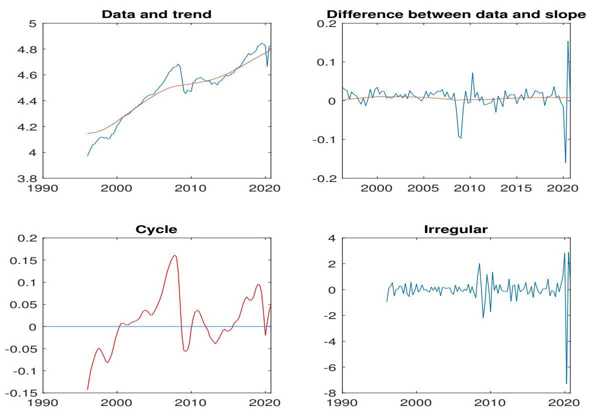


Figure D6: Estimated components of services sector variable

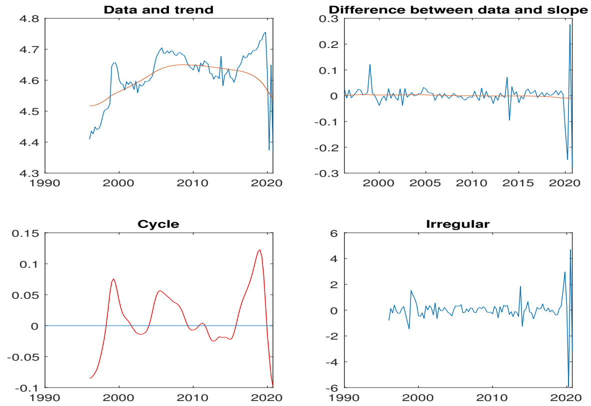


Figure D7: Estimated components of tradable sector output variable

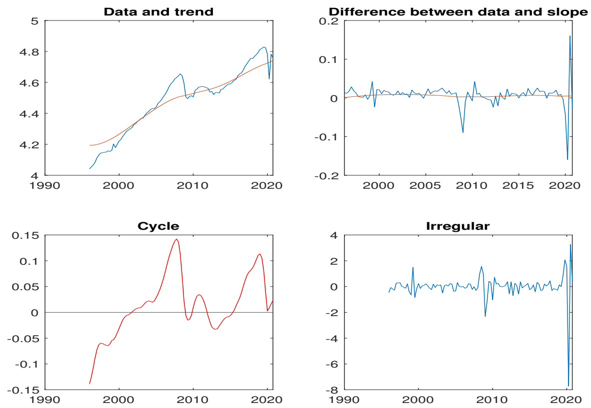


Figure D8: Estimated components of non-tradable sector output variable

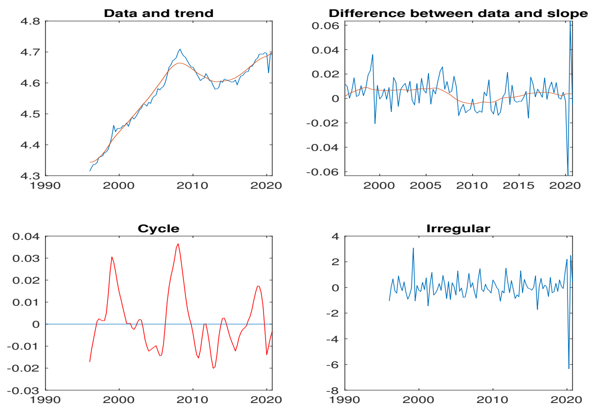


Figure D9: Estimated components of exports variable

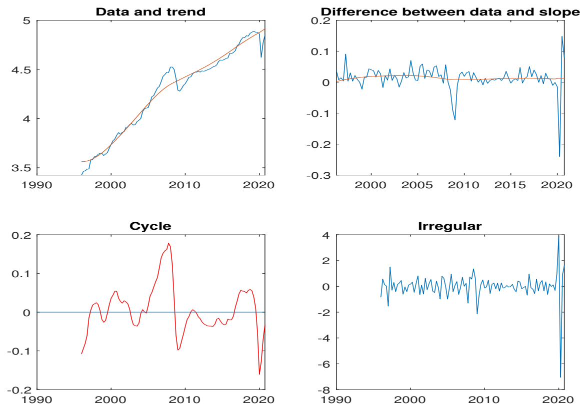
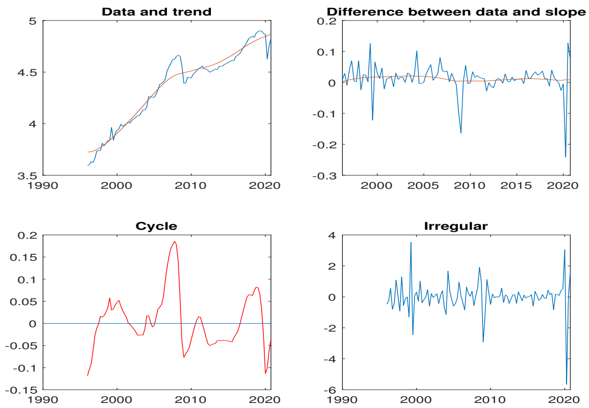
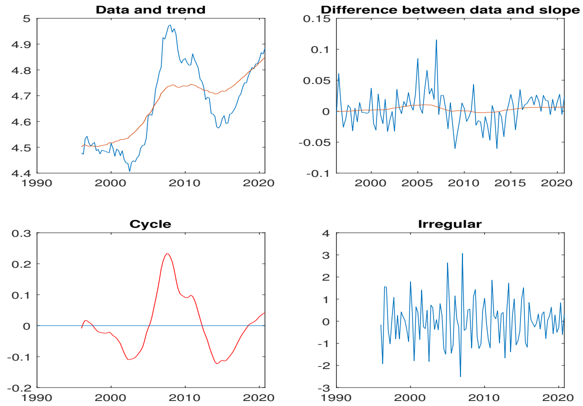


Figure D10: Estimated components of imports variable



Residential real estate prices:

Figure D11: Estimated components of residential real estate prices variable



Financial cycle variables:

Figure D12: Estimated components of banks' balance sheet variable

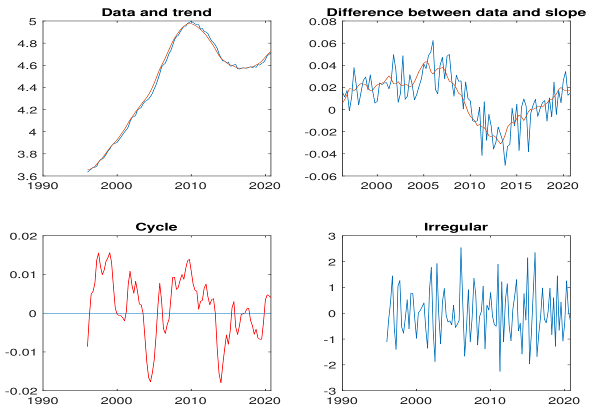


Figure D13: Estimated components of total loans variable

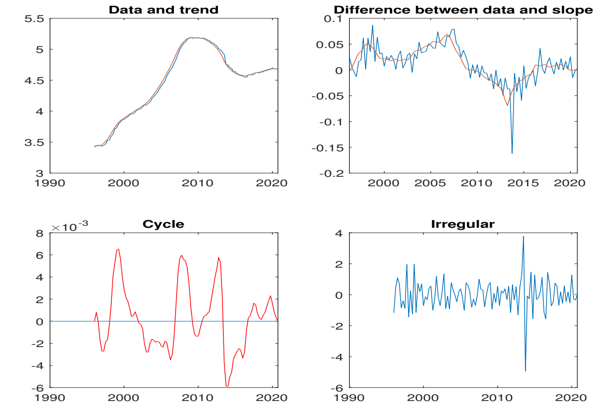


Figure D14: Estimated components of loans to NFC variable

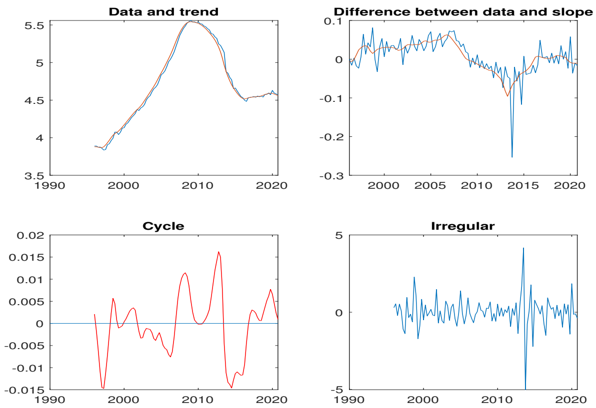


Figure D15: Estimated components of loans to households variable

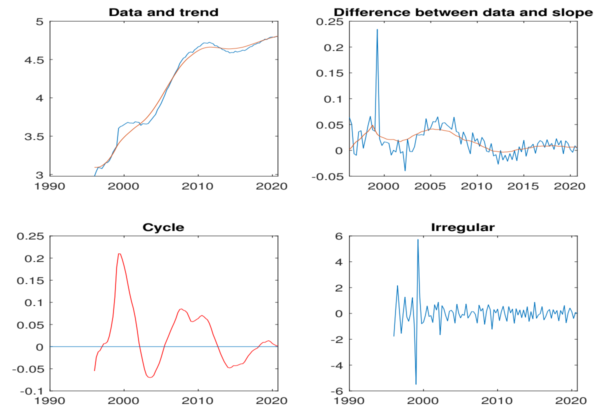


Figure D16: Estimated components of housing (mortgage) loans to households variable

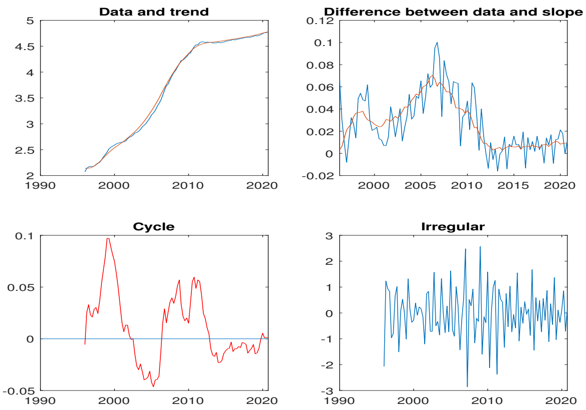


Figure D17: Estimated components of consumer loans to households variable

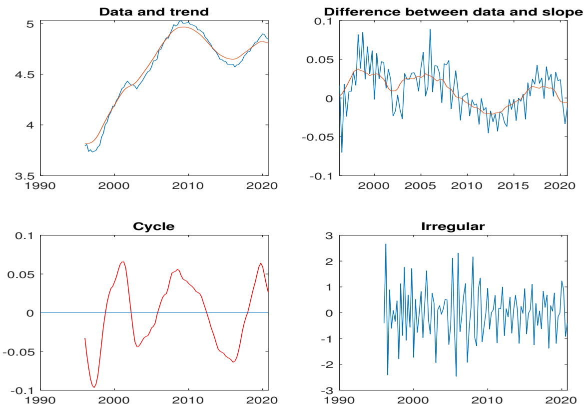


Figure D18: Estimated components of equity prices variable

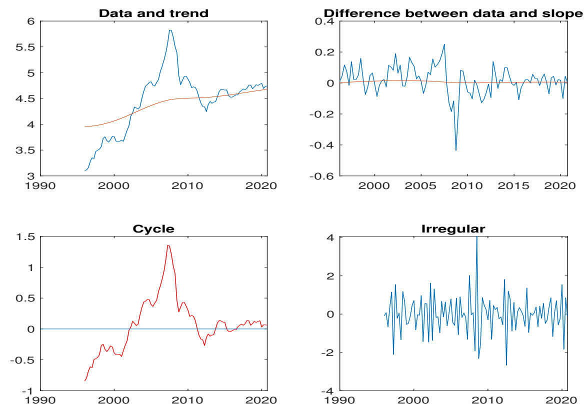


Figure D19: Estimated components of term spread variable