Assignment 2 - Econometrics 2

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1 Introduction

Main Question Using a vector autoregression (VAR), we want to analyze the dynamic relationship between GDP growth and changes in consumer confidence. In particular we wish to find out whether movements in the real economy drive consumer confidence or if the development of the economy depends on the level of consumer confidence. We will also explore contemporaneous effects.

Motivation Complex interdependent measures like the GDP or beliefs about the economy are very difficult to model with simple linear regression. Using VAR models we are able to allow for simultaneous effects of several variables, something which otherwise require the assumption of causality. In a second step we are also able to compare which variable affects the other and to which extent.

Causality Following Utaka (2003) we expect the VAR model to show us that consumer confidence has a short term positive effect on the GDP. Comparing the two time series graphically, this hypothesis might seem to be plausible. When considering the two graphs in Figure 1 we see periods where consumer confidence clearly predeceases GDP (e.g. subprime crisis 2007-2011, recovery after 2002-2003). However we would like to answer this question more profoundly.

Econometric model and conclusion We first use a unrestricted VAR model to estimate a well-specified model with a very close fit. Using Granger causality we can formulate a suggestion of causality which in turn is used to formulate a structural VAR model. Its impulse response functions put forward an estimate to which level consumer confidence growth is affecting the real GDP growth.

2 Description of data

The data for this assignment contains quarterly data (seasonally adjusted) for the real gross domestic product (GDP, chained 2010 Euros) and for the consumer confidence indicator (CC, normal = 100) for Germany covering the period 1991(1)-2020(2). The data has been downloaded from the FRED database maintained by the Federal Reserve Bank of St. Louis[1]. We logarithmize the data and further take the fourth differences to obtain yearly-difference observations. This transformation is used so the data series in Figure 1 is somewhat stationary and trend adjusted. Generally speaking, we observe some co-movements in the two variables, however as mentioned before, we tend to expect a positive impact of consumer confidence on GDP. We also notice a huge drop in the quarters for 2020 in GDP, which can be attributed to the effects of the Corona pandemic and its consequences. Regarding outlier reduction we exclude these observations in our model estimation from the beginning.

3 Economic theory

General VAR model Our VAR model is specified as:

$$Z_t = \mu + \Pi_1 Z_{t-1} + \Pi_2 Z_{t-2} + ... + \Pi_k Z_{t-k} + \epsilon_t \tag{1}$$

for $t = 1, 2, ..., T$ and conditional on k initial values $Z_0, Z_{-1}, ..., Z_{-(k-1)}$, a VAR with one lag equals:

$$\begin{aligned} Z_t &= \mu + \Pi_1 Z_{t-1} + \epsilon_t \\ \begin{pmatrix} y_t \\ x_t \end{pmatrix} &= \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix} + \begin{pmatrix} \Pi_{11} & \Pi_{12} \\ \Pi_{21} & \Pi_{22} \end{pmatrix} \begin{pmatrix} y_{t-1} \\ x_{t-1} \end{pmatrix} + \begin{pmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{pmatrix} \end{aligned}$$

Similar to a simple autoregressive (AR) model, we can reform a VAR(1) by substituting recursively:

$$\begin{aligned} Z_t &= \mu + \Pi_1 Z_{t-1} + \epsilon_t \implies Z_0 \quad given \\ &= (I_p + \Pi_1 + \Pi_1^2 + ... + \Pi_1^{t-1})\mu + \epsilon_t + \Pi_1 \epsilon_{t-1} + ... + \Pi_1^2 \epsilon_{t-1} + \Pi_1^t Z_0 \end{aligned} \tag{2}$$

Similar to the AR model, we need the power series to be convergent with $\Pi_1^k \to 0$ for $k \to \infty$ which leads to

$$\begin{aligned} E(Z_t|Z_0) &= (I_p + \Pi_1 + \Pi_1^2 + ... + \Pi_1^{t-1})\mu + \Pi_1^t Z_0 \\ &\to (I_p - \Pi_1)^{-1}\mu \\ &= E(Z_t) \end{aligned}$$

[1] https://fred.stlouisfed.org

Using an eigenvalue decomposition, the coefficient matrix Π_1 can be written as V^{-1}, with V being the matrix of eigenvectors and Λ the matrix with the matching eigenvalues:

$$\Pi_1^2 = V\Lambda V^{-1} V\Lambda V^{-1} = V\Lambda^2 V^{-1} \implies \Pi^k = V\Lambda^k V^{-1}$$
$$V = (v_1, ..., v_p) \qquad \Lambda = \begin{pmatrix} \lambda_1 & 0 & 0 \\ 0 & ... & 0 \\ 0 & 0 & \lambda_p \end{pmatrix} \implies \Lambda^k = \begin{pmatrix} \lambda_1^k & 0 & 0 \\ 0 & ... & 0 \\ 0 & 0 & \lambda_p^k \end{pmatrix} \tag{3}$$

When considering a VAR model with multiple lags we can rewrite it to fit into a one lag structure again:

$$Z_t = \mu + \Pi_1 Z_{t-1} + \Pi_2 Z_{t-2} + \Pi_3 Z_{t-3} + \epsilon_t$$

$$\underbrace{\begin{pmatrix} Z_t \\ Z_{t-1} \\ Z_{t-2} \end{pmatrix}}_{W_t} = \underbrace{\begin{pmatrix} \mu \\ 0 \\ 0 \end{pmatrix}}_{\tilde{\mu}} + \underbrace{\begin{pmatrix} \Pi_1 & \Pi_2 & \Pi_3 \\ I_p & 0 & 0 \\ 0 & I_p & 0 \end{pmatrix}}_{\tilde{\Pi}_1} \underbrace{\begin{pmatrix} Z_{t-1} \\ Z_{t-2} \\ Z_{t-3} \end{pmatrix}}_{W_{t-1}} + \underbrace{\begin{pmatrix} \epsilon_t \\ 0 \\ 0 \end{pmatrix}}_{\eta_t} \tag{4}$$

with $\tilde{\Pi}_1$ to be considered the companion matrix. By using the MA-representation of the VAR(1) model shown in Equation 3 for the now restructured multi-lag VAR model, we can conclude that the spectral decomposition also works for the new defined companion matrix.
Under the stationarity condition:

$$Z_t = \epsilon_t + C_1\epsilon_{t-1} + C_2\epsilon_{t-2} + ... + C_{t-1}\epsilon_1 + C_0$$
$$\frac{\partial Z_t}{\partial \epsilon_t'} = I_p \quad \frac{\partial Z_{t+1}}{\partial \epsilon_t'} = C_1 \quad \frac{\partial Z_{t+2}}{\partial \epsilon_t'} = C_2 \quad ... \tag{5}$$

with C_0 being a function of the constant term and the initial values. The remaining C are called the impulse response functions and converge to zero exponentially fast.

Assumptions for general VAR model

- **Normality & no autocorrelation in residuals**: $\epsilon_t | Z_{t-1}, Z_{t-2}, ..., Z_{t-k} \xrightarrow{d} N(0, \Omega)$, with ϵ_t being serially uncorrelated and Ω positive definite and symmetric. The residuals in the VAR can be correlated in the same period $corr(\epsilon_{1t}, \epsilon_{2t}) > 0$, but should not across different time periods.
- **Stationarity & weak dependence**: For the process of a VAR model to be stationary, we need the power series shown in Equation 2 to converge to zero. Looking at the spectral decomposition shown in Equation 3, this convergence holds if the eigenvalues $(\lambda_1^k, ..., \lambda_p^k) < |1|$ are all inside the unit circle (no unit root). For a multiple lag VAR model, stationarity is given if all eigenvalues of the components of the companion matrix $\tilde{\Pi}_1$ are inside the unit circle.

Structural VAR model As the contemporeaneous residuals ϵ_{1t} and ϵ_{2t} of a regular VAR model are likely to be correlated, one cannot analyse how one variable reacts to a shock of the other variable. As a solution we can reformulate the VAR model into a structural VAR model:

$$\begin{pmatrix} y_t \\ x_t \end{pmatrix} = \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix} + \begin{pmatrix} \Pi_{11} & \Pi_{12} \\ \Pi_{21} & \Pi_{22} \end{pmatrix} \begin{pmatrix} y_{t-1} \\ x_{t-1} \end{pmatrix} + \begin{pmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{pmatrix} \tag{6}$$
$$\implies \begin{pmatrix} 1 & -\omega \\ 0 & 1 \end{pmatrix} \begin{pmatrix} y_t \\ x_t \end{pmatrix} = \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix} + \begin{pmatrix} \Pi_{11} & \Pi_{12} \\ \Pi_{21} & \Pi_{22} \end{pmatrix} \begin{pmatrix} y_{t-1} \\ x_{t-1} \end{pmatrix} + \begin{pmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{pmatrix} \tag{7}$$
$$\begin{pmatrix} y_t \\ x_t \end{pmatrix} = \begin{pmatrix} 1 & -\omega \\ 0 & 1 \end{pmatrix}^{-1} \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix} + \begin{pmatrix} 1 & -\omega \\ 0 & 1 \end{pmatrix}^{-1} \begin{pmatrix} \Pi_{11} & \Pi_{12} \\ \Pi_{21} & \Pi_{22} \end{pmatrix} \begin{pmatrix} y_{t-1} \\ x_{t-1} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix} \tag{8}$$

Unlike ϵ_t, u_t are uncorrelated. $\omega = \Omega_{12}\Omega_{22}^{-1}$ with Ω being the correlation matrix of ϵ.

Assumptions structural VAR model The structural VAR model relies on an assumption which is not to be made lightly. By including the term of ω we also assume for x_t to have a causal direction on y_t given with $x_t \rightsquigarrow y_t$, as the opposite effect is considered negligible. The assumption of causality should therefore be well based on sound economic reasoning or a test-statistic which might suggest a direction of causality.

Forecasting Given the information set $I_T = \{Z_T, Z_{T-1}, ...\}$ forecasting is done similarly to a univariate autoregressive model:

$$Z_{T+h|T} = E(Z_{T+h}|I_T) \implies Z_{T+1|T} = E(\mu + \Pi_1 Z_{T+1} + \epsilon_{T+2}|I_T) = \mu + \Pi_1 Z_{T+1|T} \tag{9}$$

With the forecast error variance (FEV) being defined through the individual forecast period error η_h:

$$\begin{aligned} \eta_1 = Z_{T+1} - Z_{T+1|T} = \epsilon_{T+1} &\implies FEV(1) = E(\eta_1^2|I_T) = E(\epsilon_{T+1}^2|I_T) = \Omega \\ \eta_h = Z_{T+h} - Z_{T+h|T} &= \epsilon_{T+h} + C_1\epsilon_{T+h-1} + C_2\epsilon_{T+h-2} + ... + C_{h-1}\epsilon_{T+1} \\ FEV(h) = \Omega + C_1\Omega C_1' &+ C_2\Omega C_2' + ... + +C_{h-1}\Omega C_{h-1}' \end{aligned} \tag{10}$$

Granger Causality Is considered a testing procedure which helps in finding and distinguishing the direction of causality in the components of Z. Granger causality requires two assumptions, namely:

- The cause comes prior to the impact.
- A causal variable is helpful in forecasting. Knowing about a variable e.g. x is better for forecasting, than not knowing about x.

For Granger causality we compare two forecasts conditional on an information set, in which one information set omits all values of one component:

$$\begin{aligned} &I_T = \{y_T, x_T, y_{T-1}, x_{T-1}, ...\} &&\tilde{I}_T = \{y_T, y_{T-1}, ...\} \\ &\eta_h \equiv y_{T+h} - E[y_{T+h}|I_T] &&\tilde{\eta}_h \equiv y_{T+h} - E[y_{T+h}|\tilde{I}_T] \end{aligned}$$

Where x is considered Granger causal on y if it holds that:

$$E(\eta_h^2|I_T) < E(\tilde{\eta}_h^2|I_T)$$

Given a VAR(2) model with 2 components:

$$\begin{pmatrix} y_t \\ x_t \end{pmatrix} = \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix} + \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix} \begin{pmatrix} y_{t-1} \\ x_{t-1} \end{pmatrix} + \begin{pmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{pmatrix} \begin{pmatrix} y_{t-2} \\ x_{t-2} \end{pmatrix} + \begin{pmatrix} \epsilon_1 \\ \epsilon_2 \end{pmatrix} \tag{11}$$

the hypothesis for no-Granger-Causality of x on y is formulated as: $H_0 : x \nrightarrow y$ with $A_{12} = B_{12} = 0$. Given the models are correctly specified, the test statistic is $\chi^2(2)$ distributed.

Tests As long as the VAR-model is stable, i.e. a stationary and weakly dependent process, all the usual t-ratios are distributed $t \sim N(0, 1)$. Furthermore, all Wald tests or likelihood ratio tests for hypotheses on the parameters have limiting χ^2-distributions. The likelihood ratio statistics can be calculated as twice the difference in log-likelihoods. Regarding the misspecification tests, they are just generalized versions of the ones applied in univariate autoregressions to the VAR case. We apply them to the individual equations in the model themselves as well as the full VAR model.

- Residual autocorrelation (x periods): Breusch-Godfrey LM test, H_0: No AC, $\xi_{AR} = T \cdot R^2 \xrightarrow{d} \chi^2(x)$
- Residual normality: Jarque-Bera test, H_0: Error terms are normally distributed, $\xi_{JB} = \xi_S + \xi_K \xrightarrow{d} \chi^2(2)$
- Heteroskedasticity (k regressors): Standart LM-test, H_0: Errors are homoscedastic, $\xi_{HET} = T \cdot R^2 \xrightarrow{d} \chi^2(2k)$

Our model For our model we select a VAR model with multiple lags. The lag structure is consistent in each of the selected lags for both components x and y. However, as we select a different number of lags for x and y we use the notation:

$$Z_t = \mu + \Pi Q + \epsilon_t$$

The estimator and its properties For estimating the model, we consider the MLE or OLS estimator. As shown by Equation 1 and Equation 4 the VAR model has a clear linear structure and can also be linearly rearranged if needed to fulfill different properties. Given the requirements for stationarity for the VAR model, the MLE estimator equals the closed form OLS estimator. Assuming a multivariate Gaussian density, the maximum likelihood estimation for the VAR model is very similar to the AR model:

$$logL(\theta) = \underbrace{\sum_{t=1}^{T} log\ell_t(\theta)}_{similarAR} = \underbrace{\sum_{t=1}^{T} logf(Z_t|Z_{t-1};\theta)}_{VAR} \qquad \theta = \{\mu, \Pi_1, \Omega\}$$

$$\epsilon_t(\theta) = Z_t - \mu - \Pi_1 Z_{t-1} + ... + \Pi_k Z_{t-k} = Z_t - \Phi \tilde{Z}_{t-k}$$

$$\Phi = (\mu, \Pi_1, ..., \Phi_k) \quad \tilde{Z}_{t-k} = (1', Z'_{t-1}, ..., Z'_{t-k})'$$

$$\hat{\Phi} = \sum_{t=1}^{T} Z_t \tilde{Z}_{t-1} \left(\sum_{t=1}^{T} \tilde{Z}_{t-1} \tilde{Z}'_{t-1} \right)^{-1} \qquad \hat{\Omega} = \frac{1}{T} \sum_{t=1}^{T} \hat{\epsilon}_t \hat{\epsilon}'_t$$

If the eigenvalues of the companion matrix are inside the unit circle and ϵ_t $iid(0, \Omega)$ then it holds that the MLE has approximately a Gaussian distribution.

4 Empirical analysis

4.1 Model selection

We start by estimating a general VAR model with GDP and consumer confidence as dependant variables and their nine period-lags as regressors. This number has been chosen after having a look at the ACF / PACF plots (Figure 1), which show for both variables that lags after the tenth period do not seem to be of great importance. Having in mind that there are outliners in our data set (Figure 1) as well as due to the rejection of residual normality in the first model estimation, we immediately choose to correct for this. After inspection of the individual residuals in several ways, we insert dummy variables for the quarters 1994(2), 2002(4) and 2009(1) and exclude the first two periods of the year 2020 completely from our data set.

We then continue by removing insignificant lags. Our criterion hereby is a likelihood-ratio-test (LR), testing the significance of the lag-coefficient in both equations together. We eliminate the least significant each time and estimate a new model afterwards. What we end up with is the model that can be seen in Table 2 to the left. We choose robust standard errors (HCSE) due to heteroscedasticity problems in the equation for D4y. The miss specification tests cannot reject no-auto-correlation and normality in all settings, and also not no-heteroscedasticity in the overall VAR, which makes our model a well-defined one. We also test for no-auto-correlation on the whole vector, i.e. adjusted to the lag-length in our model, which is nine periods. This test also fails to reject the hypothesis of no-auto-correlation (see Table 2: No autocorr. 1-9 D4c/D4y)

As we have removed lags always in both VAR-equations, we can still use the closed OLS form for our MLE estimator. Furthermore, all eigenvalues are inside the unit circle. After all, we compare our model with the model that is chosen by running an automatic model selection (AMS) algorithm with outlier detection in OxMetrics two times. We observe that apart from a D4log(CC)_9 instead of a D4log(CC)_8 it is identical. Nevertheless, we choose to continue our analysis by the model suggested by AMS as its log-likelihood is slightly bigger.

We formulated our model as follows:

$$Z_t = \mu + \Pi \times Q_t + \epsilon_t \tag{12}$$

more specifically:

$$\begin{pmatrix} D4logGDP_t \\ D4logCC_t \end{pmatrix} = \begin{pmatrix} \mu_{D4logGDP_t} \\ \mu_{D4logCC_t} \end{pmatrix} + \underbrace{\begin{pmatrix} a_1 & a_4 & a_5 & a_8 & a_9 & b_1 & b_2 & b_3 & b_4 & b_5 & b_6 & b_9 \\ c_1 & c_4 & c_5 & c_8 & c_9 & d_1 & d_2 & d_3 & d_4 & d_5 & d_6 & d_9 \end{pmatrix}}_{\Pi} \underbrace{\begin{pmatrix} D4logGDP_{t-1} \\ D4logGDP_{t-4} \\ D4logGDP_{t-5} \\ D4logGDP_{t-8} \\ D4logGDP_{t-9} \\ D4logCC_{t-1} \\ D4logCC_{t-2} \\ D4logCC_{t-3} \\ D4logCC_{t-4} \\ D4logCC_{t-5} \\ D4logCC_{t-6} \\ D4logCC_{t-9} \end{pmatrix}}_{Q_t} + \begin{pmatrix} \epsilon_{D4logGDP_t} \\ \epsilon_{D4logCC_t} \end{pmatrix} \tag{13}$$

Our estimates result in:

$$Z_t = \hat{\mu} + \hat{\Pi} \times Q_t + \hat{\epsilon}_t \tag{14}$$

For the OLS estimation of the linear model we need the time series to be stationary and weakly mixing. The residuals must not be auto correlated.

Miss specification tests and link to economic theory The miss specification tests show, that the residuals are not auto correlated, therefore the OLS estimator is consistent. The estimated residuals $\hat{\epsilon}_{D4logGDP_t}$ are heteroscedastic which we account for by using a heteroscedasticity robust standard error estimation. This way we can rely on a consistent estimation of the standard errors of the coefficients in the first row of our linear model.

Granger causality To test for no-Granger-Causality of the growth rate of consumer confidence on the GDP growth, looking at Equation 13 we construct χ^2-tests which each test the joint hypotheses that all effects of one variable on the other are zero:

$$H_0 : D4logCC \nrightarrow D4logGDP \Leftrightarrow b_1 = b_2 = \cdots = b_9 = 0 \tag{15}$$

Equivalently the other way around, for no-Granger-Causality of the GDP growth on the growth rate of consumer confidence:

$$H_0 : D4logGDP \nrightarrow D4logCC \Leftrightarrow c_1 = c_4 = \cdots = c_9 = 0 \tag{16}$$

Executing both tests (results Table 1) we can reject no-Granger-Causality of the growth in consumer confidence on the GDP growth on a significance level of 5%. We cannot reject no-Granger-Causality of GDP growth on growth in consumer confidence. This indicates, that if there is a causal relationship between consumer confidence and economic growth it is more likely that consumer confidence causes economic growth than the other way around. This corresponds to our original thesis, stated in the introduction.

Structural VAR estimation To examine the effect of consumer confidence on GDP growth we formulate a structural VAR model. The advantage of structural VAR models over ordinary VAR models is that one can examine the effects of shocks because the residuals are per definition uncorrelated:

$$Z_t = \begin{pmatrix} 1 & -\hat{\omega} \\ 0 & 1 \end{pmatrix}^{-1} \mu + \begin{pmatrix} 1 & -\hat{\omega} \\ 0 & 1 \end{pmatrix}^{-1} \hat{\Pi} \times Q_t + \begin{pmatrix} u_{D4logGDP_t} \\ u_{D4logCC_t} \end{pmatrix} \tag{17}$$

With the estimated covariance matrix in table 2 we receive an $\hat{\omega}$ of about 0.4172. With the transformed first equation we repeat the estimation.

Impulse Responses In the previous sections we gathered indications for a possible causal effect of consumer confidence on economic growth. With the uncorrelated residuals in the structural VAR model we can now interpret shocks in consumer confidence growth with respect to their effect on economic growth. The impulse response is to be treated with caution as we cannot conclude with a causal effect, we can still only assume it. Another required assumption is, that there is no contemporaneous effect of economic growth on consumer confidence growth. Both are backed by our tests for no-Granger-Causality. Looking at Figure 2, we observe a significant positive effect of a shock to consumer confidence growth on GDP growth for about seven quarters. After this period the effect is no longer significant and converges to zero.

Interpretation of the empirical results With the no-Granger-Causality tests we found further arguments for a causal effect of consumer confidence on economic growth. These allowed us to estimate a structural VAR model to examine those effects which are statistically significant.

5 Discussion and Conclusion

We formulated the thesis that there might be a causal effect of consumer confidence on economic growth. To examine this relationship we formulated a VAR model that explains the underlying dynamics. No-Granger-Causality tests as well as a graphic analysis strengthen our thesis. However, we can not conclude that there is a causal effect as we do not have sufficient evidence. We formulate a structural VAR model anyway, knowing that our (well-founded) causality assumption might be wrong. With this model we observe significant changes in GDP growth caused by a change in consumer confidence. A huge flaw in our models is, that we only include two variables. At least other macroeconomic control variables would be necessary to extract the real dynamics between consumer confidence and economic growth. Our results are therefore very blurred. Also, for statistic exploration of causality we should consider looking for instrumental variables. Although we cannot conclude with the finding of causality, we definitely found further arguments and gathered evidence.

6 Appendix

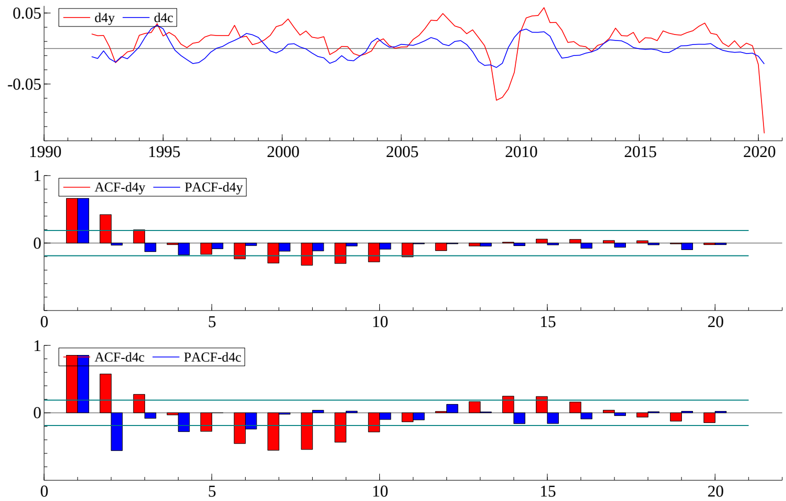
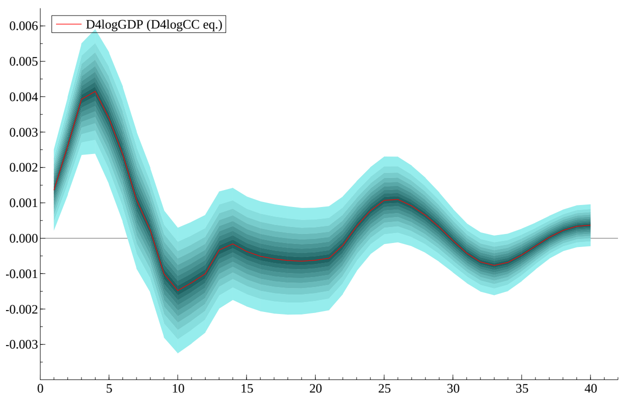
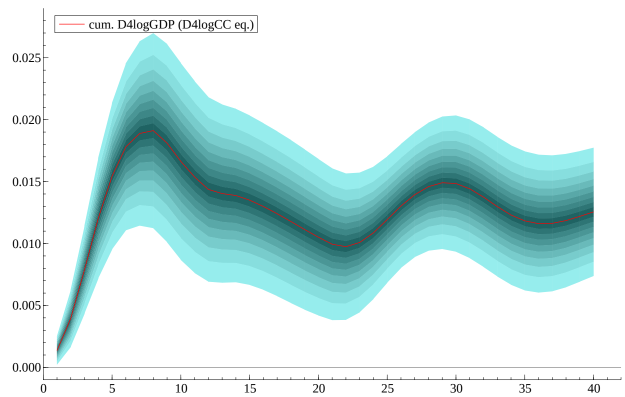


Figure 1: Time series for 4th differences of the log for German GDP and consumer confidence



Impulse response function



Cumulated effects

Figure 2: Effects of change in consumer confidence growth (CC) on GDP growth.

Excluding	lags	χ^2-Test	χ^2-Test (HCSE)
CC in GDP equation (D4log(CC))	1,...,6,9	24.015 [0.0011]**	16.792 [0.0188]*
GDP in CC equation (D4log(GDP)	1,4,5,8,9	11.877 [0.0365]*	10.073 [0.0732]

Table 1: Two χ^2-tests for no-Granger-Causality, p-values in $[\cdot]$

	Our Model	(draft)	AMS	(selected)
	D4c	D4y	D4c	D4y
Constant	0.002	0.007	0.002	0.007
	(2.56)	(4.58)	(2.76)	(4.93)
D4log(GDP)_1	−0.041	0.815	−0.050	0.781
	(−1.19)	(14.3)	(−1.40)	(12.5)
D4log(GDP)_4	0.047	−0.556	0.053	−0.534
	(1.13)	(−5.11)	(1.28)	(−5.12)
D4log(GDP)_5	−0.106	0.349	−0.115	0.315.
	(−2.25)	(3.20)	(−2.44)	(2.98)
D4log(GDP)_8	0.028	−0.343	0.035	−0.314
	(0.63)	(−3.14)	(0.85)	(−3.15)
D4log(GDP)_9	−0.045	0.229	−0.059	0.178
	(−1.08)	(2.63)	(−1.40)	(2.25)
D4log(CC)_1	1.622	0.526	1.608	0.475
	(19.3)	(2.46)	(19.9)	(2.25)
D4log(CC)_2	−1.255	−0.267	−1.230	−0.174
	(−7.52)	(−0.76)	(−7.69)	(−0.47)
D4log(CC)_3	0.711	−0.024	0.718	−0.001
	(3.27)	(−0.06)	(3.33)	(0)
D4log(CC)_4	−0.612	0.216	−0.637	0.128
	(−2.98)	(0.59)	(−3.16)	(0.35)
D4log(CC)_5	0.564	0.046	0.577	0.088
	(3.20)	(0.14)	(3.42)	(0.27)
D4log(CC)_6	−0.370	−0.085	−0.341	0.029
	(−3.48)	(−0.43)	(−3.68)	(0.16)
D4log(CC)_8	0.088	0.329	.	.
	(1.63)	(2.89)		
D4log(CC)_9	.	.	0.084	0.307
			(1.59)	(3.06)
I:1994(2)	0.012	0.005	0.013	0.006
	(5.03)	(1.12)	(5.25)	(1.32)
I:2002(4)	−0.012	0	−0.012	0
	(−8.57)	(−0.11)	(−8.29)	(0.12)
I:2009(1)	−0.009	−0.049	−0.010	−0.050
	(−5.40)	(−15.4)	(−5.89)	(−16.1)
$\hat{\sigma}$	0.0033	0.0072	0.0033	0.0071
Log-lik.	825.29	.	826.02	.
Global F-test: F(30,172)	60.098	[0.0000]	60.5673	[0.0000]
Regressors F-test: F(2,86)	all at 1%	.	D4y_9 at 5%	.
Correlation URF residuals	D4c	D4y	D4c	D4y
D4c	0.0033	0.1974	0.0033	0.1907
D4y	0.1974	0.0072	0.1907	0.0071
No autocorr. 1-5 D4c/D4y	[0.96]	[0.12]	[0.97]	[0.15]
No autocorr. 1-9 D4c/D4y	[1.00]	[0.47]	[0.99]	[0.52]
No hetero. D4c/D4y	[0.73]	[[0.01]*	[0.76]	[0.01]**
Normality D4c/D4y	[0.39]	[0.72]	[0.46]	[0.57]
No autocorr.	[0.37]	.	[0.31]	.
No hetero.	[0.29]	.	[0.26]	.
Normality	[0.62]	.	[0.60]	.
T	103/105	103/105	103/105	103/105
Sample start	1994(2)	1994(2)	1994(2)	1994(2)
Sample end	2019(4)	2019(4)	2019(4)	2019(4)

Table 2: The table shows estimates of the models with various restrictions imposed. t-ratios in $(\cdot)$ and p-values in $[\cdot]$ for misspecification tests.