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Economic Theory

Advertising, Consumption and Economic Growth: An Empirical Investigation*

- Preliminary Version -

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Abstract

It is sometimes argued that more advertising raises consumption which in turn stimulates output and so economic growth. We test this hypothesis using annual German data expressed in terms of GDP for the period 1950-2000. We find that advertising does not Granger-cause growth but Granger-causes consumption. Consumption, in turn, Granger-causes GDP growth. The data imply that the immediate impact of more advertising on consumption is positive. However, the long-run effect is *negative*. Furthermore, the immediate impact of higher consumption on growth is negative. But the long-run effect is *positive*. These results raise interesting questions for standard theory, political debates and advertising practioners.

KEYWORDS: Advertising, Consumption, Economic Growth

JEL Classification: O4, M3, E2

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1 Introduction

In this paper we investigate the link between advertising, consumption and economic growth. This link deserves attention because it is often argued that domestic demand deficiencies may be the cause of low growth.

For the short run it has become a regular finding by business cycle research that output co-varies pro-cyclically with private consumption and investment.[1] These two aggregates are clearly important in national income accounting and for growth research. It is also well known that consumption in most advanced countries makes up around 60 percent of national income compared to around 15 percent that is made up by private investment. Thus, changes in private consumption should have a relatively important impact on aggregate demand and output.

It is, thus, argued that more consumption would raise output. One way to stimulate the former might be an increase in advertising. Clearly, advertising, at least in the consumer goods sector, is targeted directly at potential buyers of (final) goods.[2] If the effect of advertising is to persuade customers to buy a good and they indeed do that, then advertising should have a positive effect on measured consumption. Hence, it is often hypothesized that more advertising raises consumption which in turn stimulates output and so economic growth. Although the hypothesis has intuitive appeal, theory leads one to be cautious about the validity of this chain of reasoning.

To our knowledge the direct link between advertising and economic growth has not been analyzed in detail so far.[3] This is a bit unfortunate since advertising is a pervasive phenomenon that has been around for a long time. For example, the

[1] For the United States see, for example, Blanchard and Fischer (1989), p. 16. For Germany see, for example, Tichy (1994), p. 78.

[2] A similar logic holds for advertising in the investment goods sector. If advertising there leads to more purchases of investment goods, this is expected to raise investment, bearing positively on output and personal incomes. Higher incomes then often also lead to more consumption.

[3] For an earlier analysis see, for example, Galbraith (1972), chs. 18-20. He argues that advertising serves to "manage" demand. The continuous upholding of high levels of the latter is argued to increase or keep output at a higher level than it would otherwise be. Thus, he basically advocates a hypothesis that higher advertising implies higher demand (consumption) and - thinking in Keynesian terms - that that would stimulate output and its growth. For an earlier formal analysis on these links see, for example, Frey (1969). The ensuing debates from that hypothesis were not really settled, however, and have not been taken up in more recent times.

history of brand creation can at least be dated back to the times of the Industrial Revolution. One such brand is "Made in *Country X*" which was created around that time.

Clearly, many business people consider advertising an important economic factor nowadays as the budgets spent on it testify. Thus, some theory on the relationship between advertising and growth would appear to be desirable.

On the other parts of the "causal" links embedded in the hypothesis theory would suggest the following: In accumulation-driven growth models in the tradition of Solow (1956) higher consumption cannot really lead to higher growth. Growth depends on investment and savings. Thus, in a simple Solow growth model a higher consumption share (aggregate private consumption in terms of GDP) would lower the savings share and would usually imply lower growth for some time, that is, in the transition from the old to a new steady state with higher consumption.[4] Also, innovation-driven growth models like Romer (1986), Romer (1990), or Aghion and Howitt (1992) suggest the same. Hence, no clear and, if at all, rather a negative relationship between consumption shares and economic growth is usually predicted by theory.[5]

The issue of the interaction between advertising and consumption has primarily been analyzed by economists in the industrial economics literature.[6] (See e.g. Tirole (1988), ch. 7, or Martin (2002), ch. 9.) The focus here has usually been on the decision of firms to invest in advertising in order to get a competitive edge in a non-cooperative world. Illuminating for our purpose is the seminal paper by Dixit and Norman (1978). They model advertising as having a direct positive effect on utility. ("Don't we all feel happy when we see those smiling people on billboards or tv?") But firms in an oligopolistic market will compete in advertising investment which will raise the price of goods and might be bad

[4]Of course, in a simple Solow growth model the long-run steady state growth rate would not be affected by these changes. In that sense Solow (1956) would still imply that the *long-run* response to an increase in the consumption share would be zero and thus neutral. The same would usually apply to other accumulation-driven growth models. See e.g. Barro and Sala–i–Martin (1995).

[5]In the 1990s many commentators argued that the increase in growth rates in the U.S. was *consumption-driven*. However, no clear academic research agenda in economics emanated from this, perhaps debatable, claim for long-run phenomena.

[6]Clearly, the business administration literature has devoted a bulk of literature on the subject. However, for lack of space we confine ourselves to the debates featuring in the economics literature in this paper. For an early economics study of the advertising industry in the United Kingdom see, for example, Kaldor (1950).

for demand of the product. They show that the combined effect of more advertising is negative for welfare. Thus, demand might actually fall due to increases in advertising.

Summarizing, we find that the theoretical predictions on the relationship between advertising, consumption and growth is not clear. Thus, in this paper we test the hypothesis of the link from advertising to consumption to growth empirically. Our focus is on the long run because we want to link up to current growth research, and growth is ultimately a long-run phenomenon.

For our test we use annual German data expressed in terms of GDP for the period 1950-2000. The reason for focusing on Germany is threefold. First Germany is a big market. In terms of GDP it is the third largest economy in the world and the largest one in the European Union. Thus, consumption and advertising in that country should have an impact on its trading partners in a globalized world. Second, we have obtained reliable data for German advertising expenditure from sources that we are more familiar with. This is because knowledge of everyday advertising impacts on consumer behaviour appears to be required as "off-the-record-information" to relate to arguments by advertising practitioners in any country. In our case this is Germany. Third, we compare our findings to those obtained by earlier studies focusing on the United States as the world's largest economy in terms of GDP. Hence, we compare findings for the largest economy in the world to the largest European one.

The data in this paper are taken from the German Statistical Office (Statistisches Bundesamt) and the German Central Association of Advertising Business (Zentralverband der Werbewirtschaft, ZAW). Our key variables are the consumption share, that is, the ratio of private consumption to GDP, the advertising share, that is, the ratio of total advertising expenditure GDP, and the growth rate of GDP.

We use standard methods to analyze our variables. For the data it turns out that all three variables are stationary. Next, we conduct pairwise comparisons of the time series of our data to check for Granger-causality.[7] We find that advertising does not Granger-cause growth but Granger-causes consumption. Consumption, in turn, Granger-causes GDP growth. For all other pairs we cannot reject the null hypothesis that no causality is present.

[7]Granger-causality establishes whether one series helps to predict another series. This concept is explained in more detail below.

These results are interesting. For instance, Ashley, Granger, and Schmalensee (1980) find for U.S. data that aggregate consumption Granger-causes aggregate advertising expenditure using quarterly data.[8] Their results would suggest that consumption predicts advertising, whereas we find a one way "causality" according to which advertising predicts consumption in Germany. Of course, their data are of higher frequency so that the results are not necessarily incompatible with each other. As our focus is on the long run, our findings do, however, suggest a different prediction pattern - at least for Germany.

Furthermore, the exercise casts doubt on the maintained link. Granger causality is *not* transitive. Thus, the direct Granger-causal effect of advertising on growth is not present in our data. Also, one cannot conclude from the other relationships that there is a link from advertising through consumption on growth. Thus, the causality analysis alone casts doubt on the hypothesis.

Building on these causality results we use standard, well established statistical arguments to build empirical models that best describe the time series of our data.

These models yield some surprising results. We find that the immediate impact of more advertising on consumption is positive. However, the long-run effect is *negative*. Furthermore, the immediate impact of higher consumption on growth is negative. But the long-run effect of higher consumption on growth is *positive*.

These results raise interesting questions for standard theory. We offer these suggestive explanations of our findings for the long run:

The negative effect of more advertising on consumption may indeed lend support to arguments in line with Dixit and Norman (1978). However, their conclusion focuses on welfare whereas we find that more advertising may ultimately be bad for more consumption at the macro level. Of course, our results only hold relative to GDP. An alternative viewpoint would be that more advertising does not foster more consumption - at least not in Germany. Furthermore, the result has suggestive implications for consumer sovereignty that are discussed in the main text.

The consumption-growth result is peculiar. It would cast doubt on standard growth models - at least for Germany. It might also be taken to imply for accumulation-driven growth models that investment may actually be driven by

[8] In this context, Jung and Seldon (1995) find that consumption and advertising are characterized by a feedback relationship in the U.S. according to which advertising "causes" consumption which in turn "causes" advertising.

consumption. This would suggest that some form of accelerator in the spirit of e.g. Samuelson (1939) is at work determining investment and economic growth - at least in Germany.[9]

The paper is organized as follows. Section 2 describes the data and presents some descriptive statistics. In section 3 we analyze stationarity and Granger-causality. Section 4 derives models capturing the times series properties of the data. Section 5 concludes.

2 The Hypothesis and the Data

It is convenient to restate succinctly the main claim we wish to test.

Hypothesis Advertising is good for consumption. Consumption is good for output and output growth. Hence, advertising is good for economic growth.

We test this claim using German, yearly data for the period 1950-2000. As our focus is on economic growth and, thus, on the long run, 50 years of observations serve our purposes well.[10] The data sources and precise definitions of our variables are presented below.

2.1 The growth rate

The yearly growth rate of *real*, aggregate GDP is defined in a standard way as

$$g_t = (Y_t^r - Y_{t-1}^r)/Y_t^r$$

where Y_t^r denotes real, aggregate GDP in period t. Data for g_t are taken from publications of the Federal Statistical Office, Germany, (Statistisches Bundesamt).[11] For this paper we use the yearly growth rates of real GDP in constant prices.

[9] For a recent publication that models growth as positively depending on the consumption share see, for example, Commendatore, D'Acunto, Panico, and Pinto (2003).

[10] Similar times spans and so number of observations have been used for empirical arguments in the growth literature. See, for example, Jones (1995). For a multivariate time series analysis with a relatively smaller sample of twenty nine observations see, for instance, Teräsvirta (2004).

[11] In particular, we have used Table 23.2 of Statistisches Bundesamt (2004b), and Statistisches Bundesamt (2004c), Table 1.3.2.

Data are available for the period 1950-1970 in constant prices of 1991 and for the period 1971-2000 in constant prices of 1995.[12]

Note we do not use the growth rate of GDP per capita as is often done in growth empirics. As GDP growth is a prerequisite for growth of GDP per capita and since the population in Germany has hardly grown, except for the one-time population shock due to unification, the results are (perhaps heroically) taken to apply to both concepts. Even if this does not apply, do we believe that concentrating on the growth rate of GDP is interesting in its own right and relevant for growth research.

2.2 The consumption share

Various sources provide data on the consumption share. We have chosen to construct our measure of the consumption share as much as possible from German data sources. First, we define the consumption share as

$$c_t = C_t^N / Y_t^N,$$

where C_t^N and Y_t^N denote the *nominal* aggregate consumption expenditures of the private sector and the *nominal* aggregate GDP at time t in billions of Euros.[13] c_t is taken to proxy for the same variable when consumption and output would have been measured in real terms. This procedure is often applied in the growth empirics literature and is followed here.

2.3 The advertising share

Investment in advertising comprises such expenditures as those on salaries, media and the production of means of publicity. The German Central Association of

[12] Thus, no growth rate is provided for 1970. To circumvent the problem of missing values in software packages that we used for our analysis we choose to specify a value of the growth rate for 1970. All checks revealed that the growth rate of 1970 was not an outlier in the evolution of growth rates over the immediate time period leading to and starting from 1970. It was around 5 percent. Thus, we have chosen to set g_{70} at the average value of g_{69} and g_{71} which was 5.4 percent. This also seems a reasonable choice when checking for the growth rate of German GDP in 1970 on the internet.

[13] It is important to note that we concentrate on private sector consumption. Thus, our consumption share does *not* include government consumption. See the appendix for more details.

Advertising Business (Zentralverband der deutschen Werbewirtschaft, ZAW) in Bonn publishes data on these expenditures for the whole industry and for various years.[14]

The data refer to gross expenditures in advertising and are expressed in billions of Euros and are, thus, in nominal terms. In order to relate to the growth rate we constructed the variable

$$ad_t = (\text{Advertising Expenditure})_t / Y_t^N$$

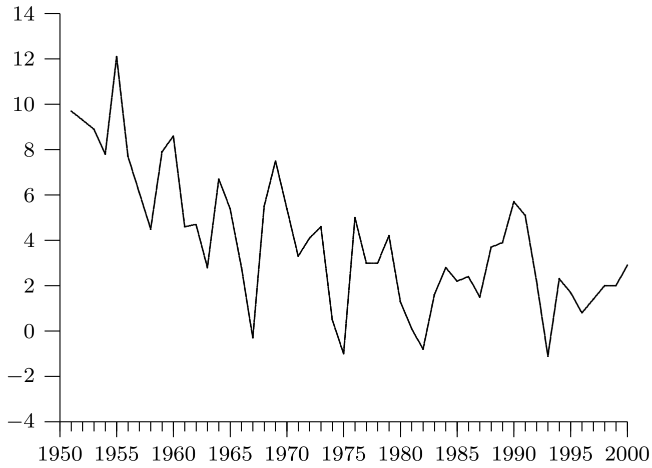
so that ad_t denotes the advertising share in nominal GDP at time t. We again assume that ad_t is a proxy for the same variable when investment in advertising and output would have been measured in real terms.

2.4 Descriptive Statistics

The growth rate of German GDP has fluctuated quite a lot over the last fifty years as Figure 1 demonstrates. Around 1950 the growth rate was 10 percent and raises to a maximum of 12 percent in 1955. From the figure one clearly identifies the recessions of 1967, 1974 (first oil price shock), 1981 (second oil price shock) and 1993 when the growth rate fell to zero and approximately minus one percent, respectively. Since 1970 the German growth rate fluctuates between -1 percent and +5 percent. Furthermore, for the period after 1990 it looks as if there is a downward trend in the growth rate, which may be interpreted as being a consequence of German reunification.

[14] See ZAW (1950-2000), Table "Investitionen in Werbung" (Investment in Advertising). The data were courteously assembled for and made available to us by ZAW.

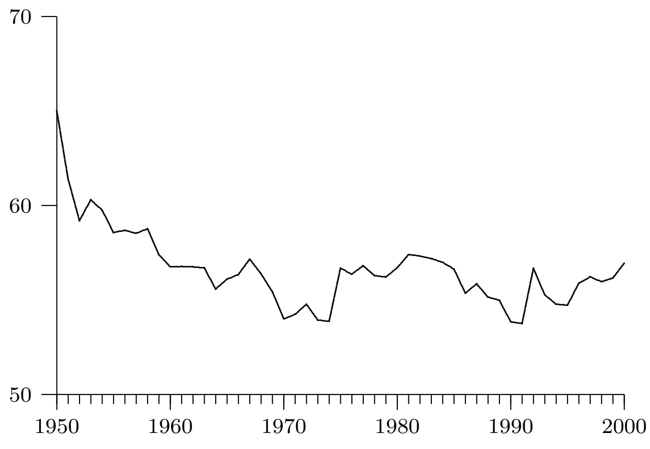
Figure 1: The Growth Rate of GDP (in percentage points)



Source: Statistisches Bundesamt and own calculations

In comparison to the growth rate the (private) consumption share has fluctuated far less. The consumption share starts at a high value of 65 percent in 1950 and seems to fall to lower levels subsequently. Since the 1960s the consumption shares have been somewhere between 54 percent and 58 percent. Interestingly, they are quite high during, or right after the recessions of 1967 and 1981-1984. On the other hand, preceding the recession of 1974 the consumption shares for the years 1970 to 1974 are relatively low. Since 1990 the consumption share for all of Germany does not seem to follow a particular trend.

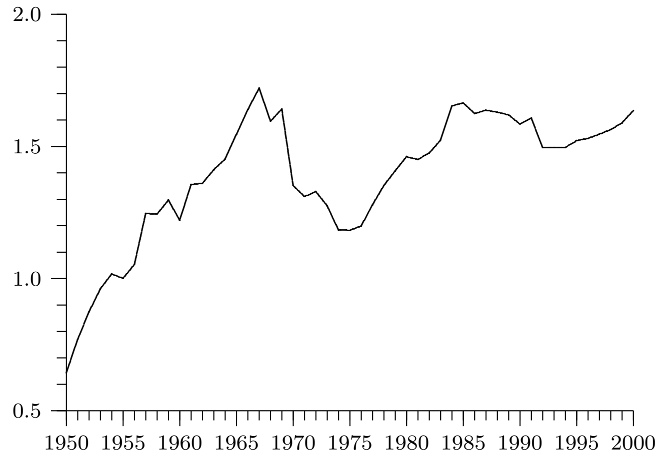
Figure 2: The Share of Private Consumption (in percentage points)



Source: Statistisches Bundesamt and own calculations

Figure 3 depicts the evolution of the advertising share. Advertising investment has increased from 0.64 percent of GDP in 1950 to a maximum of 1.72 percent in 1967. The advertising share then falls to a level of 1.2 percent in 1974 and then increases again. There does not seem to be a clear trend in the series after 1985, even after reunification. Since 1995, however, the advertising share appears to increase.

Figure 3: The Advertising Share (in percentage points)



Source: Zentralverband der Deutschen Werbewirtschaft (ZAW) and own calculations

The following table summarizes the main descriptive properties of the series:

Table 1: Descriptive Statistics

Series	Period	Obs.	Mean	Maximum	Minimum	Std. Dev.
g_t	1951-2000	49	3.930	12.10	-1.10	3.02
c_t	1950-2000	50	0.570	0.65	0.53	0.02
ad_t	1950-2000	50	0.014	0.017	0.006	0.002

Over the sample period the mean growth rate of GDP was 3.93 percent, the mean consumption share was 57 percent, and that for the advertising share amounted to 1.4 percent. We note that the means of the series are all positive.

3 Stationarity and Granger-causality

3.1 Stationarity

We wish to relate the time series of three economic variables to each other. In order to apply standard econometric techniques the series must at least have the property of (weak) stationarity. The latter is given when (a) the mean of a series x_t is independent of t, (b) the variance of x_t is independent of t, and (c) the covariance between x_t and x_s depends only on the difference between t and s (and not on t or s separately).[15]

Looking at the graphs suggests that the series fluctuate around some positive value and that ad_t appears to be trending upwards, whereas g_t seems to have a negative trend. However, visual inspection may lead one astray, as statistical concepts often prove differently. This we will check next.

In oder to test for (weak) stationarity one has to assume whether the series has a deterministic trend or is fluctuating around some particular value. If the latter is zero, the series is a random walk. As the descriptive statistics imply that the mean values of the three series are non-zero, the latter assumption is not checked any further.

For analyzing whether a series is (weakly) stationary it is common to employ the Augmented Dickey Fuller (ADF) test. If we do not know whether a series fluctuates around a constant term and/or has a trend, Hamilton (1994), p. 501, suggests that one tests whether the estimated coefficient ρ in the regression with a constant term

$$\Delta x_t = \alpha + \rho x_{t-1} + \sum_{i=2}^{p} \beta_i \Delta x_{t-i+1} + \epsilon_t \tag{1}$$

where $\Delta x_t \equiv x_t - x_{t-1}$, or whether ρ in the regression with a constant term and a trend

$$\Delta x_t = \alpha + \delta \cdot t + \rho x_{t-1} + \sum_{i=2}^{p} \beta_i \Delta x_{t-i+1} + \epsilon_t \tag{2}$$

is significantly different from zero.[16] The recommendation to proceed in this way

[15]See, for example, Harvey (1990), p. 23, Hamilton (1994), p. 45, or Greene (2003), p. 612.

[16]Of course, we also assume that the error terms in these regressions have the standard prop-

is particularly made for series that have non-zero means, as in our case.[17] Here α represents the presence of a constant term and δ that of a time trend. In both expressions the term $\sum_{i=2}^{p} \beta_i \Delta x_{t-i+1}$ is included in order to correct for possible serial correlation in the series and, in particular, the error terms. The unknown here is the order p of sum of the (first order) lags in Δx_{t-i+1}.

To determine that lag structure we follow a "top down" approach for each series. We start with ten lags and, hence, with a regression of the form

$$x_t = \beta_0 + \beta_1 x_{t-1} + \beta_2 x_{t-2} + \ldots + \beta_{10} x_{t-10} + u_t$$

where $x_t = g_t, c_t$, or ad_t. In each case we found support for a simple AR(1) process $x_t = \beta_0 + \beta_1 x_{t-1} + u_t$. The (heuristic) criteria were t-statistics, R^2, the Durbin-Watson statistic and other criteria such as the Aikaike and Schwartz information criterion as indicators of the quality of the models, especially of the presence of serial correlation in the error terms. (See appendix B.) The results imply that the terms $\sum_{i=2}^{p} \beta_i \Delta x_{t-i+1}$ do not play any important role in the Augemented Dickey Fuller Tests. Thus, serial correlation does not seem to be a problem for the error terms so that we perform (simple) Dickey Fuller tests of the form

$$M1: \quad \Delta x_t = \alpha + \rho x_{t-1} + \epsilon_t \quad , \quad M2: \quad \Delta x_t = \alpha + \delta \cdot t + \epsilon_t. \tag{3}$$

with $\epsilon_t \sim N(0, \sigma^2)$. The results of these tests are presented below.

erties of being normally distributed with a zero mean and a constant variance, $\epsilon_t \sim N(0, \sigma^2)$.

[17]The null hypothesis, H_0, for these tests is $\rho = 1$. Thus, a stationary series would have $-1 < \rho < 1$. Hence rejecting H_0 under the usual criteria of statistical significance implies that the alternative hypothesis of (weak) stationarity would then command higher probability and would be preferred.

Table 2: Tests for Stationarity

Variable	M	ADF	p-val.	$\text{ADF}^{**}_{0.95}$	$\text{ADF}^{*}_{0,90}$	α	δ	R^2	DW	Obs.
g_t	1	-3.393	0.011	-2.933	-2.601	0.013 (2.44)		0.196	2.052	49
g_t	2	-4.461	0.002	-3.504	-3.182	0.042 (3.51)	-0.001 (-2.68)	0.305	1.865	49
c_t	1	-5.063	0.000	-2.930	-2.600	0.169 (5.01)		0.348	1.876	50
c_t	2	-4.456	0.002	-3.500	-3.180	0.194 (4.29)	-0.000 (-0.826)	0.357	1.824	50
ad_t	1	-3.249	0.017	-2.930	-2.598	0.002 (3.55)		0.180	1.845	50
ad_t	2	-2.832	0.185	-3.500	-3.180	0.002 (3.47)	-0.000 (0.80)	0.191	1.809	50

T-statistics in parentheses. M refers to which model is contemplated. $\text{ADF}^{**}_{0.95}$ ($\text{ADF}^{*}_{0,90}$) denotes the critical value at the 95 % (90 %) of statistical significance for the rejection of the hypothesis of a unit root, $\rho = 1$. The critical values are from MacKinnon (1991) and used by EVIEWS 4.0 (2000). The column "p-value" presents the probability of a unit root.

The hypothesis of the series not being (weakly) stationary can broadly be rejected at the 95 percent level of statistical significance. This is because the ADF statistic of the sample is smaller than the critical values $\text{ADF}^{**}_{0.95}$ ($\text{ADF}^{*}_{0,90}$). According to that criterion the hypothesis that the series g_t and c_t are not (weakly) stationary at the 95% (and higher) level of statistical significance can be rejected, no matter whether we include a constant, or a constant and a trend for the test. For the advertising share we find that the series appears to be stationary if we only include a constant, $ADF = -3.249 < -2.920 = ADF^{**}_{0.95}$. However, if we also include a trend term the hypothesis of non-stationarity cannot be rejected at the 90% level. Although the value of -2.832 is not too far from the critical value of -3.179, the probability of rejecting the "H_0: Non-stationarity" is lower than 90 percent. However, it is still higher (approximately 81 percent) than a probability that would lead one to definitely reject the alternative hypothesis of stationarity, i.e. "H_a: Stationarity".[18]

[18]Model 2 (M 2) in equation (3) may look more general than M 1 since the test is about both a constant and a trend. One way to get stationarity would be to take first differences of ad_t. Tests then reveal that the series Δad_t seems to be stationary. However, first differences entail an information loss. Striking a balance here we opt to attach more disadvantage of losing information than to the loss in probability when rejecting the hypothesis of non-stationarity. On this see, for example, Goldrian (1995).

Thus, in the following analysis we will proceed under the statistically backed hypothesis that the series for the growth rate g_t, the consumption share c_t and the advertising share ad_t are (weakly) stationary.

3.2 Causality

In this section we check by pairwise comparisons if one series helps to predict another one. This is the concept introduced by Granger (1969) and has become known as "Granger-causality". It should be borne in mind that this concept should not be taken as a philosophical concept in the sense of "cause and effect". Instead, "Granger-causality" is a statistical property of time series and rather refers to the possibility of temporal predictability of a series x_t by another series y_t. See, for example, Harvey (1990), p. 304.

The starting point is to look at regressions of the form

$$x_t = \alpha_0^1 + \alpha_1^1\, x_{t-1} + \ldots + \alpha_l^1\, x_{t-l} + \beta_1^1\, y_{t-1} + \ldots \beta_l^1\, y_{t-l} + \epsilon_t \tag{4}$$

$$y_t = \alpha_0^2 + \alpha_1^2\, y_{t-1} + \ldots + \alpha_l^2\, y_{t-l} + \beta_1^2\, x_{t-1} + \ldots \beta_l^2\, x_{t-l} + u_t \tag{5}$$

where by assumption the error terms are normally distributed with $\epsilon_t \sim N(0, \sigma_\epsilon^2)$ and $u_t \sim N(0, \sigma_u^2)$.

The test then implies performing an F-test on the null hypothesis

$$H_0: \quad \beta_1^j = \beta_2^j = \ldots = \beta_l^j = 0$$

where $j = 1, 2$ depending on the direction of "Granger-causality" that is being maintained. In this context it is useful to use the notation below.

Table 3: Patterns of Causality

Description	Notation
(1) x and y are unrelated	$(x\ ,\ y)$
(2) Instantaneous causality only	$(x - y)$
(3) x causes y only and not instantaneously	$(x \rightarrow y)$
(4) x causes y only and instantaneously	$(x \Rightarrow y)$
(5) y causes x only and not instantaneously	$(x \leftarrow y)$
(6) y causes x only and instantaneously	$(x \Leftarrow y)$
(7) Feedback, not instantaneously	$(x \leftrightarrow y)$
(7) Feedback and instantaneous causality	$(x \Leftrightarrow y)$

Furthermore, we use the symbol ”$\neg$” for ”not”. Thus, $\neg(x \rightarrow y)$ would denote that ”x does not, only and not instantaneously, Granger-cause y”. The meaning of ”instantaneous” in this context is explained farther below.

It is standard to test for relationships of the form $\neg(x \rightarrow y)$ first. Given our definitions the results for the simple ”Granger-causality” tests of our data for hypotheses of the form $\neg(x \rightarrow y)$ are summarized below.

Table 4: Granger-Causality Tests I

	Lag 1			Lag 2			Lag 3			Lag 4		
H_0	Obs.	F	Prob.	Obs.	F	Prob.	Obs.	F	Prob.	Obs.	F	Prob.
$\neg(c_t \rightarrow ad_t)$	50	1.914	0.173	49	1.026	0.367	48	0.195	0.899	47	0.342	0.848
$\neg(ad_t \rightarrow c_t)$	50	4.090	0.049	49	4.322	0.019	48	3.404	0.026	47	2.872	0.358
$\neg(g_t \rightarrow ad_t)$	49	0.791	0.378	48	0.746	0.480	47	0.767	0.519	46	0.602	0.664
$\neg(ad_t \rightarrow g_t)$	49	2.306	0.136	48	1.742	0.187	47	0.528	0.666	46	0.834	0.512
$\neg(g_t \rightarrow c_t)$	49	0.235	0.630	48	1.146	0.327	47	0.477	0.700	46	0.441	0.778
$\neg(c_t \rightarrow g_t)$	49	10.468	0.000	48	5.542	0.007	47	2.372	0.085	46	1.631	0.187

F denotes the F-statistic.

We have chosen a maximum lag length of four, because we do not think that a change in advertising investment impacts on consumption after more than four years.[19] The results then suggest the following when concentrating on a conventional 5 percent (or even 10 percent) level of statistical significance.

[19] We have checked longer lags, but the qualitative features of the results do not change. In particular, the most significant results all seem to be captured by looking at 4 lags. The results for longer lags are available on request.

$(ad_t \rightarrow c_t)$:	Lag 1, 2, 3, 4	$\neg(c_t \rightarrow ad_t)$:	Lag 1, 2, 3, 4	$(c_t \rightarrow g_t)$:	Lag 1, 2, 3
$(c_t\ ,\ g_t)$:	Lag 4	$\neg(g_t \rightarrow c_t)$:	Lag 1, 2, 3, 4	$(ad_t\ ,\ g_t)$	Lag 1, 2, 3, 4

In most cases there is no Granger-causal relationship. In particular, there seems to be no "causal" relationship between advertising and growth. We find Granger-causality between the consumption share and the growth rate for lags 1, 2, and 3, and between the advertising and the consumption share for all considered lags. This leads us to the hypothesis that bivariate relationships exist between ad_t and c_t, and between c_t and g_t. The first case may justify regressing c_t on ad_t, and the second one provides an argument for regressing g_t on c_t. Furthermore, the results imply that such regressions might command the highest probability when regressing c_t on ad_t when introducing a lag of 2. This is because the hypothesis of "Non-Granger-causality" in this case is lower (1.9 percent probability) than for the other lags. For a regression of g_t on c_t a lag structure of order one seems to be a reasonable choice, given the lowest probability (zero percent) of rejecting "Non-Granger-causality" in that case.

Although we will use similar arguments below, we cannot apply them here since we also have to check for instantaneous Granger-causality.

3.3 Instantaneous Granger-causality

Instantaneous Granger-causality is given when we also allow for a contemporaneous effect of a variable y_t on x_t. More precisely, we check in a regression with the standard assumptions on the error term

$$x_t = \alpha_0^1 + \alpha_1^1\, x_{t-1} + \ldots + \alpha_l^1\, x_{t-l} + \beta_0^1\, y_t + \beta_1^1\, y_{t-1} + \ldots \beta_l^1\, y_{t-l} + \epsilon_t \qquad (6)$$

whether the coefficient β_0^1 is different from zero. The difference between equations (4) and (6) is that we now also allow (contemporaneous) y_t, and possible lags thereof, to have an effect on x_t.

This concept is important in our context, because we use annual data and the association between our variables may change relatively quickly within a year. However, our focus remains the long run. Thus, even if intra-annual changes matter, they will have an impact on the long run.

To test for instantaneous causality, $(y - x)$, the null hypothesis is $H_0 : \beta_0 = 0$, no matter how many other lags of y_t are included in the regression. A simple F-test for one variable or a conventional t-test for the statistical significance of y (in the regression for x) can then be employed.[20] Notice that this test is symmetric, that is, if $(y - x)$, then also $(x - y)$ holds true. Thus, the concept does not establish a "causal" direction.

To test for "y causes x only and instantaneously", i.e. $(y \Rightarrow x)$, the null hypothesis is $H_0 : \beta_0 = \beta_1 = \cdots = \beta_l = 0$. Again this can be tested using an F-test on the joint significance of $y_t, y_{t-1}, \cdots, y_{t-L}$ having a bearing on x_t.

Table 5: Granger-Causality Tests II

	Lag 1			Lag 2			Lag 3			Lag 4		
H_0	Obs.	F	Prob.	Obs.	F	Prob.	Obs.	F	Prob.	Obs.	F	Prob.
$\neg(c_t - ad_t)$	50	3.774	0.058	49	3.972	0.053	48	3.320	0.076	47	4.319	0.045
$\neg(c_t \Rightarrow ad_t)$	50	2.901	0.065	49	2.054	0.120	48	0.984	0.427	47	1.161	0.347
$\neg(ad_t \Rightarrow c_t)$	50	4.053	0.024	49	4.400	0.009	48	3.527	0.015	47	3.362	0.013
$\neg(g_t - ad_t)$	49	0.848	0.362	48	1.205	0.279	47	0.995	0.324	46	0.742	0.394
$\neg(g_t \Rightarrow ad_t)$	49	0.818	0.448	48	0.902	0.448	47	0.824	0.518	46	0.627	0.681
$\neg(ad_t \Rightarrow g_t)$	49	1.573	0.219	48	1.568	0.211	47	0.645	0.634	46	0.811	0.550
$\neg(g_t - c_t)$	49	7.870	0.007	48	9.037	0.004	47	10.970	0.002	46	9.539	0.004
$\neg(g_t \Rightarrow c_t)$	49	4.070	0.023	48	3.920	0.015	47	3.190	0.023	46	2.342	0.061
$\neg(c_t \Rightarrow g_t)$	49	9.951	0.000	48	7.397	0.000	47	4.965	0.002	46	3.514	0.011

F denotes the F-statistic.

From table (5) the following can be inferred when taking a 10 percent level of statistical significance as our benchmark:

There seems to be a feedback relationship between g_t and c_t. Thus, we find $(g_t \Leftrightarrow c_t)$ for all four lags. There is instantaneous causality between ad_t and c_t, that is, $(ad_t - c_t)$, for all lags. Furthermore, for all lags we find "ad_t causes c_t only and instantaneously", $(ad_t \Rightarrow c_t)$. For lag 1 there appears to be a feedback relationship $(ad_t \Leftrightarrow c_t)$. It is a surprise to find that, as in the simple Granger-causality tests, there is no "causal" relationship between growth and the advertising share, $(ad_t \;,\; g_t)$, at a 10 percent level of statistical significance, even when checking for instantaneous causality. This surely casts doubt on an important part of the hypothesis that we wish to test.

[20] Usually, t-statistics for β_0 are reported. But since a squared t-statistic is the F-statistic in a single variable case such as here, we report the F-statistic for convenience.

3.4 Summary

In terms of our hypothesis the most important finding is that there is no "causal" relationship between advertising and growth.

Result 1 *For the advertising share and the rate of economic growth in Germany for annual data from 1950-2000 we do not find any Granger-causal relationship. Thus, the statement that advertising "causes" growth may be problematic.*

Recall that Granger-causality is not transitive. Given our evidence that no direct, "causal" relationship exists, we do not analyze this relationship any further. We think that the relationship is probably more complicated and may be non-linear. This is discussed further below.[21]

As we find sufficient probability of the assumption of causal as well as feedback relationships for the pairs g_t and c_t, as well as for ad_t and c_t we will analyze these pairs in more detail below.

4 Econometric Models

As a starting point to build models that capture the relationships between our variables best, we look at the cross-correlations of our data. This also reveals whether there are highly linear associations between our variables so that multicollinearity might be a problem.

It is well known that correlations between variables in excess of 0.8 indicate - as a rule of thumb - that multicollinearity might be a problem in any regression featuring highly collinear variables as independent variables.[22]

[21] The following argument is also possible. Suppose the relationship is non-linear. Finding insignificant results in a linear model may also be an indication that the relationship is at some optimum of an underlying non-linear relationship. Of course, the shape of that would have to be known. Optimality would then imply that we are at a (local) maximum or minimum. Given this interpretation, one may also argue that our result just captures that there is an inverted U-shaped relationship between ad_t and g_t, and that the value of ad_t is optimal for g_t. We plotted g_t (y-axis) against ad_t (x-axis) and fitted a quadratic curve to find that the relationship appears to be a U-shaped one, however. We will leave a more detailed analysis of this question for future research.

[22] When multicollinearity is present then, this may affect the analysis in the following way: (a) Wide swings in the parameter estimates may be produced by small changes in the data. (b) The coefficients may have very high standard errors and low significance levels even though they are jointly significant. The R^2 for the regression is quite high. (c) The coefficients may have the 'wrong' sign or implausible magnitudes. See Greene (2003), p. 57.

4.1 Multicollinearity and Cross-Correlations

Table 6: Correlation Matrix

	ad_t	ad_{t-1}	ad_{t-2}	c_t	c_{t-1}	c_{t-2}	g_t	g_{t-1}
ad_{t-1}	0.93*	1.00						
ad_{t-2}	0.87*	0.94*	1.00					
c_t	-0.47	-0.60	-0.72	1.00				
c_{t-1}	-0.43	-0.53	-0.65	0.83*	1.00			
c_{t-2}	-0.45	-0.53	-0.62	0.73	0.84*	1.00		
g_t	-0.51	-0.48	-0.50	0.31	0.53	0.65	1.00	
g_{t-1}	-0.56	-0.55	-0.53	0.35	0.36	0.58	0.65	1.00
g_{t-2}	-0.60	-0.59	-0.59	0.44	0.40	0.43	0.44	0.67

Values greater than 0.80 are marked by *. Number of observations: 48.

Thus, there seems to be a problem with ad_t, ad_{t-1} and ad_{t-2}. There also is a problem with c_t, c_{t-1} and c_{t-2}. A number of other interesting results emerges for the table: First, all the cross-correlations between the consumption and the advertising shares are negative. Furthermore, all the cross-correlations between advertising share and the growth rate are negative, and all those between the consumption share and the growth rate positive.

This suggests that one is likely to get a negative (instantaneous) relationship between advertising and consumption, as well as advertising and growth. But we might expect a positive relationship between growth and consumption.

Given this information on correlations that do not reveal anything about causality per se, we now turn to a multivariate analysis, starting with a concept that does not presuppose any causality.

4.2 Vector Autoregressive Regression (VAR) Analysis

In our context, VARs have the advantage that they do not assume any a priori causality. Thus, they serve our purposes well since we have found that feedback relationships may exist between our variables of interest.

4.2.1 Theory

Consider the following vector autoregressive process of the order p.

$$\begin{bmatrix} x_t \\ y_t \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \sum_{p=1}^{P} \begin{bmatrix} a_{11}^p & a_{12}^p \\ a_{21}^p & a_{22}^p \end{bmatrix} \begin{bmatrix} x_{t-p} \\ y_{t-p} \end{bmatrix} + \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{bmatrix} \tag{7}$$

where a_{ij}^p and $i, j = 1, 2$ denotes the $p-$lag coefficient in the coefficient matrix measuring the (linear) effect of the j-th variable at lag p on the i-th dependent variable at time t in the system. By assumption the errors terms $\epsilon_{i,t}$ are assumed to be normally distributed, uncorrelated over time and across the equations, with a zero mean and constant variance each. The μ_i denote the constants in the regression for the i-th dependent variable.

We are interested in short and long-run effects of our variables. In a VAR the estimated coefficients for a_{12}^1 would capture the *immediate* impact of a shock in y_{t-1} (e.g now) on x_t (e.g. next year). Likewise, a_{21}^1 would capture the *immediate* effect of a change in x_{t-1} on y_t.

For the long-run we have to ask the following: Once the system has been shocked and reacted to it, there will be an overall, worked-out effect on the variables in the long-run. The long-run response of a variable is obtained as follows: First, we re-express our system in matrix form. Let

$$\mathbf{z_t} \equiv \begin{bmatrix} x_t \\ y_t \end{bmatrix}, \mu \equiv \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}, \mathbf{A_p} \equiv \begin{bmatrix} a_{11}^p & a_{12}^p \\ a_{21}^p & a_{22}^p \end{bmatrix}, \quad \epsilon_\mathbf{t} \equiv \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{bmatrix}$$

Then equation (7) can be represented as

$$\mathbf{z_t} = \mu + \mathbf{A_1 z_{t-1}} + \cdots + \mathbf{A_P z_{t-P}} + \epsilon_\mathbf{t}.$$

We can then reformulate this process in its Wold moving average (MA) representation as follows: Using the concept of a lag operator, which is defined as $L^i x_t = x_{t-i}$ for $i = 1, \cdots, P$, we have

$$\begin{aligned} \left[\mathbf{1} - \mathbf{L^1 A_1} + \cdots + \mathbf{L^P A_P}\right] \mathbf{z_t} &= \mu + \epsilon_\mathbf{t} \\ \mathbf{z_t} = \left[\mathbf{1} - \mathbf{L A_1} + \cdots + \mathbf{L^P A_P}\right]^{-1} \mu &+ \left[\mathbf{1} - \mathbf{L A_1} + \cdots + \mathbf{L^P A_P}\right]^{-1} \epsilon_\mathbf{t}. \end{aligned} \tag{8}$$

where $\mathbf{1}$ denotes the identity matrix. The first $p \leq P$ elements of the inverse matrix represent the response of the system due to (unforseen) innovations at some date t in the system captured by changes in ϵ_t. These first $p \leq P$ elements with $p = 1, 2, \cdots, P$ of the matrix $\left[1 - L\mathbf{A_1} + \cdots + \mathbf{L^P A_P}\right]^{-1}$ are usually called *dynamic multipliers* and capture how the system reacts at that date due to an innovation in a particular variable in the system. They are used when looking at the *impulse response* of the system due to an innovation in a variable. In particular, the *short-run* multiplier is given by a_{ij}^i and captures the immediate effect on impact on the system.

In the long-run the system is stable, that is, stationary and settled at an equilibrium. This steady state situation is given when $\mathbf{z_t} = \cdots = \mathbf{z_{t-p}} = \mathbf{z}^*$, where $\mathbf{z}^*$ does not depend on time anymore. In a long-run equilibrium the expectations are met so that the error terms in ϵ_t should be zero. In that case

$$\mathbf{z_t}^* = \left[\mathbf{1} - \mathbf{A_1} + \cdots + \mathbf{A_P}\right]^{\mathbf{-1}} \mu$$

which denotes the *steady state value* of z_t, and where the elements of the inverse matrix are called *long-run* dynamic multipliers. Let $\mathbf{\Gamma}$ denote that matrix, i.e. $\mathbf{\Gamma} \equiv \left[\mathbf{1} - \mathbf{A_1} + \cdots + \mathbf{A_P}\right]^{\mathbf{-1}}$.

For a growth analysis they are particularly intuitive. The elements of $\mathbf{\Gamma}$ capture the long-run (underlying) relationships. Among other things the elements of $\mathbf{\Gamma}$ tell one how a *steady state* element of $\mathbf{z}^*$ changes, if, for instance, another element of that vector $\mathbf{z}^*$ changes.[23] Thus, the long-run multipliers capture how *steady state* variables are related in a multivariate, time series setting, if another *steady state* variable changes.

To see more clearly what this involves we consider a simple VAR of order one. If $P = 1$, then the impact multiplier is a_{ij}^1 of variable j on variable i at date 1. Recalling the definition of $\mathbf{A_1}$ above, it is then easy to show that the *long-run multipliers* in a first order VAR are given by

$$\begin{aligned} \mathbf{\Gamma} \equiv \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix} = \left[\mathbf{1} - \mathbf{A_1}\right]^{\mathbf{-1}} &= \left[\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} - \begin{bmatrix} a_{11}^1 & a_{12}^1 \\ a_{21}^1 & a_{22}^1 \end{bmatrix}\right]^{-1} \\ &= \Delta \begin{bmatrix} 1 - a_{22}^1 & a_{12}^1 \\ a_{21}^1 & 1 - a_{11}^1 \end{bmatrix} \end{aligned} \quad (9)$$

[23]Of course, that change would have to come from the other element of μ really. For instance, we can ask how x^* changes if μ_2, associated with the equation for y^*, changes by some small amount. Later we see that Γ yields a similar answer to the question of what happens to z_t in the long run if there is an unexpected shock in ϵ_t.

where $\Delta = \dfrac{1}{1 - a_{11}^1 - a_{12}^1 - a_{12}^1 \cdot a_{21}^1 - a_{22}^1 + a_{11}^1 \cdot a_{22}^1}$. For instance, to get the long-run response of variable x_t, i.e. x^* in steady state, due to a change in y_t, that is, y^* in steady state, in a VAR(1) like in equation (7) would be to look at the value of $\gamma_{12} = \Delta \times a_{12}^1$. These long-run multipliers will play an important role below.

4.2.2 Estimation

In section 3 we found support of the hypothesis that the variables are stationary when including a constant in the regressions. We generally did not find enough support to include a time trend for the analysis. Thus, we consider VARs with a constant and no time trend.

Motivated by the "causality" results we consider two models. One analyzes the relationship between ad_t and c_t, and the other one the relationship between c_t and g_t. For each of the two VAR specifications we first checked the optimal lag structure according to the Akaike, Final Prediction Error, Hannan-Quinn, and Schwarz Criteria. All of them suggest that the optimal lag length for each VAR is one period. Thus, we take the VAR lag length to be one in each model.[24]

4.2.3 Model 1: c_t and ad_t

The estimation results for the first model are presented below (with standard errors in parentheses).

$$\begin{bmatrix} c_t \\ ad_t \end{bmatrix} = \begin{bmatrix} \underset{(0.053)}{0.254} \\ \underset{(0.004)}{-0.004} \end{bmatrix} + \begin{bmatrix} \underset{(0.081)}{0.583} & \underset{(0.679)}{-1.373} \\ \underset{(0.007)}{0.009} & \underset{(0.056)}{0.923} \end{bmatrix} \begin{bmatrix} c_{t-1} \\ ad_{t-1} \end{bmatrix} + \begin{bmatrix} u_{1,t}^2 \\ u_{2,t}^2 \end{bmatrix}. \quad (10)$$

The estimated coefficients for $a_{11}^1, a_{12}^1, a_{22}^1$ and μ_1 are all statistically significant at the 5 percent level, whereas the estimate for a_{21}^1 is statistically insignificant with probability of 0.166. The latter measures the effect of consumption on advertising in the second row of the VAR. This effect may therefore be zero. Also μ_2 may be zero with a probability of 0.361. For our analysis, we have decided to keep

[24]For the estimation we used *JMulTi* by Lütkepohl and Krätzig (2004) to obtain our results. The programme is available free of charge at *www.jmulti.de*.

insignificant results in the VAR in order to keep as much, even if redundant, information as possible.

We have checked the goodness of the model by a battery of standard tests. (See appendix C.) As regards serial correlation of the residuals, we find that the plots of the residuals, their autocorrelations and cross-correlations do not show convincing signs of serial correlation. The portmanteau test rejects serial correlation with a probability of 89 percent. The LM test for autocorrelation (Breusch-Godfrey) with five lags has a probability of 0.16, with the null hypothesis of there being no correlation. This is not too high, but does not lead us to accept the alternative. The test for joint non-normality due to Doornik and Hansen (1994) rejects non-normality with a probability of 100 percent. The Jarque-Bera test for normality for each residual reveals no problems for the innovations in c_t, i.e. $u(c,t)$, but rejects normality in $u(ad,t)$. Of course, this is of concern for some tests and t-statistics. We tested whether that is no autoregressive conditional heteroskedasticity (ARCH) in the residuals and found that that had a probability of 30 percent for $u(c,t)$, and 99 percent for $u(ad,t)$. The multivariate ARCH-LM test with five lags for no ARCH has a probability of 45 percent.

We also checked for structural breaks. The plots of the cumulate sum of the residuals and the squared residuals, CUSUM and CUSMSQ, do not suggest an important break point problem. The Chow tests for sample-split, break-point, or forecasts identify 1971 and 1991/1992 as problematic.[25] However, never do all three tests identify breaks simultaneously. Given this, probably very strong, criterion we argue that structural breaks are not a severe problem for our analysis. We also present recursive parameter estimates in the appendix and do not find clear indications of parameter instability.

Thus, we think that the model is not performing too badly as regards the standard assumptions. As our focus is on the point estimates for the ensuing analysis, we will keep our model as capturing the time series association of our

[25] For a more detailed explanation of the tests see, for example, Lütkepohl, H. (2004), p. 135. We used the bootstrapped Chow test statistics as provided by JMulTi, and were, thus, able to evaluate almost every year in the sample. We found that the forecast test never identifies a break. For the other tests we note the following: For the year 1971 we do not have a good guess why there should be a break in a system with ad and c. Maybe it was the important change in the German government in 1969 that may have caused different behaviour. The other date is probably driven by German re-unification.

variables sufficiently well.

Next, we looked at the impulse responses from our model. We choose to represent them up to 20 periods, because we believe that such a time period is long enough to capture the economically important responses. Figures 4 and 5 depict the impulse responses of one of the variables due to an innovation in the other variable.[26]

Figure 4: Impulse Response of c_t due to innovation in ad_t

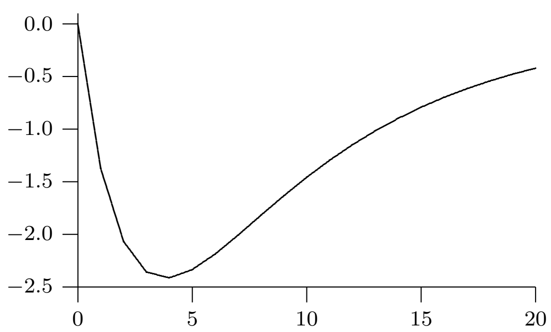
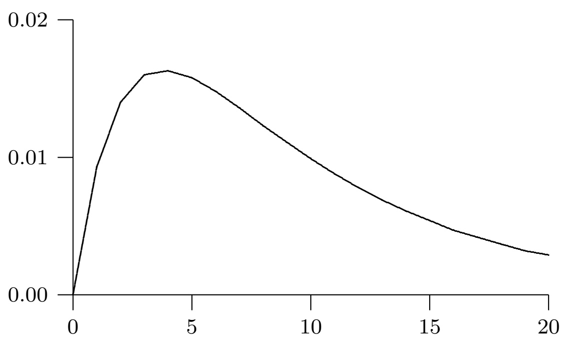


Figure 5: Impulse Response of ad_t due to innovation in c_t



Thus, c_t reacts negatively to an innovation in ad_t, but ad_t reacts positively to an innovation in c_t. As regards the dynamic multipliers, equation (10) tells us that the immediate response of c_t due to a change in ad_t is *negative* and given by $a_{12} = -1.373$. The impact multiplier for ad_t for a change in c_t is $a_{21} = 0.009$ and, thus, positive. In turn the long-run multipliers are given by

$$\mathbf{\Gamma} = \begin{bmatrix} 1.732 & -30.878 \\ 0.202 & 9.378 \end{bmatrix} \tag{11}$$

where we again denote the elements of $\mathbf{\Gamma}$ by γ_{ij} and i denotes the row and j the column position in this matrix. Thus, the long-run multiplier of ad_t affecting c_t is *negative* and given by $\gamma_{12} = -30.878$. That for c_t affecting ad_t is positive and

[26]We have used *forecast error impulse responses*. See, for example, Breitung, Brüggemann, and Lütkepohl (2004), p. 166, for a detailed explanation. Roughly speaking, these impulse responses tell one how y_t changes if there is an innovation in the residuals u_{jt}, where $j = x, y$. In the graphs below we concentrate on $u(y, t)$. The results for both models are qualitatively similar, when using the alternative of *orthogonalized impulse responses*, also explained by those authors. The results based on the latter concept are available upon request.

given by $\gamma_{21} = 0.202$.

To interpret the latter results we can invoke the concept of an elasticity. For instance, around the sample means of the series[27]

$$E_{(x,y)} = \gamma_{(x,y)} \frac{\bar{y}}{\bar{x}} \approx \frac{\partial x/\bar{x}}{\partial y/\bar{y}}$$

can be interpreted as an elasticity. See, for example, Pindyck and Rubinfeld (1998), p. 99. For this we have used that $\gamma_{(x,y)}$ is the coefficient of the regression of x on y and the bars over the variables denote variables at their sample means. Thus, $E_{(x,y)}$ measures how a 1 percent increase in y induces an $E_{(x,y)}$ percent change in x. In our case $\overline{c_t} = 0.57$ and $\overline{ad_t} = 0.014$, and so

$$E_{c,ad} = \gamma_{12} \cdot \frac{\overline{ad}}{\bar{c}} = -0.76 \quad , \quad E_{ad,c} = \gamma_{21} \cdot \frac{\bar{c}}{\overline{ad}} = 8.22.$$

Thus, a one percent increase in ad_t lowers the consumption share by 0.76 percent. Around the means the new, long-run consumption share would then be 0.566 instead of 0.570. In turn, a one percent increase in c_t raises the advertising share by 8.22 percent. Then the new, long-run advertising share would be 0.015.

Finally, we again checked for Granger causality in the VAR. The following table summarizes the results.[28]

	F(1,1,94)	Prob.-F	$\chi^2(1)$	Prob.-χ^2
$\neg(ad_t \rightarrow c_t)$	4.090	0.046	-	-
$\neg(c_t \rightarrow ad_t)$	0.046	0.170	-	-
$(c_t - ad_t)$	-	-	3.524	0.061

There is instantaneous causality between c_t and ad_t at the 6 percent level of

[27]It is not difficult to calculate the steady state values x^* and y^* for the series. In the first model they turn out to be very close to the sample means of the series. The elasticity concept would, of course, also hold when evaluating at the steady state values x^* and y^*. The effects might be different then, however. For model I we find $ad^* = 0.014$ and $c^* = 0.56$. Thus, they are very similar to the sample means.

[28]We follow Lütkepohl, H. (2004), p. 149, and note that for a VAR "testing for instantaneous causality can be done by determining the absence of instantaneous residual correlation. Because of the asymptotic properties of the estimator of the residual covariance matrix of a VAR process are unaffected by the degree of integration and cointegration in the variables, a test statistic based on the usual Wald or likelihood ratio principles has an asymptotic χ^2−distribution under the standard assumption." He also points out that the concept does not specify a causal direction. The latter must be determined from other sources. Furthermore, there may be indirect links between the two variables that may have to be taken into account.

statistical significance. If one is strict at the 5 percent level of significance, one would not accept the hypothesis that there is instantaneous causality.

The probability of causality from c_t to ad_t is around 17 percent. Thus, this hypothesis can be rejected at a 10 percent level of statistical significance. The probability of causality from ad_t to c_t is around 4.6 percent. Thus, we accept this hypothesis at the 5 percent (10 percent) level of significance. Hence, the evidence suggests that the probability of ad_t causing c_t is higher.

But the following caveat applies: Because of instantaneous causality, we cannot unambiguously say that ad_t always "causes" c_t. Contemporaneous effects may be important in this context, because both - advertising and consumption - may react fast to each other. To obtain the instantaneous relationship in our VAR, one has to look at the correlation matrix of residuals. The corresponding correlation coefficient is positive and given by 1.013. Thus, we cannot exclude the possibility that a contemporaneously higher consumption share leads to a higher contemporaneous advertising share and vice versa. However, if there are adjustment lags then we conclude that the bulk of evidence suggests that advertising causes consumption, and that it affects it negatively.

Result 2 *We find instantaneous causality between the advertising and the consumption shares, which is positive. If time adjustment is allowed, then there is causality from advertising to consumption. The impact and the long-run response of more advertising on consumption is found to be negative.*

Our result is in contrast to what Ashley, Granger, and Schmalensee (1980) show for the United Sates. Using quarterly data they find that consumption "causes" advertising there. Their result is interesting for the following reason: Consumer sovereignty is preserved by their results.[29] Loosely speaking: Americans are independent consumers - according to their result - and advertising responds to the consumers' needs. (Consumption leads advertising.) Our result suggests to call (long-run) consumer sovereignty of Germans into question, because at the macro level consumption seems to follow advertising in that country over longer time horizons. Furthermore, the evidence suggests that, contrary to

[29]The concept of consumer sovereignty is one of the corner stones of economic thinking. For a critique of it, see, for instance, Galbraith (1972). Notice that the results of Jung and Seldon (1995), mentioned above, suggest feedback relationships for the United States. Thus, it is not entirely clear whether there may be consumer sovereignty in the United States, either.

conventional wisdom and given no instantaneous adjustments, more advertising may not be good for consumption in Germany in the long run. On the other hand, it may be good in the very short run.

4.2.4 Model 2: c_t and g_t

The estimation results for our second model are given by

$$\begin{bmatrix} c_t \\ g_t \end{bmatrix} = \begin{bmatrix} \underset{(0.045)}{0.146} \\ \underset{(0.104)}{-0.325} \end{bmatrix} + \begin{bmatrix} \underset{(0.082)}{0.793} & \underset{(0.046)}{0.022} \\ \underset{(0.188)}{0.608} & \underset{(0.105)}{0.501} \end{bmatrix} \begin{bmatrix} c_{t-1} \\ g_{t-1} \end{bmatrix} + \begin{bmatrix} u^3_{1,t} \\ u^3_{2,t} \end{bmatrix}. \qquad (12)$$

The estimates for $a^1_{11}, a^1_{21}, a^1_{22}$ and μ_1, μ_2 are all statistically significant at the 5 percent level, whereas the estimate for a^1_{12} is statistically insignificant with probability of 0.628. The latter measures the effect of growth on consumption in the second row of the VAR. This effect is likely to be zero. Again we keep insignificant results in the VAR.

Appendix C presents the details of the checks we conducted for this model. The plots of the residuals do not suggest signs of serial correlation. The portmanteau test rejects serial correlation with a probability of 96 percent. The LM test for autocorrelation (Breusch-Godfrey) with five lags has a probability of 0.56, with the null hypothesis of there being no correlation. Thus, we do not accept the alternative. The test for joint non-normality due to Doornik and Hansen (1994) rejects non-normality with a probability of 92 percent. The Jarque-Bera test for normality for each residual reveals no problems for both of them. We tested whether there is no autoregressive conditional heteroskedasticity (ARCH) in the residuals. We found a probability of 44 percent for $u(c, t)$, and 72 percent for $u(g, t)$. The multivariate ARCH-LM test with five lags for no ARCH has a probability of 38 percent.

We also checked for structural breaks. The plots of the cumulate sum of the CUSUM and CUSMSQ do not indicate an important break point problem. The Chow tests for sample-split, break-point, or forecasts identify 1977 as problematic.[30] But all three tests never identify breaks simultaneously. Given our earlier

[30]For the year 1977 we believe that a break in the system with c and g might be explained by the wave of terrorism that shook Germany at that time. In 1977 the employer representative Hans Martin Schleyer was abducted and later killed by the Red Army Faction (RAF). In the data we identify a decrease in c_t in the following years which may reflect a concomitant drop in consumer confidence. The growth rate also dropped in that year.

criterion we argue that structural breaks are not a severe problem for our analysis of the second model. We also present recursive parameter estimates in the appendix and do not find clear indications of parameter instability.

Thus, we think the model is not performing too badly either. Hence, we will keep our second model for what is to follow.

For the impulse responses we again consider 20 periods. The results are presented in figures 6 and 7, where the definition of innovations is the same as in the last model.

Figure 6: Impulse Response of g_t due to innovation in c_t

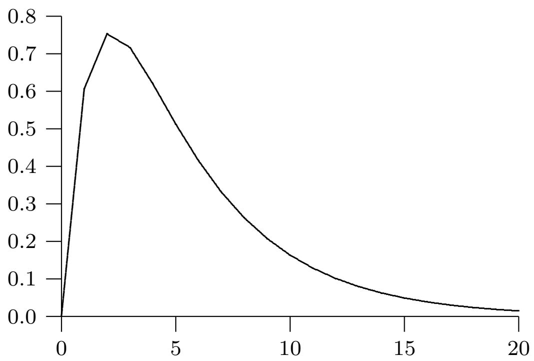
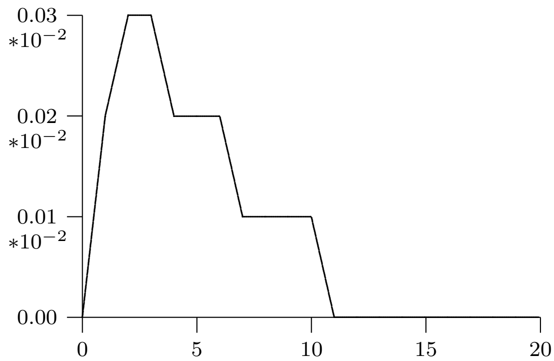


Figure 7: Impulse Response of c_t due to innovation in g_t



The impact multiplier of c_t for a change in g_t is $a_{12} = 0.022$. The impact multiplier for g_t for a change in c_t is positive at $a_{21} = 0.608$ and implies that on impact a higher consumption share raises the growth rate. The impulse response function for this effect suggests that growth reacts very strongly to an increase in c_t. This huge effect may, therefore, just highlight how quantitatively important changes in the consumption share might be for economic growth.[31]

The corresponding long-run multipliers are given by

$$\mathbf{\Gamma} = \begin{bmatrix} 5.500 & 0.245 \\ 6.762 & 2.302 \end{bmatrix} \tag{13}$$

Thus, the long-run multiplier for c_t, when affected by g_t, is positive, that is,

[31]Of course, one should not take the exact value to literally. The model ignores too many other factor that are usually also thought to be (quantitatively) important for the growth rate of aggregate GDP. But then most models suffer from this problem of making abstractions.

$\gamma_{12} = 0.245$. That for g_t, when affected by c_t, is positive and given by $\gamma_{21} = 6.762$.

In our case $\overline{c_t} = 0.57$ and $\overline{g_t} = 0.039$, and so

$$E_{c,g} = \gamma_{12} \cdot \frac{\overline{g}}{\overline{c}} = 0.245 \cdot \frac{0.039}{0.57} = 0.017 \quad , \quad E_{g,c} = \gamma_{21} \cdot \frac{\overline{c}}{\overline{g}} = 6.762 \cdot \frac{0.57}{0.039} = 98.830.$$

Thus, a one percent increase in the value of g_t would raise the long-run consumption share by 0.017 percent around the sample means.[32] Thus, this change would be small. In turn, a one percent increase in c_t raises the the growth rate by almost 99 percent. Thus, the new, long-run growth rate of aggregate GDP would almost double around the sample means.

Clearly, such a result seems drastic and leads one to be cautious about the result. But in terms of the direction of change it lends support to the *consumption-driven growth* hypothesis. That is the aspect we will focus on here.

We are reinforced in our focus when looking at Granger-causality for our second model.

	F(1,1,94)	Prob.-F	$\chi^2(1)$	Prob.-χ^2
$\neg(c_t \rightarrow g_t)$	10.468	0.002	-	-
$\neg(g_t \rightarrow c_t)$	0.235	0.629	-	-
$(c_t - g_t)$	-	-	6.349	0.012

From these results we are led to reject the hypothesis that growth "causes" consumption. However, we find support for the hypothesis that consumption "causes" growth at the 5 percent level of significance. We also find evidence for instantaneous causality. From the cross-correlations in the residuals we infer that the instantaneous relationship is negative in both ways and given by -1.412.

Result 3 *There is instantaneous causality between the consumption share and the growth rate. The association is negative. For the longer run with time adjustments we find support of the hypothesis that growth is consumption-driven in Germany. The quantitative effect of a higher consumption share on the long-run growth rate may be huge.*

[32]For the steady state we found $c^* = 0.731$ and $g^* = 0.239$, which seem implausibly high. We simply interpret this as suggesting that the long-run equilibrium combination of c_t and g_t is higher than what the sample means for our time horizon capture. This would also suggest that Germany was not in a steady state over the period and for the variables considered in our second model. Recall that the first model would approximately imply a steady state for the relation ad_t and c_t.

5 Concluding Remarks

The paper focuses on the popular hypothesis that advertising is good for consumption and that higher consumption means higher output and higher economic growth.

Using standard techniques we analyze these claims empirically. Using German data for the period 1950 to 2000 we find that parts of the hypothesis do not stand up to our empirical checks, when focussing on the causality concept of Granger.

For instance, we find that there is no direct, "causal" relationship between advertising and growth. As Granger causality is not transitive, we conclude that it is very likely that the relationship between advertising and economic growth is more complicated as suggested by simple linear empirical models. We conjecture that the long-run relationship may be non-linear and that advertising may indeed work through consumption on long-run economic growth. But this would require a more elaborate (formal) theory.

For the other links we find the following: There seems to be evidence that advertising is contemporaneously positively related to consumption. However, in the longer run advertising "causes" consumption, but negatively so. Thus, the short and long-run effects are very different. Second, we find evidence that the current consumption share is negatively associated with the current growth rate. When allowing for adjustment lags we find that consumption "causes" growth and the long-run effect of a higher consumption share may be huge.

Of course, we must acknowledge the limitations of a study such as the present one. We wonder whether our results generalize to more economies. We have only considered bivariate relationships due to the intransitive nature of Granger causality. That is restrictive. We have focused on simple linear empirical models only. In our context, non-linearity may be the driving force of the hypothesized relationships. In defence of our analysis we may note, however, that linear empirical models can be interpreted as first order approximations to some (possibly) highly non-linear relationship.

Despite these reservations do we think that further work on the hypothesis analyzed in this paper would be valuable. The present analysis should be regarded as one contribution in that direction.

A The data and its sources

All the data used in this paper refer to the Federal Republic of Germany for the period 1950 to 2000 and treat the Federal Republic as a single entity in its current and its pre-1990 form.

$\mathbf{AD_t}$**:** Investment in advertising including expenditures on salaries, media and the production of means of publicity in billions of Euros for the period 1950-2000. The data are taken from the various ZAW Jahrbücher and were collected and provided to us by courtesy of Volker Nickel of the Zentralverband der deutschen Werbewirtschaft (ZAW). See also $http://www.interverband.com/u-img/184/zaw\_home\_18\_01\_05.htm$.

$\mathbf{Y_t^N}$ **and** $\mathbf{C_t^N}$**:** Nominal GDP is denoted by Y_t^N and nominal private consumption expenditure by C_t^N. Both are in current prices in billions of Euros. The data for 1950-1969 are from Table 8 (interne lange Reihe) of Statistisches Bundesamt (2004a) and were made available to us by courtesy of Statistisches Bundesamt, Wolfgang Garjonis, SB III A. We transformed the data into Euros using the official exchange rate of the former Deutsche Mark to the Euro. The data for the period 1970-2000 are taken from Table 1.3.1 of Statistisches Bundesamt (2004c). See $http://www.destatis.de$.

$\mathbf{g_t}$**:** The annual growth rate of real GDP, where the data for the latter are taken from Statistisches Bundesamt (2004b), Table 23.2, and Statistisches Bundesamt (2004c), Table 1.3.2, and are for 1950-1970 in constant prices of 1991, for 1971-2000 in constant prices of 1995. No growth rate is (initially) calculated for the year 1970.

$\mathbf{c_t}$ and $\mathbf{ad_t}$: These variables were generated as explained in the main text.

Table 7: The Data

Year	AD_t	Y_t^N	ad_t	C_t^N	c_t	g_t
1950	0.32	49.70	0.006	32.32	0.65	n.a.
1951	0.47	61.00	0.008	37.46	0.614	0.097
1952	0.61	69.80	0.009	41.32	0.592	0.093
1953	0.72	74.90	0.01	45.16	0.603	0.089
1954	0.82	80.60	0.01	48.16	0.598	0.078
1955	0.92	91.90	0.01	53.83	0.586	0.121
1956	1.07	101.60	0.011	59.63	0.587	0.077
1957	1.38	110.70	0.012	64.79	0.585	0.061
1958	1.48	119.00	0.012	69.94	0.588	0.045
1959	1.69	130.30	0.013	74.79	0.574	0.079
1960	1.89	154.80	0.012	87.86	0.568	0.086
1961	2.30	169.60	0.014	96.29	0.568	0.046
1962	2.51	184.50	0.014	104.71	0.568	0.047
1963	2.76	195.50	0.014	110.84	0.567	0.028
1964	3.12	214.80	0.015	119.39	0.556	0.067
1965	3.63	234.80	0.015	131.72	0.561	0.054
1966	4.09	249.60	0.016	140.64	0.563	0.028
1967	4.35	252.80	0.017	144.51	0.572	-0.003
1968	4.35	272.70	0.016	153.77	0.564	0.055
1969	5.01	305.20	0.016	169.19	0.554	0.075
1970	4.76	352.00	0.014	190.08	0.540	*0.054
1971	5.11	390.00	0.013	211.52	0.542	0.033
1972	5.68	427.50	0.013	234.17	0.548	0.041
1973	6.08	476.70	0.013	257.13	0.539	0.046
1974	6.08	513.60	0.012	276.67	0.539	0.005
1975	6.34	536.00	0.012	303.8	0.567	-0.010
1976	7.00	583.90	0.012	329.15	0.564	0.050
1977	7.98	623.70	0.013	354.32	0.568	0.030
1978	9.05	669.30	0.014	376.75	0.563	0.030
1979	10.17	722.50	0.014	406.14	0.562	0.042
1980	11.2	766.60	0.015	434.70	0.567	0.013
1981	11.61	800.20	0.015	459.35	0.574	0.001
1982	12.27	831.80	0.015	476.85	0.573	-0.008
1983	13.29	872.20	0.015	498.85	0.572	0.016
1984	15.13	915.00	0.017	521.47	0.570	0.028
1985	15.90	955.30	0.017	541.05	0.566	0.022
1986	16.41	1 010.20	0.016	559.24	0.554	0.024
1987	17.08	1 043.30	0.016	582.76	0.559	0.015
1988	17.90	1 098.50	0.016	605.82	0.551	0.037
1989	18.92	1 168.30	0.016	642.40	0.550	0.039
1990	20.20	1 274.90	0.016	686.49	0.538	0.057
1991	22.29	1 387.10	0.016	745.62	0.538	0.051
1992	24.13	1 613.20	0.015	914.30	0.567	0.022
1993	24.75	1 654.20	0.015	950.66	0.553	-0.011
1994	25.97	1 735.50	0.015	985.75	0.548	0.023
1995	27.41	1 801.30	0.015	1 024.79	0.547	0.017
1996	28.07	1 833.70	0.015	1 052.26	0.559	0.008
1997	28.94	1 871.60	0.015	1 079.77	0.562	0.014
1998	30.17	1 929.40	0.016	1 111.18	0.560	0.020
1999	31.44	1 978.60	0.016	1 155.97	0.562	0.020
2000	33.21	2 030.00	0.016	1 196.79	0.569	0.029

AD_t, Y_t and C_t are in billions of Euros. The growth rate for 1970 is interpolated, as explained in the main text.

B Lag Selection for the Stationarity Analysis

B.1 Selection of the lag for g_t

Dependent Variable: GR
Method: Least Squares
Sample(adjusted): 1961 2000
Included observations: 40 after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.012318	0.007725	1.594424	0.1217
GR(-1)	0.422177	0.182042	2.319120	0.0276
GR(-2)	-0.266384	0.196746	-1.353951	0.1862
GR(-3)	-0.005968	0.201967	-0.029552	0.9766
GR(-4)	0.128841	0.194792	0.661432	0.5136
GR(-5)	-0.073824	0.196188	-0.376292	0.7094
GR(-6)	-0.061171	0.182332	-0.335491	0.7397
GR(-7)	0.136203	0.174541	0.780347	0.4415
GR(-8)	-0.029162	0.183294	-0.159099	0.8747
GR(-9)	0.119486	0.182550	0.654540	0.5179
GR(-10)	0.082480	0.164516	0.501352	0.6199

R-squared	0.301888	Mean dependent var	0.028875
Adjusted R-squared	0.061160	S.D. dependent var	0.021013
S.E. of regression	0.020360	Akaike info criterion	-4.722040
Sum squared resid	0.012022	Schwarz criterion	-4.257598
Log likelihood	105.4408	F-statistic	1.254061
Durbin-Watson stat	1.992457	Prob(F-statistic)	0.300559

AFTER ELIMINATING INSIGNIFICANT (5 percent level of significance) REGRESSORS:

Dependent Variable: GR
Method: Least Squares
Sample(adjusted): 1952 2000
Included observations: 49 after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.012646	0.005176	2.443437	0.0184
GR(-1)	0.647716	0.103831	6.238196	0.0000

R-squared	0.452948	Mean dependent var	0.038449
Adjusted R-squared	0.441309	S.D. dependent var	0.029133
S.E. of regression	0.021776	Akaike info criterion	-4.776064
Sum squared resid	0.022287	Schwarz criterion	-4.698847
Log likelihood	119.0136	F-statistic	38.91508
Durbin-Watson stat	2.052080	Prob(F-statistic)	0.000000

B.2 Selection of the lag for c_t

Dependent Variable: CS
Method: Least Squares
Sample(adjusted): 1960 2000
Included observations: 41 after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.216710	0.091198	2.376268	0.0241
CS(-1)	0.664880	0.183754	3.618310	0.0011
CS(-2)	-0.031964	0.218910	-0.146014	0.8849
CS(-3)	0.018904	0.217972	0.086726	0.9315
CS(-4)	0.151230	0.213870	0.707110	0.4850
CS(-5)	-0.009273	0.210330	-0.044086	0.9651
CS(-6)	-0.245758	0.212032	-1.159063	0.2556
CS(-7)	0.008965	0.215650	0.041574	0.9671
CS(-8)	0.075730	0.207058	0.365743	0.7171
CS(-9)	-0.008299	0.230142	-0.036060	0.9715
CS(-10)	-0.011769	0.155316	-0.075773	0.9401

R-squared	0.477878	Mean dependent var	0.558783
Adjusted R-squared	0.303837	S.D. dependent var	0.010785
S.E. of regression	0.008999	Akaike info criterion	-6.359297
Sum squared resid	0.002429	Schwarz criterion	-5.899559
Log likelihood	141.3656	F-statistic	2.745781
Durbin-Watson stat	1.989876	Prob(F-statistic)	0.015737

AFTER ELIMINATING INSIGNIFICANT (5 percent level of significance) REGRESSORS:

Dependent Variable: CS

```
Method: Least Squares
Sample(adjusted): 1951 2000
Included observations: 50 after adjusting endpoints

       Variable    Coefficient Std. Error  t-Statistic Prob.

C       0.169366    0.033795    5.011536    0.0000
CS(-1)  0.698094    0.059634    11.70637    0.0000

R-squared           0.740595        Mean dependent var      0.564727
Adjusted R-squared  0.735191        S.D. dependent var      0.016775
S.E. of regression  0.008632        Akaike info criterion  -6.627397
Sum squared resid   0.003577        Schwarz criterion      -6.550917
Log likelihood      167.6849        F-statistic           137.0390
Durbin-Watson stat  1.875881        Prob(F-statistic)       0.000000
```

B.3 Selection of the lag for ad_t

```
Dependent Variable: AD
Method: Least Squares
Sample(adjusted): 1960 2000
Included observations: 41 after adjusting endpoints

Variable Coefficient Std. Error  t-Statistic Prob.

C       0.002850    0.001323    2.154388    0.0394
AD(-1)  0.918361    0.178104    5.156330    0.0000
AD(-2)  0.168676    0.242410    0.695830    0.4919
AD(-3)  -0.275131   0.233551    -1.178032   0.2480
AD(-4)  0.111359    0.229033    0.486215    0.6303
AD(-5)  -0.028907   0.226883    -0.127409   0.8995
AD(-6)  -0.046621   0.222396    -0.209629   0.8354
AD(-7)  -0.128295   0.221811    -0.578399   0.5673
AD(-8)  0.066898    0.220369    0.303573    0.7635
AD(-9)  -0.175768   0.222802    -0.788898   0.4364
AD(-10)  0.201698    0.152125    1.325872    0.1949

R-squared   0.820212                Mean dependent var      0.014786
Adjusted R-squared  0.760283        S.D. dependent var      0.001492
S.E. of regression  0.000730        Akaike info criterion -11.38195
Sum squared resid   1.60E-05        Schwarz criterion     -10.92221
Log likelihood    244.3300          F-statistic            13.68635
Durbin-Watson stat  1.938562        Prob(F-statistic)       0.000000

AFTER ELIMINATING INSIGNIFICANT (5 percent level of significance) REGRESSORS:

Dependent Variable: AD
Method: Least Squares
Sample(adjusted): 1951 2000
Included observations: 50 after adjusting endpoints

Variable Coefficient Std. Error  t-Statistic Prob.

C       0.002014    0.000568    3.548780    0.0009
AD(-1)  0.868619    0.040439    21.47986    0.0000

R-squared           0.905769        Mean dependent var      0.014017
Adjusted R-squared  0.903805        S.D. dependent var      0.002256
S.E. of regression  0.000700        Akaike info criterion  -11.65305
Sum squared resid   2.35E-05        Schwarz criterion      -11.57656
Log likelihood      293.3261        F-statistic             461.3842
Durbin-Watson stat  1.844943        Prob(F-statistic)       0.000000
```

C Model 1: Diagnostic Tests

Table 8: Standardized Residuals 1951-2000

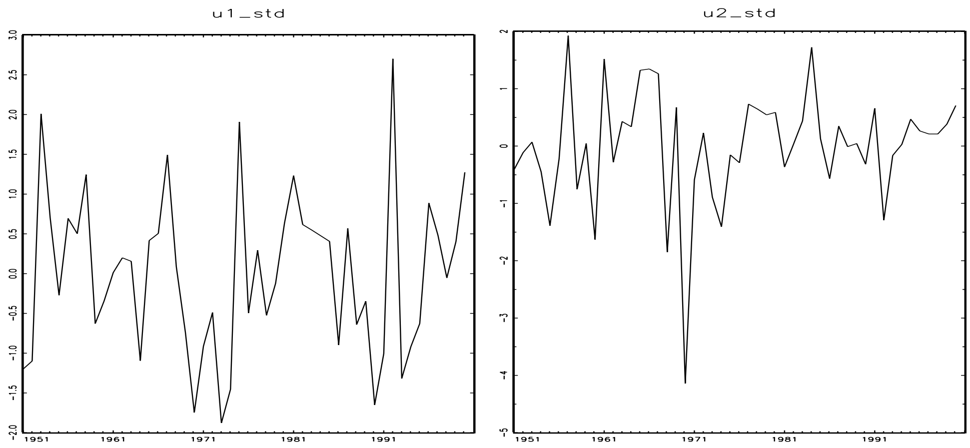
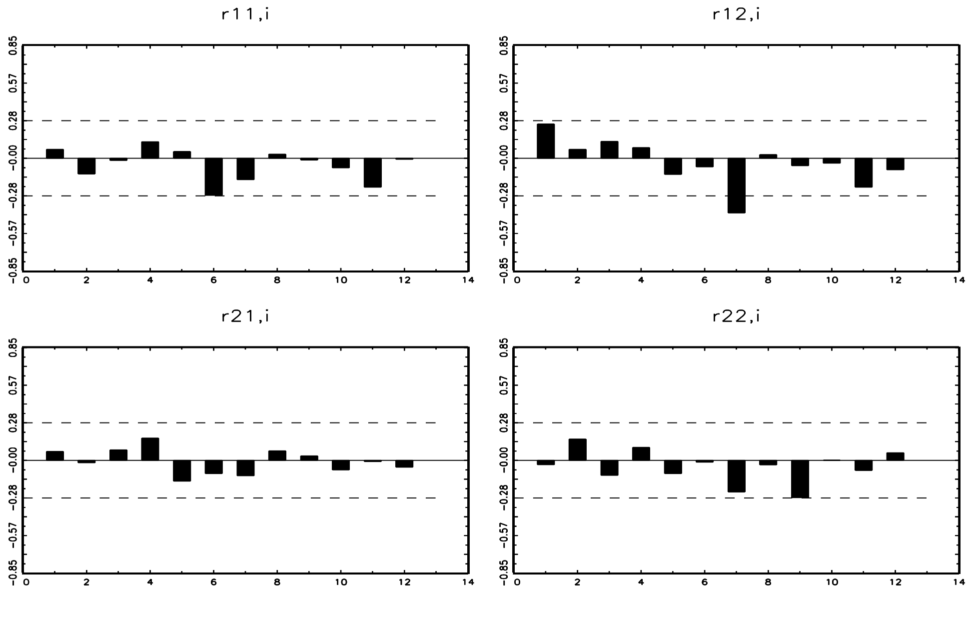


Table 9: Residual Autocorrelations and Cross-correlations

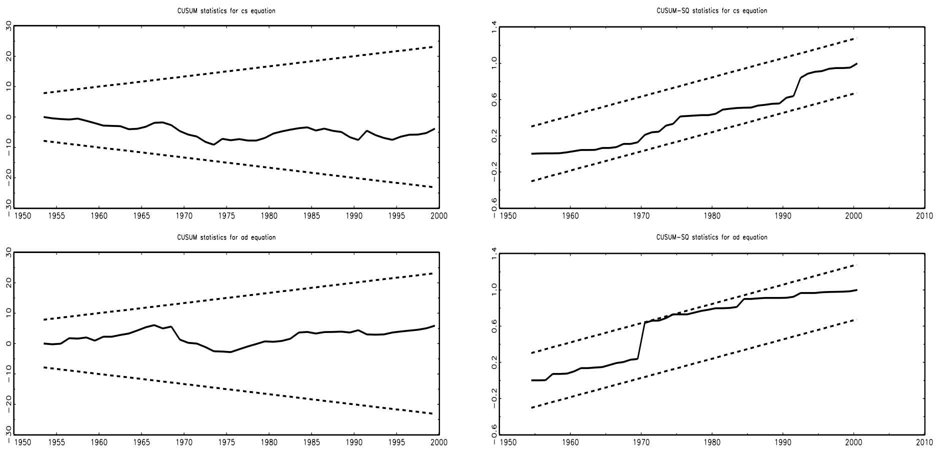


```
PORTMANTEAU TEST (H0:Rh=(r1,...,rh)=0)
Reference: Lütkepohl (1993), Introduction to Multiple Time Series Analysis, 2ed, p. 150.
tested order:             16
test statistic:           46.8134
 p-value:                 0.8931
adjusted test statistic:  56.0296
 p-value:                 0.6215
degrees of freedom:       60.0000

LM-TYPE TEST FOR AUTOCORRELATION with 5 lags
Reference: Doornik (1996), LM test and LMF test (with F-approximation)
LM statistic:             26.0993
 p-value:                 0.1626
 df:                      20.0000
LMF statistic:            1.3468
 p-value:                 0.1793
 df1:                     20.0000
 df2:                     72.0000

TESTS FOR NONNORMALITY

Reference: Doornik & Hansen (1994)
joint test statistic:     31.4260
 p-value:                 0.0000
degrees of freedom:       4.0000
skewness only:            13.0713
 p-value:                 0.0015
kurtosis only:            18.3547
 p-value:                 0.0001

Reference: Lütkepohl (1993), Introduction to Multiple Time Series Analysis, 2ed, p. 153
joint test statistic:     29.4532
 p-value:                 0.0000
degrees of freedom:       4.0000
skewness only:            12.6286
 p-value:                 0.0018
kurtosis only:            16.8246
 p-value:                 0.0002

JARQUE-BERA TEST

variable        teststat   p-Value(Chi^2)  skewness   kurtosis
u1              0.8763     0.6452           0.3159    2.8539
u2              51.9653    0.0000          -1.3222    7.2368

ARCH-LM TEST with 16 lags

variable        teststat   p-Value(Chi^2)  F stat     p-Value(F)
u1              18.1786    0.3135          2.4416     0.0384
u2              3.2203     0.9997          0.2223     0.9979

MULTIVARIATE ARCH-LM TEST with 5 lags

VARCHLM test statistic:   44.7240
 p-value(chi^2):          0.4836
 degrees of freedom:      45.0000
```

C.1 Stability

Table 10: CUSUM and CUSUMSQ

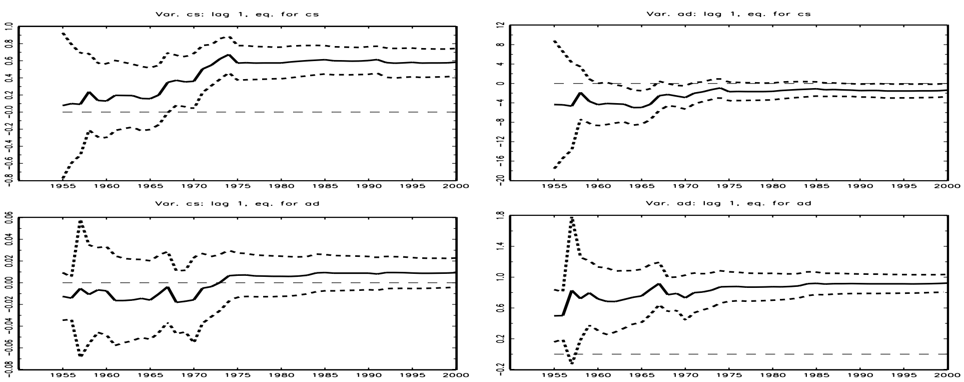
CUSUM: c_t (top), ad_t (bottom) CUSUMSQ: c_t (top), ad_t (bottom)



These plots reveal that the CUSUM and the CUSUMSQ are within the bands of a significance level of 1 percent. However, there could be breaks. Especially, from the CUSUMSQ for ad_t one may infer that there might be a problem around 1970 and around 1990.

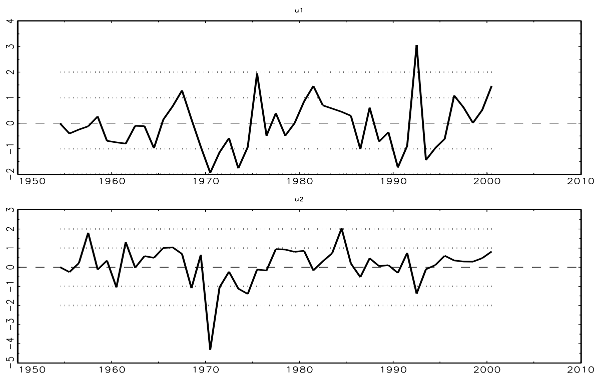
The plots of the recursive coefficients reveals that for the period after 1975 the estimates look stable. This also holds true for the coefficients for μ which are not presented here.

Table 11: Recursive Coefficients I



The recursive residuals suggest that there might be a break problems around 1970 and 1990.

Table 12: Recursive Residuals



C.1.1 Chow Tests

We searched for breaks over the whole sample period of model 1. A routine in JMulTi calculates the asymptotic χ^2 proability values and bootstrapped probability values for the Chow sample-split, break-dates, and forecast tests. This identified 1971 and 1991 as possible dates.[33]

Then we conducted the three Chow test for these particular years. When specifying particular dates the test uses more observations. The results are presented below.

```
tested break date:            1971
(20 observations before break)

break point Chow test:        25.1596
 bootstrapped p-value:        0.0400
 asymptotic chi^2 p-value:    0.0028
 degrees of freedom:          9

sample split Chow test:       7.5160
 bootstrapped p-value:        0.4800
 asymptotic chi^2 p-value:    0.2758
 degrees of freedom:          6

Chow forecast test:           0.6459
 bootstrapped p-value:        0.9200
 asymptotic F p-value:        0.9281
 degrees of freedom:          60, 32
```

```
tested break date:            1991
(40 observations before break)

break point Chow test:        36.8616
 bootstrapped p-value:        0.0200
 asymptotic chi^2 p-value:    0.0000
 degrees of freedom:          9

sample split Chow test:       19.4244
 bootstrapped p-value:        0.0100
 asymptotic chi^2 p-value:    0.0035
 degrees of freedom:          6

Chow forecast test:           1.0387
 bootstrapped p-value:        0.3800
 asymptotic F p-value:        0.4312
 degrees of freedom:          20, 72
```

As one can see, the Chow forecast test never accepts breaks at the 5 percent level of significance. This is the argument we use in the main text.

[33] These results are available on request, but can easily be replicated by the reader.

D Model 2: Diagnostic Tests

Table 13: Standardized Residuals 1951-2000

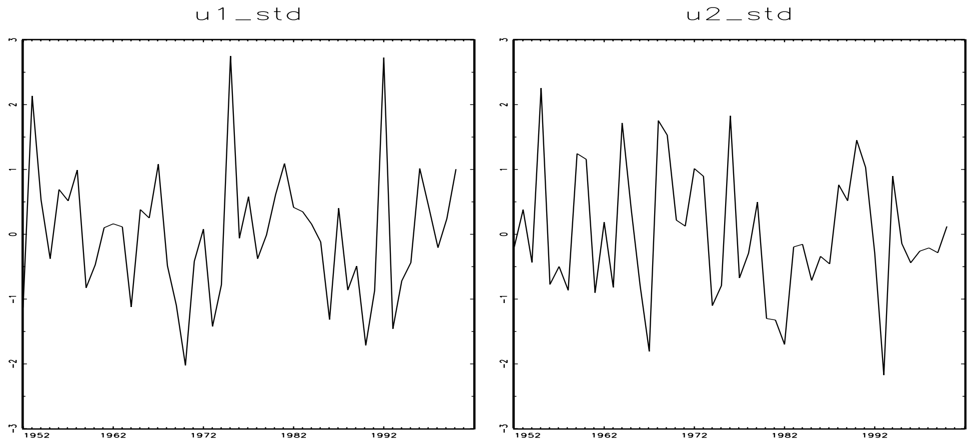
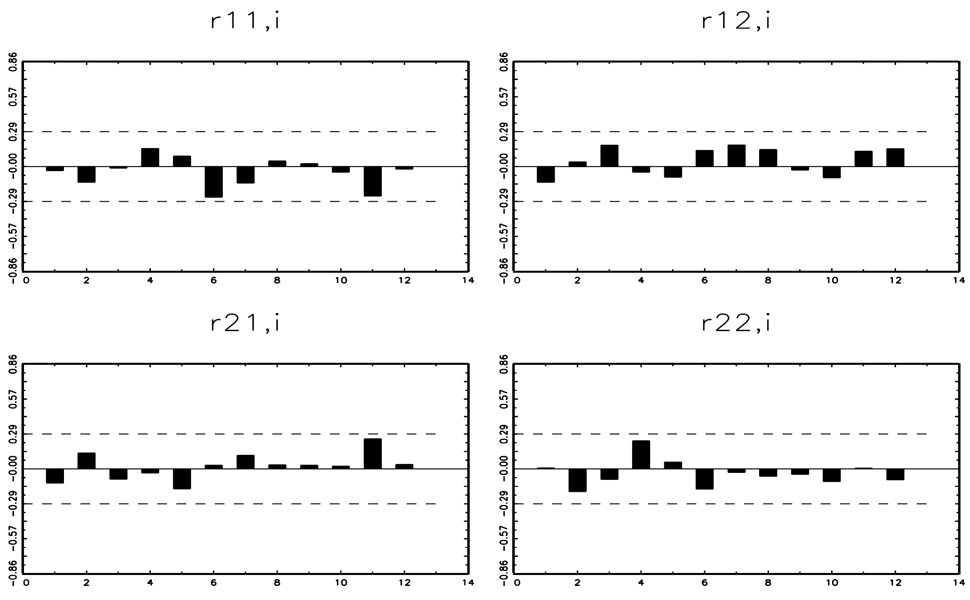


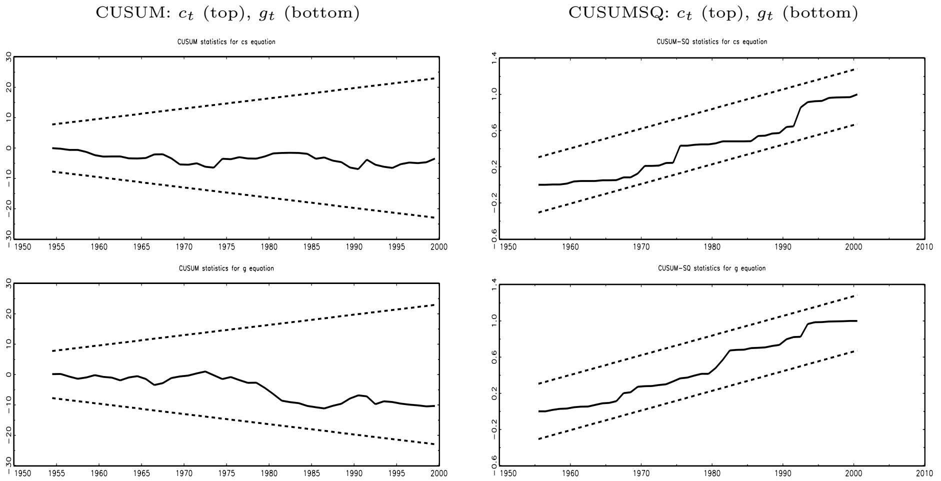
Table 14: Residual Autocorrelations and Cross-correlations



```
PORTMANTEAU TEST (H0:Rh=(r1,...,rh)=0)
Reference: Lütkepohl (1993), Introduction to Multiple Time Series Analysis, 2ed, p. 150.
tested order:             16
test statistic:           42.0101
 p-value:                 0.9625
adjusted test statistic:  51.4698
 p-value:                 0.7756
degrees of freedom:       60.0000

LM-TYPE TEST FOR AUTOCORRELATION with 5 lags
Reference: Doornik (1996), LM test and LMF test (with F-approximation)
LM statistic:             18.4211
 p-value:                 0.5597
 df:                      20.0000
LMF statistic:            0.8334
 p-value:                 0.6663
 df1:                     20.0000
 df2:                     70.0000

TESTS FOR NONNORMALITY

Reference: Doornik & Hansen (1994)
joint test statistic:     8.3313
 p-value:                 0.0802
degrees of freedom:       4.0000
skewness only:            2.1721
 p-value:                 0.3375
kurtosis only:            6.1592
 p-value:                 0.0460

Reference: Lütkepohl (1993), Introduction to Multiple Time Series Analysis, 2ed, p. 153
joint test statistic:     4.4863
 p-value:                 0.3442
degrees of freedom:       4.0000
skewness only:            2.9982
 p-value:                 0.2233
kurtosis only:            1.4881
 p-value:                 0.4752

JARQUE-BERA TEST

variable        teststat   p-Value(Chi^2)  skewness   kurtosis
u1              3.9848     0.1364          0.5875     3.7558
u2              0.8061     0.6683          0.2250     2.5614

*** Sun, 4 Feb 2007 14:36:13 ***
ARCH-LM TEST with 16 lags

variable        teststat   p-Value(Chi^2)  F stat     p-Value(F)
u1              16.1615    0.4417          1.9796     0.0914
u2              12.2305    0.7280          1.2145     0.3511

MULTIVARIATE ARCH-LM TEST with 5 lags

VARCHLM test statistic:   47.2603
 p-value(chi^2):          0.3804
 degrees of freedom:      45.0000
```

D.1 Stability

Table 15: CUSUM and CUSUMSQ



These plots reveal that the CUSUM and the CUSUMSQ are both well within the bands of a significance level of 1 percent. From them we do not infer that there is a problem with stability.

The recursive estimates for μ look very stable and are not presented for lack of space. The recursive parameter estimates of the coefficients are given below.

Table 16: Recursive Coefficients II

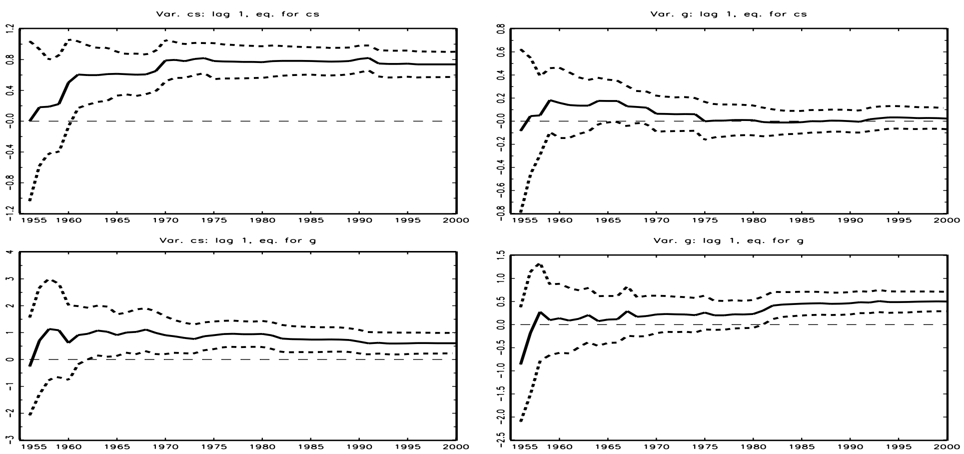
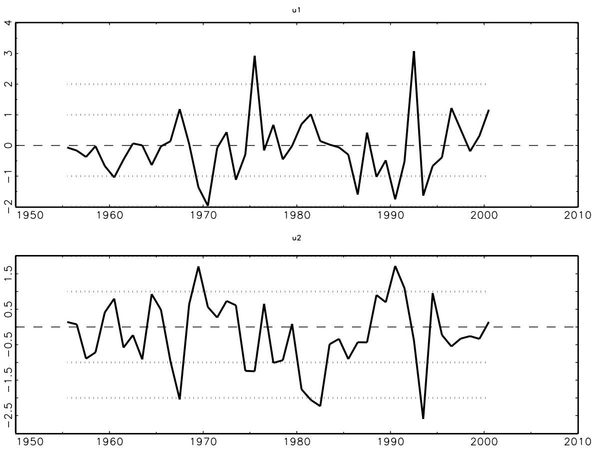


Table 17: Recursive Residuals



D.1.1 Chow Tests

We searched for breaks over the sample period of model 2 as in section C.1.1. This identified 1977 as a possible break date. Again we then conducted the Chow test 1977, using more observations. The results are presented below.

```
CHOW TEST FOR STRUCTURAL BREAK
On the reliability of Chow-type tests..., B. Candelon, H. Lütkepohl, Economic Letters 73 (2001), 155-160

sample range:              [1952, 2000], T = 49
tested break date:         1977 (25 observations before break)

break point Chow test:     20.6684
 bootstrapped p-value:     0.1200
 asymptotic chi^2 p-value: 0.0142
 degrees of freedom:       9

sample split Chow test:    18.0809
 bootstrapped p-value:     0.0600
 asymptotic chi^2 p-value: 0.0060
 degrees of freedom:       6

Chow forecast test:        0.8811
 bootstrapped p-value:     0.7100
 asymptotic F p-value:     0.6658
 degrees of freedom:       48, 42
```

As one can see, the Chow forecast test does not accept the break in 1977 at the 5 percent level of significance. This is the argument we use in the main text.

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