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Business Cycle Volatility in Germany

by

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Abstract

Stylized facts suggest that output volatility in OECD countries has declined in recent years. However, the causes and the nature of this decline have so far been analyzed mainly for the United States. In this paper, we analyze whether structural breaks in the dynamics and the volatility of the real output process in Germany can be detected. We report evidence that output volatility has declined in Germany. Yet, this decline in output volatility is not as clear-cut as it is in the case of the United States. In consequence, it is difficult to answer the question whether the decline in output volatility in Germany reflects good economic and monetary policy or merely 'good luck'.

Key Words: Business Cycle; Volatility; Germany

JEL Classification: F36; F41; F47; E32; G15

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1 Introduction

The integration of international markets, new communication and information technologies, and changes in the stance of economic policy have altered the world's economic landscape. This raises the question whether the dynamics of the business cycle may have changed as well and, in particular, whether business cycle volatility may have declined.

Evidence for the U.S. suggests that business cycles have indeed become less volatile. Yet, both the nature of and the sources behind the decline in business cycle volatility remain subject to controversy. While Stock and Watson (2002) and Blanchard and Simon (2001) report that there has been a trend-decline in output volatility in the U.S., Kim and Nelson (1999) and McConnell and Perez-Quiros (2000) report a discrete step-reduction in U.S. output volatility in the mid-1980s. Moreover, the decline in U.S. business cycle volatility has been attributed to structural shifts in the economy (Zarnowitz and Moore 1986) and the IT revolution (McConnell and Perez-Quiros 2000), improved (monetary) policy (Taylor 1999), or simply 'good luck', i.e., smaller economic shocks (Blanchard and Simon 2001, Stock and Watson 2002).

Given this ambiguity of findings and interpretations, evidence from countries other than the U.S. might yield important insights into the nature and the sources of changes in business cycle volatility. So far, however, empirical research is relatively silent in this respect. While a number of studies conclude that business cycle volatility has historically been on a decline in OECD countries (Blanchard and Simon 2001, Basu and Taylor 1999, Bergman et al. 1998, Dalsgaard et al. 2002), systematic evidence on the causes and the nature of this trend is lacking for most of these countries. The notable exceptions are studies of Simon (2001) for Australia or Debs (2001) for Canada.

In this paper, we analyze whether a structural change in output volatility can be detected in German data. Apart from the fact that Germany is the largest economy in Europe, accounting for roughly 30% of union-wide output, Germany is an interesting case because, unlike the U.S., Germany has experienced large exogenous shocks in the 1990s through re-unification and through the opening up of Central and Eastern Europe. Generally, being more integrated into international trade and capital flows than the U.S., Germany has potentially been exposed to the effects of the globalization to a greater degree as well. Hence, our analysis helps to clarify whether the decline in output volatility discussed in the literature is a U.S. specific or a more universal phenomenon.

Our sample covers the past 30 years (1970-2000). For this period, we find some evidence supporting the view that output volatility in Germany has declined. Yet, the downward trend in volatility was interrupted by periods during which output volatility tended to rise. Specifically, such a period of relatively high output volatility began in the aftermath of German reunification. Hence, evidence for a decline in output volatility in the case of Germany is not as strong as it is for the United States.

What are the determinants of the decline in output volatility? Three possible explanations for changes in output volatility are usually considered in the empirical literature: good luck, good policy, and changes in the structure of the economy. To distinguish good luck from good policy, we follow the literature and estimate a vector autoregressive model which we use for a counterfactual VAR-analysis (see also Boivin and Giannoni 2002; Stock and Watson 2002). This technique allows studying the issue whether changes in the shocks that have hit the economy or changes in the propagation mechanisms are behind changes in the volatility of output. The results we obtain from our counterfactual VAR analysis show that, as in the U.S., the reduction in volatility in the 1990s seems to be the result at least in part of good luck rather than good policies.

In addition to the counterfactual VAR analysis, we use spectral analysis to study the changes in business cycle dynamics at different frequencies. This analysis shows that a substantial part of the decline in German output volatility occurred at business-cycle frequencies. Following Ahmed, Levin, and Wilson (2002), this result can be interpreted as evidence that improved economic policy may be an important factor behind the decline in German output volatility as well.

Finally, we look into the dynamics of various components of GDP to analyze whether, for instance, a lower volatility of inventories has been behind the decline in output volatility. In the literature, lower volatility of inventories has been interpreted as evidence for better inventory management techniques (see, e.g., Daalsgard et al. 2002). Our analysis indicates that part of the decline in the volatility of aggregate output may indeed come from a reduction in the volatility of inventories. This result in principle confirms the findings of McConnell and Perez-Quiros (2000) for U.S. data. Yet, in the case of Germany, the decline in the inventory volatility should be interpreted mainly as a statistical artifact rather than the reflection of a more fundamental structural change. The reason is that the national accounts treat inventory investments merely as the statistical difference between total value added and demand components other that inventories. This is in contrast to the practice in the US, where economically more meaningful statistics on inventories are available.

We organize the remainder of the paper as follows. In Section 2, we describe the data we use in our empirical study and provide some descriptive evidence on the dynamics of output volatility in Germany. In Section 3, we use quantitative tests to study whether structural shifts in the output volatility in Germany can be detected. In Section 4, we use a vector autoregressive model to analyze to which extent changes in the magnitude of shocks and changes in the stance of (monetary) policy may have contributed to the dynamics of output volatility in Germany. In Section 5, we study in detail the role played by the sectoral composition of aggregate output and by the volatility of sectoral growth contributions for aggregate output volatility in Germany. In Section 6, we discuss our results.

2 The Data

To analyze the dynamics of output volatility in Germany, we use the newly released quarterly EVSG data on Gross Domestic Output (*GDP*; *Bruttoinlandsprodukt*) recently released by the German Federal Statistical Office (*Statistisches Bundesamt*). [1] The data are available for a period from 1970:1 through 2001:1. The EVSG data set is particularly suited for our purposes because it has been constructed by the German Statistical Office by applying the same method of calculating GDP for the entire sample period from 1970:1 through 2001:1. Thus, the EVSG data set makes it possible to calculate long-run time series for output volatility. In addition, the EVSG data have the key advantage that they contain a long time series for so-called "other" investment goods. This demand component mainly comprises investment

1 Data covering the period from 1970 to 1991 have been released in summer 2002.

spending for software and other immaterial investment goods, which can be used to study the impact of the so-called "New Economy" on the business cycle.

To account for the German re-unification, we use West German data up to 1991 and German data from 1992 onwards. We link the German and the West German data by calculating the level of the German time series using the quarterly growth rates of the West German series. We use the Census X-11 procedure to seasonally adjust the levels of the series. To estimate the output gap, we use the filter suggested by Hodrick and Prescott (1997). We choose a smoothing parameter of 1600, which is the "industrial standard" for quarterly data.[2]

— Insert Figure 1 about here. —

To obtain a first impression of business cycle volatility in Germany, we follow Blanchard and Simon (2001) and calculate five-year-moving-averages of the variance of the output gap and of the growth rate of real GDP (Figure 1). Both volatility series suggest that there is a tendency of output volatility to decline. However, when compared to the results documented in the empirical literature for the U.S., the decline in output volatility in Germany is only moderate. In addition, the downward trend of output volatility is obviously interrupted at the beginning of the 1990s. This is because German re-unification and the opening up of Central and Eastern Europe led to growth rates and output gaps far above historical averages. In consequence, output volatility increased.

3 Has Output Volatility Declined?

The informal evidence summarized in Figure 1 indicates that the volatility of aggregate output in Germany may have declined. In this section, we study whether this decline in output volatility reflects a discrete breakpoint in output volatility or a longer-term trend towards lower volatility. To test for a discrete breakpoint in output volatility, we use a test advanced by Aggarwal, Inclan, and Wilson (1996, 1999). To check for the robustness of the results given by this test, we specify in

2 As an alternative, we use the Band-pass filter suggested by Baxter and King (1999). However, results appear less reliable and are thus not used in the following.

addition an autoregressive conditional heteroskedasticity model (ARCH) model (Engle 1982) for the output gap. We use the conditional variance equation of this model to test for a breakpoint in output volatility. Moreover, we use the ARCH methodology to study whether a (negative) trend rather than a discrete breakpoint in output volatility can be detected.

The test suggested by Aggarwal, Inclan, and Wilson (1996, 1999) allows a finite number of structural breaks in the variance of a time series to be detected. To setup their test, we model in a first step the quarterly output gap as an autoregressive (AR) process of order four. This is necessary because the test requires as input a mean-zero time series of an independently distributed variable. The output process is given by:

$$y_t = \gamma_0 + \gamma_5 \sum_{s=1}^{4} y_{t-5} + \varepsilon_t \tag{1}$$

The variance of this equation may not be constant over time. Therefore, in a second step, we store the squared residuals of this model. In a third step, we compute the cumulative sum of squared residuals. We let $C_k = \sum_{t=1}^{k} \hat{\varepsilon}_t^2$, $k = 1,2,...,T$ denote the cumulative sum of squared residuals from the start of the sample to the *k*th observation, where $\hat{\varepsilon}_t$ are the estimated residuals from the AR(4) model we have specified for the output gap. Finally, we compute the test statistics as follows:

$$D_k = (\sqrt{T/2})[C_k / C_T - k/T], \tag{2}$$

where $k = 1,2,...,T$, $D_0 = D_T = 0$. The factor before the term in square brackets is used to standardize the distribution of the D_k test statistic. If the variance of the analyzed time series does not change over time, the test statistic D_k should hover around zero. If, in contrast, one or more structural breakpoints at $k = k^*$ show up in the variance of the time series, then the test statistic D_k will drift away from zero. The null hypothesis of a constant variance is rejected if $\max_k |D_k|$ at $k = k^*$ exceeds the critical values reported in Inclan and Tiao (1994).

— Insert Figure 2 about here. —

Upon computing the absolute value of this test statistic, we obtained the results summarized in Figure 2. The horizontal line drawn in this figure gives the 95 percent critical value of the test statistic D_k . Because the test statistic does not cross this critical line, we cannot reject the null of the test of a homogenous variance of the volatility of aggregate output, i.e. there seems to be no structural break in the output volatility in Germany. Yet, at the beginning of the 1990s, the outcome of the test statistic tends to move in the direction of the (asymptotic) critical value. This provides some evidence that output volatility may have changed following German re-unification. However, one should not stretch this interpretation too far because the German re-unification may have changed, for purely statistical reasons, the data-generating process.

To check for the robustness of this result, we estimate an ARCH model to compute a time–varying conditional output volatility. With the conditional volatility series at hand, we can then add a dummy variable to the conditional variance of our ARCH model to discuss whether output volatility in Germany has changed over time. To implement this approach, we again use the AR(4) model for the output gap given in Eq. (1). We obtain estimates of the conditional variance of the output gap by modeling the squared residual series of this equation as an ARCH(1) process:

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 \ , \ \varepsilon_t | \Omega_{t-1} \sim N(0, \sigma_t), \tag{3}$$

where Ω_{t-1} denotes the set of information available in period t-1, and σ_t^2 symbolizes the variance of output conditional on this information set. The conditional variance, thus, depends on a mean ω and on the lagged squared residuals ε_{t-1}^2 from the mean equation.

To test for a structural break in Eq. (3), we follow the literature (see e.g. Choi and Kim 1991; Lastrapes 1989) and extend the basic ARCH model to incorporate a dummy variable into the conditional variance equation (3). A dummy variable coefficient significantly different from zero indicates there is a structural break in the conditional volatility equation. We can test for the significance of the dummy variable by computing the standard normally distributed z-statistic, where we use the algorithm advanced by Bollerslev and Woolridge (1992) to obtain robust standard errors. We use the following equation for the conditional variance:

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \Theta D_t \ . \tag{4}$$

The dummy variable, D_t, assumes the value one after a possible structural break and zero before. Because we have no clear-cut information about the timing of a structural break in output volatility, we employ a recursive estimation procedure. Beginning in the first quarter of 1980, we move the possible breakpoint forward in time at a quarterly frequency and estimate the extended ARCH model consisting of Eqs. (1) and (4) recursively by maximum likelihood.

— Insert Figure 3 about here. —

Figure 3 gives the estimation results for the coefficient of the dummy variable of the extended ARCH model together with the 95 percent and 99 percent critical values. There is some evidence for a structural break in output volatility in the late-1980s. Moreover, it seems that the coefficient of the dummy variable has changed in the beginning of the 1990s. Thus, the two possible candidates for a break in German output volatility are the mid-1980s and the beginning of the 1990s. Also note that in contrast to the situation prevailing in the mid-1980s, it seems that the coefficient of the dummy variable has increased at the beginning of the 1990s.

Next, we study whether there is empirical evidence supporting the hypothesis that output volatility may have experienced a trend decline rather than a single, discrete downward shift. To analyze this hypothesis, we again estimate an ARCH model with a conditional variance equation of the format given in Eq. (4). Now, however, we re-interpret this equation by assuming that our dummy variable, D_t, represents a time trend. The estimation results show that the coefficient of the time trend in the conditional variance equation is significantly different from zero and has the expected negative sign (Table 1). The empirical evidence, thus, indicates that output volatility in Germany has experienced a significant downward trend during the past 30 years.

— Insert Table 1 about here. —

In sum, we find some empirical evidence for discrete breakpoints in output volatility. The ARCH model implies that a discrete structural break in output volatility may have occurred in the mid-1980s and at the beginning of the 1990s. Moreover, visual inspection of Figure 1 as well as the quantitative analysis contained in this section provide hints that output volatility may have experienced a downward trend rather than a discrete step-jump.

4 Lower Output Volatility: Better Policy or Good Luck?

The above results suggest that output volatility may not only have declined in the U.S. but that there is also some – albeit weaker – evidence for a decline in output volatility in Germany as well. This raises two interesting questions: (a) can specific factors be identified that have contributed to the decline in output volatility in Germany, and, (b) if so, are these factors different in Germany than in the U.S.

We use two methods to address these questions. First, we perform a counterfactual VAR analysis to study whether the sources of output volatility in Germany have changed over time. A priori, two effects are conceivable. On the one hand, the shocks hitting the German economy may have changed. German re-unification, the opening up of Eastern Europe, the creation of a common currency in Europe, and globalization as such may have changed the nature of disturbances. On the other hand, economic policy may have responded to these changed external constraints as well, and it may have become more effective in cushioning the effects of external shocks. Generally, we find that the German data do not allow for a clear distinction between these two interpretations. Hence, we use spectral analysis as a second method to gain further insights into the nature of the reduction in output volatility. Following Ahmed, Levin, and Wilson (2002), we can attribute part of the decline in output volatility at business cycle frequencies to changes in economic policy.

4.1 Counterfactual VAR Analysis

We address the question whether the decline in output volatility in Germany is the result of ‘good luck’ (i.e., smaller shocks) or ‘good policy’ on a fairly broad level. More specifically, we follow Boivin and Giannoni (2002) and Stock and Watson (2002) by performing the following counterfactual experiment. We, in a first step, break down our sample into two sub-samples. Since most of the external shocks addressed above have occurred or have gained momentum in the 1990s, we distinguish the 1990s from the 1970s and 1980s. In line with the results of our tests for structural breaks in the volatility of output (see Figure 3), we also slice our sample in the mid-1980s to study the sensitivity of our results.

In a second step, we ask the following questions: What would have been the volatility of output in the 1990s if the shocks of the 1970s and 1980s had occurred?

And what would have been the volatility of output in the 1990s if the propagation mechanisms had remained unchanged from the earlier sub-sample? Finding that a lower volatility of output in the second sub-period was due mainly to smaller shocks would support the 'good luck' story. Finding, in contrast, that lower volatility was due to changes in the way shocks have propagated through the economy would be in support of the 'good policy' story.

Technically, we proceed as follows. We estimate a vector autoregressive (VAR) model. The set of endogenous variables in our VAR consists of GDP growth, the consumer-price inflation rate, and the short-term interest rate (call money rate).[3] The reduced-form VAR is given by the equation:

$$X_t = \Theta(L)X_{t-1} + \varepsilon_t, \tag{5}$$

where X_t denotes the vector of endogenous variables, the matrix polynomial $\Theta(L)$ contains the coefficients to be estimated, and the residuals (ε_t) have the variance-covariance matrix $Var(\varepsilon_t) = \Sigma_\varepsilon$. Since we are using quarterly data, we use four lags of the endogenous variables.

The VAR model given in Eq. (5) implies that the variance of the endogenous variables can be described in terms of the coefficients contained in Θ and in terms of the variance-covariance matrix of the reduced-form residuals, Σ_ε. While Σ_ε summarizes the impact of the variance (i.e., the magnitude) of the exogenous shocks on the variance of X_t, the matrix Θ summarizes the effect of the dynamic structure of the economy (i.e., how the exogenous shocks propagate through the economy) on the variance of X_t. The question that the counterfactual analysis addresses is to what extent changes in the variance of the *i*th endogenous variable ($X_{t,i}$) are due to changes in the VAR forecasts errors, in the dynamics of the VAR, or a combination of these two. By noting that the variance of $X_{t,i}$ is given by

$$Var(X_{t,i}) = \sigma_i(\Theta_i, \Sigma_i)^2, \tag{6}$$

we can perform a counterfactual analysis by computing $Var(X_{t,i})$ for different values of Θ and Σ. Specifically, we replace the population parameters in period 2 with sample estimates for period 1 (and vice versa).

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3 For a similar specification see Stock and Watson (2002) and Boivin and Giannoni (2002).

Before turning to the counterfactual analysis, we study the temporal stability of the variance and of the dynamics of this system of equations (i.e., the propagation mechanism). Table 6 gives the results of Goldfeld-Quandt tests for the temporal stability of the variances of the equations given in Eq. (5). Table 7 contains the results of Chow tests for stability of the respective coefficients of the lagged endogenous variables on the right-hand side of Eq. (5). As potential breakpoints we consider the years 1985 and 1990. The test results indicate that the dynamics and the variance of the inflation equation have undergone structural changes. This result suggests that there might be a close link between the decline in output volatility and the dynamics of inflation volatility (Blanchard and Simon 2001). In the case of the other equations in the system, the evidence in favor of breakpoints is less clear.

— Insert Table 2 and Table 3 about here. —

Table 4a gives the results of the counterfactual VAR analysis. There are two ways of looking at this evidence. The first is to keep constant the propagation mechanisms across time while allowing for changes of the shocks. The second is to keep constant the shocks while changing the propagation mechanisms.

4.1.1 Time-Varying Shocks

By comparing the variances of GDP growth, inflation, and interest rates in columns I and II of Table 4a, we can analyze how the economy would have looked in the first sample period had the shocks of the second sample period occurred. The picture is mixed. Depending on the break-date and the macroeconomic aggregate we study, the hypothetical first period variance is larger or smaller than the actual variance.

Imposing, in contrast, the shocks of the first sample period on the second period while keeping constant the second period propagation mechanism (columns III and IV) gives a much clearer picture: had the shocks of the 1970s and 1980s occurred in the 1990s, volatility would have been higher than it actually was, and this pattern is consistent for all variables under study. Hence, this finding suggests that, as in the U.S., the reduction in volatility in the 1990s seems to be the result mainly of good luck rather than good policies.

One potential criticism of the VAR we use to compute the results given in Table 4a is that it does not contain any external factors in its set of regressors. Because the

German economy is a relatively open economy, such external factors may have played an important role for output volatility in Germany. As a proxy for external factors, we thus include a measure of financial openness. We compute gross capital flows as the sum of FDI, portfolio investment, and international bank lending as a proxy.[4] Results are given in Table 4. By and large, results remain unchanged. There is, in particular, relatively strong evidence that volatility had been larger in the second sub-sample had the shocks of the first period occurred.

4.1.2 Time-Varying Propagation Mechanisms

By comparing columns I and III and columns II and IV, respectively, we can furthermore analyze to what extent changes in the propagation mechanism have led to changes in volatility. These results can be used to gauge the importance of changes in the stance of economic policy for volatility.

Comparing column I and III gives the impact of first period shocks on volatility under different assumptions on propagation mechanisms. Generally, the volatilities reported in column III are larger than those reported in column I. This implies that the output volatility in the first sample would have been higher had the propagation mechanism of the second sample period worked in the first sub-sample. At the same time, the propagation mechanism that were in place in the early sample period would have been ill-suited to deal with second period shocks. This can be seen by comparing columns II and IV of Table 4b. Volatilities in column IV are generally lower than those in column II. Taking together these two pieces of evidence, the counterfactual VAR analysis has thus provided evidence that Germany has, in the 1990s, to some extent benefited from smaller shocks. At the same time, it is difficult to argue that the propagation mechanism or, for that matter, economic policy has improved.

4.2 Spectral Analysis

Though our counterfactual VAR analysis revealed some weak evidence supporting the 'good luck' hypothesis, the results of the VAR analysis are somewhat ambigu-

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4 Generally, our qualitative results are invariant to using the first difference of capital flows instead.

ous at the same time. We therefore follow Ahmed, Levin, and Wilson (2002) and use frequency-domain techniques as an alternative method to assess the relative contribution of 'good luck' and 'good policy' to the decline in output volatility. Because the variance of the output gap can be obtained by integrating its spectrum over all frequencies, we use the spectrum of the output gap to decompose its variance by frequency. The spectrum, $s(\omega)$, of a series is defined as:

$$s(\omega) = \sum_{j=-\infty}^{\infty} c_j e^{-i\omega j} , \qquad (8)$$

with $-\pi < \omega < \pi$ denoting the frequency, *i* being the imaginary number, and c_j giving the autocovariance of the series at lag *j*.

If the 'good luck' story were correct, it should be possible to identify a proportional downward shift of the spectrum of the output gap at all frequencies. If improved (monetary) policy had accounted for the decline in output volatility, this would affect the spectrum of the output gap mainly at business-cycle frequencies. Improved inventory management and changes in business practices, in contrast, should show up primarily as changes in the spectrum at relatively high frequencies.

We plot spectra of the output gap in Figure 4. In Panel A of Figure 4, we compare the spectrum of the output gap for the period 1970:1 – 1984:4 with its spectrum for the period 1985:1 – 2001:4. In Panel B of Figure 4, we plot the spectra of the output gap we computed upon assuming a breakpoint in 1990:1. The horizontal axis of the figure plots the frequency as a fraction of π. The shaded areas in the figure denote high, business-cycle, and low frequencies. Following Ahmed, Levin, and Wilson (2002), we adopt the convention introduced by Baxter and King (1999) and define business cycle frequencies as corresponding to cycles from 6 to 32 quarters.

— Insert Figure 4 about here. —

The spectra of output volatility offer two interesting insights. First, upon comparing the spectra for the first and second sub-samples, it can be seen that there is no proportional downward shift in the output spectrum over time. This indicates that the decline in output volatility is not merely the result of a general reduction in the variance of shocks hitting the German economy in the second sub-sample. Thus, the plotted spectra provide some evidence contradicting the 'good luck' hypothesis. Second, it seems that a larger part of the variation in output volatility is due to changes at the business cycle frequency. Thus, changes in the stance and the conduct of economic policy seem to have contributed to the decline in output volatility in Germany.

5 Sectoral Shifts and Aggregate Output Volatility

It is often argued that structural or sectoral changes or changes in the importance of particular expenditure categories may have had an impact on the volatility of overall output. To study the empirical content of this argument, we sectorally decompose the variance of the overall output in order to analyze whether the composition of aggregate output has changed significantly and, if so, whether this change has reduced volatility.

We let Y_t denote the seasonally adjusted aggregate output and let $X_{t,1}, X_{t,2} .... X_{t,p}$ denote sectoral output and different demand components, respectively. By definition, aggregate GDP can then be written as:

$$Y_t \quad = \quad X_{t,1} + X_{t,2} + ... + X_{t,p} + E_t = \sum_{j=1}^{p} X_{j,t} + E_t \,, \tag{9}$$

where E_t represents an error term capturing the difference between the sum of the seasonally adjusted data and the seasonally adjusted aggregate (see Buckle, Haugh and Thomson 2001). It follows from Eq. (9) that the growth rate of real GDP can be expressed as a weighted sum of the growth rates of its components. Taking into account that $\log(X_t) - \log(X_{t-1}) \approx (X_t - X_{t-1}) / X_{t-1}$ holds approximately for small growth rates, we can write:

$$\Delta \log(Y_t) = S_t + e_t \tag{10}$$

with $S_t = \sum_{j=1}^{p} p_{j,t-1} \Delta \log(X_{j,t})$; $t = 1,2...,T$, and $p_{j,t} = X_{t,j} / Y_t$ = contribution of the output of a given sector on (demand component) j to aggregate GDP and e_t = the logged error term. The variance of S_t is given by:

$$Var(S_t) = \sum_{j=1}^{p} p_{j,t-1}^2 Var(\Delta \log(X_{j,t})) + 2 \sum_{j<k} p_{j,t-1} p_{k,t-1} Cov(\Delta \log(X_{j,t})), \Delta \log(X_{k,t}))) \,. \tag{11}$$

This decomposition allows the impact of changes in the respective sectoral output variances and co-variances and of changes in the sector shares on the volatility of aggregate output to be studied. We follow Buckle, Haugh, and Thomson (2001) and use an 11-quarter rolling sample window to estimate variances, co-variances, and sector shares.

We first analyze the impact of changes in sector shares on aggregate output volatility. To this end, we plot in Figure 6 the volatility of total value added estimated upon assuming time-varying and constant sectoral shares, respectively. To obtain constant sector shares, we use the respective sample means. Figure 5 shows that changes in the sectoral shares have only a small impact on aggregate volatility. In fact, the Figure suggests that the difference between the variance of aggregate output obtained when flexible sectoral shares are assumed and the variance of aggregate output obtained upon assuming fixed sectoral shares is not very large.

— Insert Figure 5 about here. —

This result indicates that changes in the sectoral composition of aggregate output are of minor importance for aggregate output volatility. In contrast, changes in the covariances of the growth rates of sectoral outputs are rather important for aggregate output volatility. In fact, the results plotted in Figure 6 suggest that the changes in the covariances of sectoral outputs account for roughly half of the changes in total output volatility.

— Insert Figure 6 about here. —

This casts doubts on the hypothesis that sectoral changes due to, for instance, an increase in the importance of specific sectors such as services which feature a relatively low volatility reduce aggregate output volatility. Rather, our results suggest that if volatility in the services sector are not highly contemporaneously correlated with the volatility in the rest of the economy, then aggregate output volatility will remain high even though changes in the sectoral composition of aggregate output are taking place.

Next, we apply this kind of analysis to the demand components of real GDP. Because two demand components (net exports and inventories) can assume negative values, Eq. (10) cannot be applied directly. Rather, it is necessary to modify the procedure slightly. Using Lundberg-components or "growth contributions", we can write the growth rate of total GDP as:

$$\frac{Y_t - Y_{t-1}}{Y_{t-1}} = \frac{C_t - C_{t-1}}{Y_{t-1}} + \frac{I_t - I_{t-1}}{Y_{t-1}} + \frac{NE_t - NE_{t-1}}{Y_{t-1}} \tag{12}$$

where C_t denotes consumption, I_t denotes investment, and NE_t are net exports. Because investment is very volatile over the business cycle and may, therefore, be an important determinant of aggregate output volatility, we distinguish several investment series. Specifically, we analyze investment in machinery and equipment, investment in construction, and "other" investment. The latter category mainly subsumes investment in so-called "immaterial" goods like, e.g., software.

With the growth contributions of the demand components available, we can calculate the standard deviation of the demand components (again for an 11-quarter moving average sample window).

— Insert Figure 7 about here. —

The results suggest that there is no common trend in volatility patterns across different macroeconomic aggregates (Figure 7). In particular the decline in volatility of most time series plotted in Figure 7 is interrupted by German re-unification. Moreover, there is at least one time series (“other” investment goods) which shows a clear-cut upward trend in volatility. One possible reason is that this time series captures the boom in software spending precipitated by the “New Economy”. There is a marked decline of volatility in inventory investment.

It would be tempting to interpret this as evidence pointing to better inventory management techniques as a source of declining overall volatility. However, this conclusion would be premature. The reason is that the quality of the national account statistics on inventory investment in Germany is rather poor. The German statistical office merely *assumes* the difference between aggregate demand and the sum of the sectoral outputs aggregates to be equal to inventory investment. Of course, this first guess is revised frequently and other statistics are used to check the plausibility of the estimation. But still there is no original statistic on inventories in Germany as it is available, for example, in the U.S.. Thus, the decline of inventory volatility documented in Figure 8 is likely to be a statistical artifact, reflecting improved statistics.

To check for this possibility, we analyze data from a survey database maintained by the IFO institute. To compile this survey database, firms are asked how large their inventories are as expressed in terms of production weeks. Though only data for the manufacturing sector are collected and though these data are available for a relatively short time period that starts in the early 1980s only, a marked decline in inventory investment should be visible if structural changes have occurred.

Figure 8 shows volatility measures obtained from the survey database. There is no clear-cut decline in volatility. In fact, the results are rather mixed. As regards the volatility of the inventories of inputs like raw materials, it is hardly possible to detect a remarkable decline. In the case of the volatility of the inventories of finished goods, a slight decline can be detected. Yet, this decline emerges at the very beginning of the sampling period in the mid-eighties. Afterwards, the series remains more or less stable. Taken together, these results are somewhat at odds with the hypothesis that an improved inventory-management due to the technological progress achieved through the "New Economy" may be one of the main sources of declining output volatility.

— Insert Figure 8 about here. —

6 Conclusions

Business cycle volatility has been on a decline in most OECD countries over the past decades. This decline in volatility has important implications for economic policymakers and for academics alike. Lower volatility can have direct positive welfare implications if agents are risk-averse, and there is some evidence that lower volatility can have a positive impact on growth (Kneller and Young 2001). Moreover, lower volatility becomes a stylized fact that calibrated models should match. Hence, understanding the dynamics and the factors of changes in business cycle volatility is important.

Sound empirical evidence on the causes of the decline in business cycle volatility is scarce, however, and the available evidence focuses mainly on the United States. Therefore, this paper has provided evidence for Germany. As for the U.S., we document a decline in business cycle volatility. However, the evidence for Germany is less clear-cut. Output volatility has been particularly high in the early 1990s, i.e. at the time of re-unification and the opening up of Central and Eastern Europe. These shocks have to some extent swapped the smaller shocks that have occurred elsewhere.

Hence, we could not discriminate clearly between alternative explanations for the decline in business cycle volatility. To some extent, evidence from a counterfactual VAR analysis suggests that smaller external shocks (i.e., ‘good luck’) have, as in the U.S., been behind the decline in volatility. At the same time, results from a spectral analysis performed on German data suggest that a non-negligible portion of the change in output dynamics has occurred at business cycle frequencies and can thus be attributed to changes in economic policy.

We have also studied whether changes in the sectoral composition of output might have contributed to the decline in volatility in Germany. In the literature, lower aggregate output volatility due to a lower volatility of inventories has been interpreted as evidence for better inventory management and thus a reflection of the use of new technologies. However, our results suggest a more careful interpretation since, in Germany, national account statistics treat changes in inventories to some extent as residual items. Structural interpretations of these changes that do not take firm-level evidence on inventory management techniques into account may thus be premature.

Using macro-data, one obvious extension to the present paper would be to conduct a similar type of analysis for other European countries. Our results suggest that business cycle volatility in Germany shares some similarities with developments in the U.S.: business cycle volatility has declined, and smaller shocks are one part of the explanation. At the same time, differences between Germany and the U.S. are evident as well. The fact that the German economy has undergone quite substantial adjustments processes throughout the 1990s makes evidence for a decline in volatility less clear-cut, changes in economic policy seem to have played a larger role than in the U.S., and the interpretation of changes in the volatility of inventories differs. It would be interesting to know whether these differences hold more generally for European economies.

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Figure 1 — Wilson et al. Test on Structural Break in Output Volatility

The figure plots the absolute value of the D_k test (solid line) for a structural break in the volatility the output gap in Germany and the 95 percent asymptotic critical value for this test taken from Inclan and Tiao (1994) (dashed line).

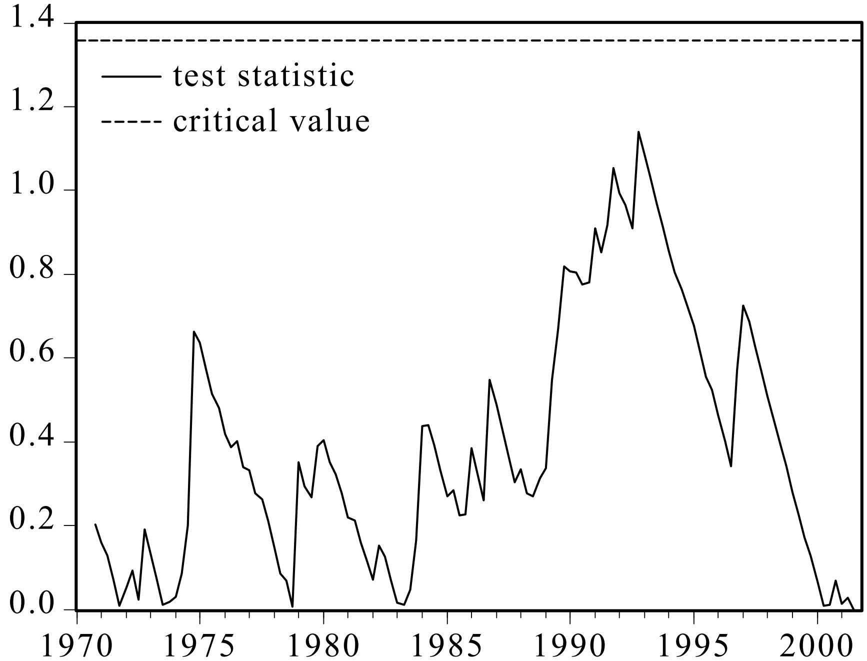


Figure 2 — Business Cycle Volatility in Germany

The figure plots the five-year rolling moving average of the standard deviation of the growth rate of real GDP and the output gap, respectively.

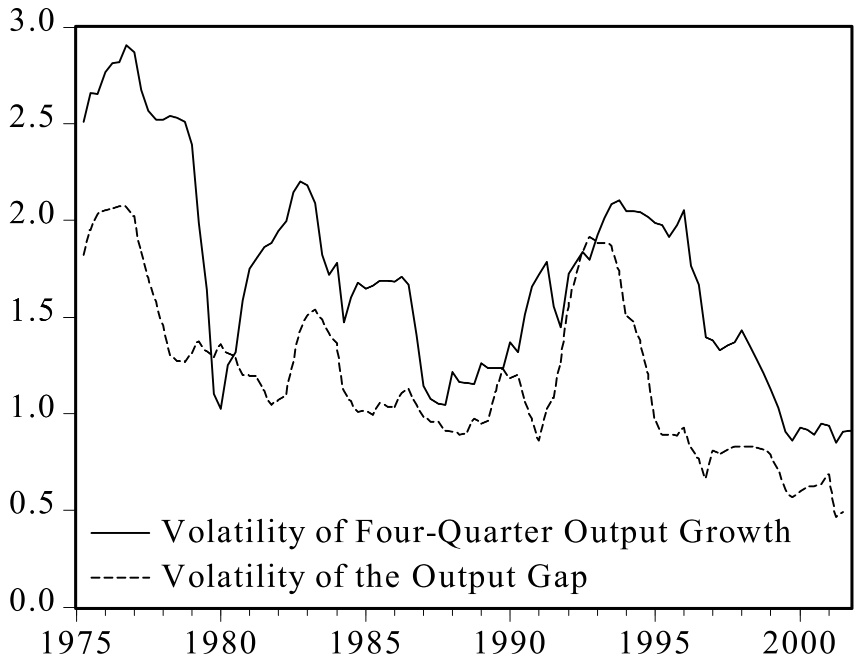


Figure 3 —Structural Breaks in Output Volatility

In this figure, we plot the standard normally distributed z-statistic for a structural-break dummy in the GARCH(1,1) model for the output gap given in Eq. (4) together with the respective 95 percent and 99 percent critical values, respectively. We obtained the plotted time series of z-statistics upon estimating the GARCH model containing the conditional variance Eq. (4) recursively.

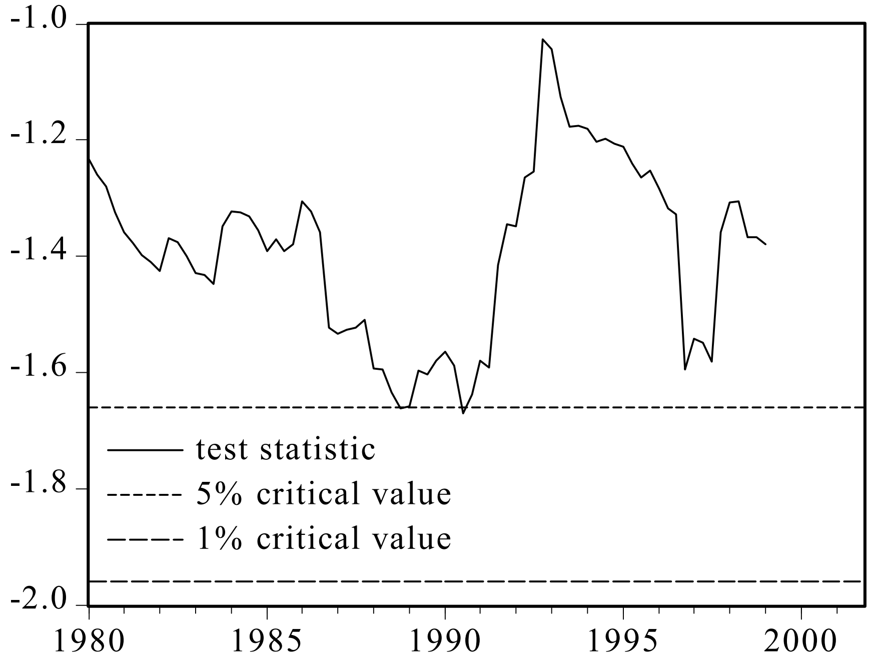
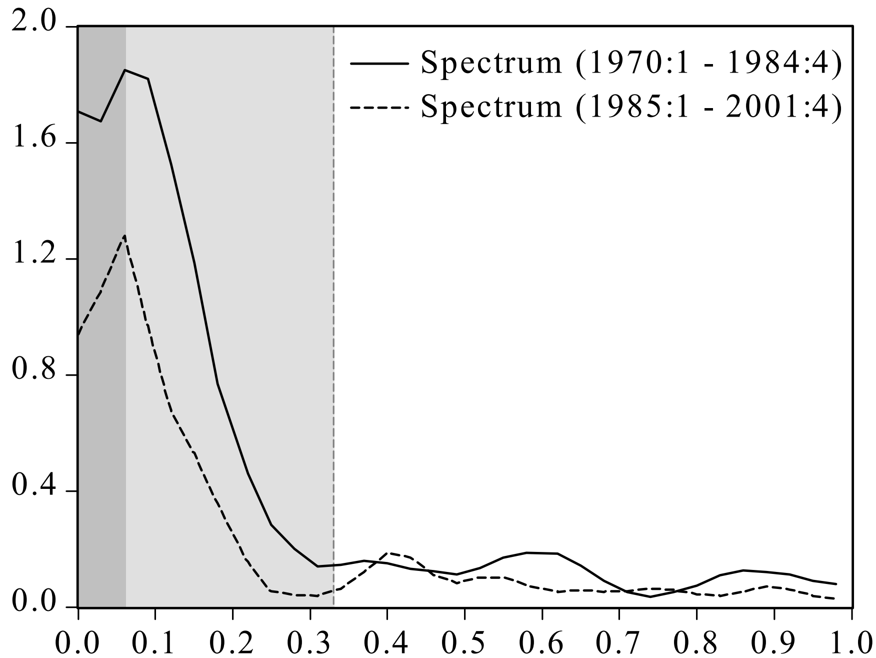


Figure 4 — The Spectrum of the Output Gap

In Panel A, we compare the spectrum of the output gap for the period 1970:1 – 1984:4 with its spectrum for the period 1985:1 – 2001:4. In Panel B, we plot the spectra of the output gap we computed upon assuming a breakpoint in 1990:1. We define business cycle frequencies s corresponding to cycles from 6 to 32 quarters. The horizontal axis of the figure plots the frequency as a fraction of π.

Panel A



Panel B

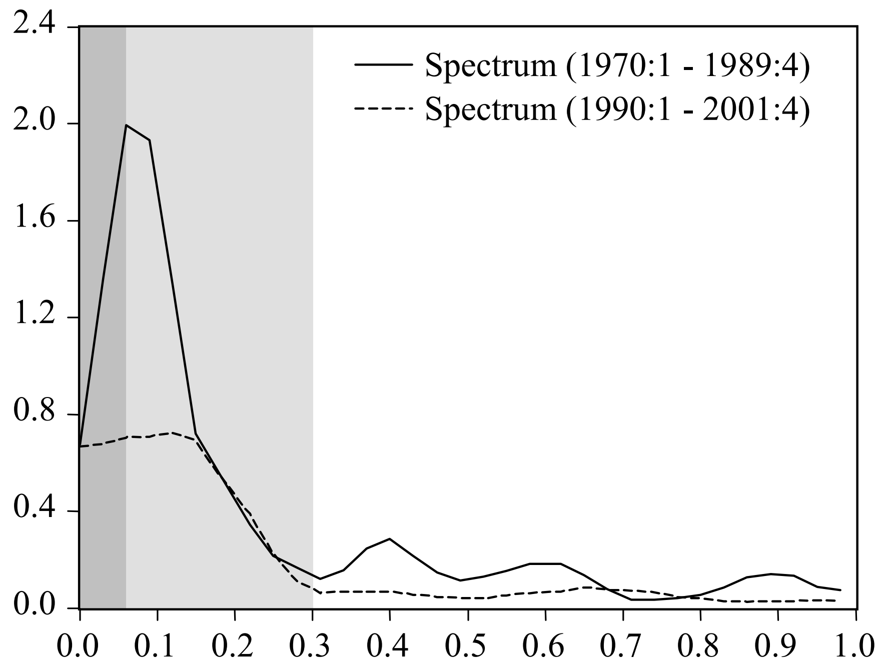


Figure 5 — Variance of the Growth Rate of Total Value Added With and Without Constant Sector Shares

The figure plots the 11-quarter rolling moving average of the standard deviation of the growth rate of real value added. See main text for details.

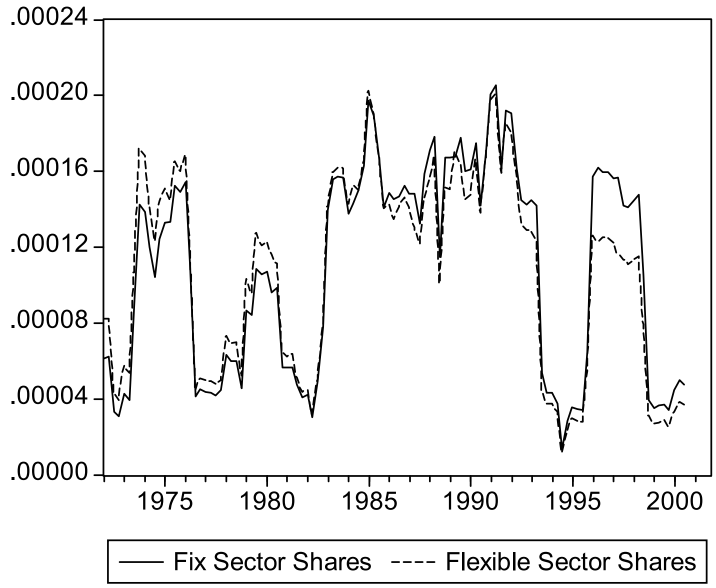


Figure 6 — Decomposition of the Variance of the Growth Rate of Total Value Added

The figure plots the 11-quarter rolling moving average of the standard deviation of the growth rate of real value added and its sectoral components. See main text for details.

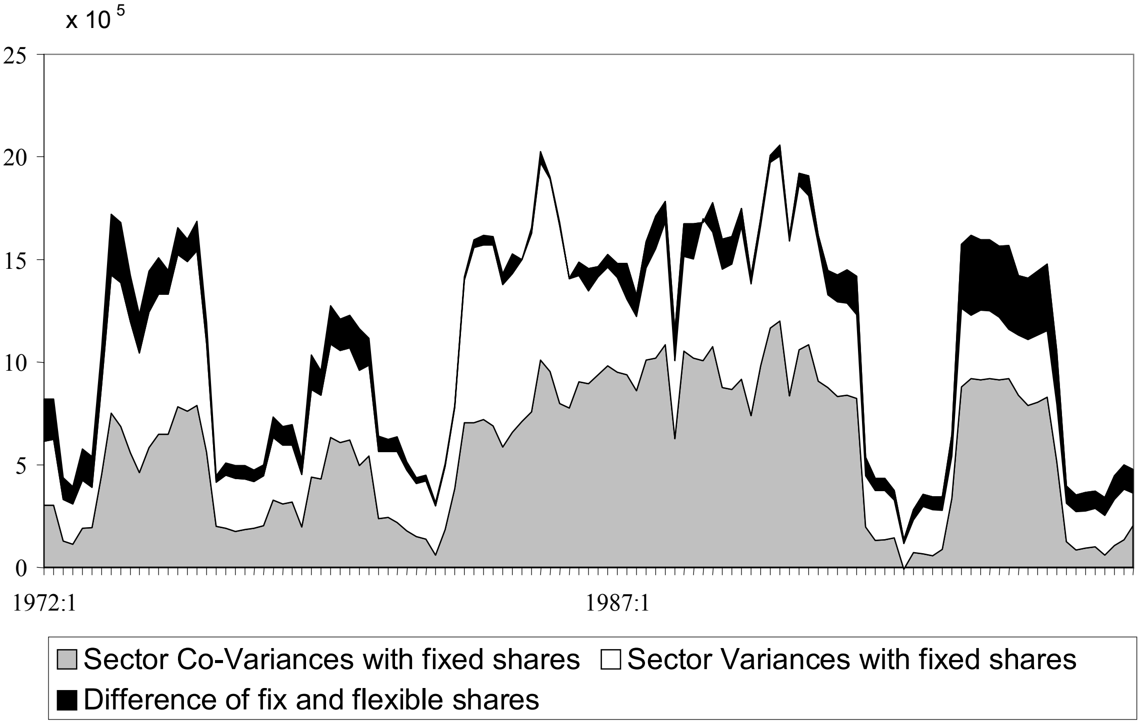


Figure 7 — Variance of the Growth Contributions of the Demand Components

The figure plots the 11-quarter rolling moving average of the standard deviation of the growth constributions of real GDP and its demand components. See main text for details.

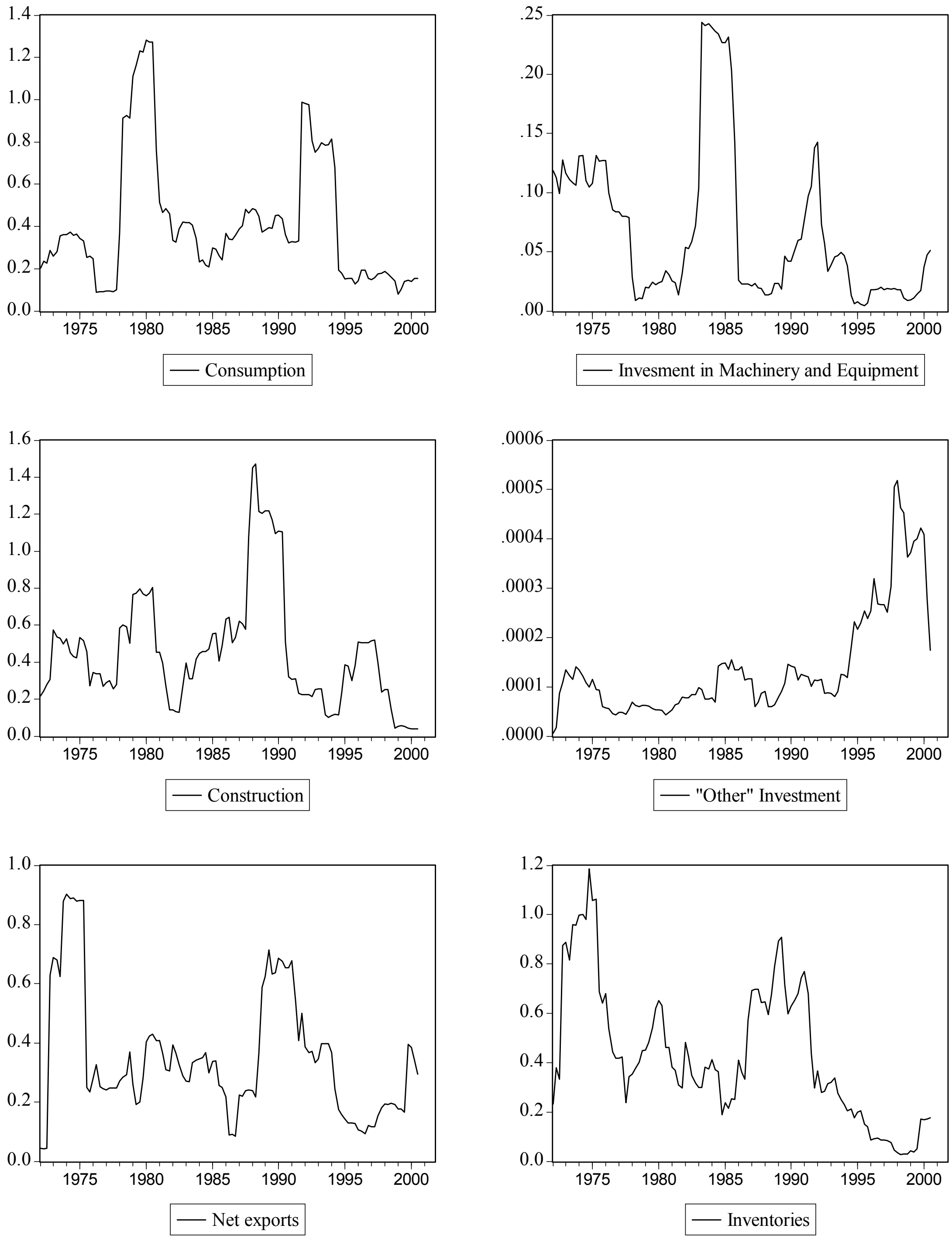


Figure 8 — Volatility of Inventory Investment - Based on Survey data and Based on National Accounts

The figure plots the five-year rolling moving average of the standard deviation of inventory investment as reported by the national accounts and the standard deviation of inventories of finished goods and raw materials expressed in production weeks as reported by the survey conducted by the ifo institute, Munich.

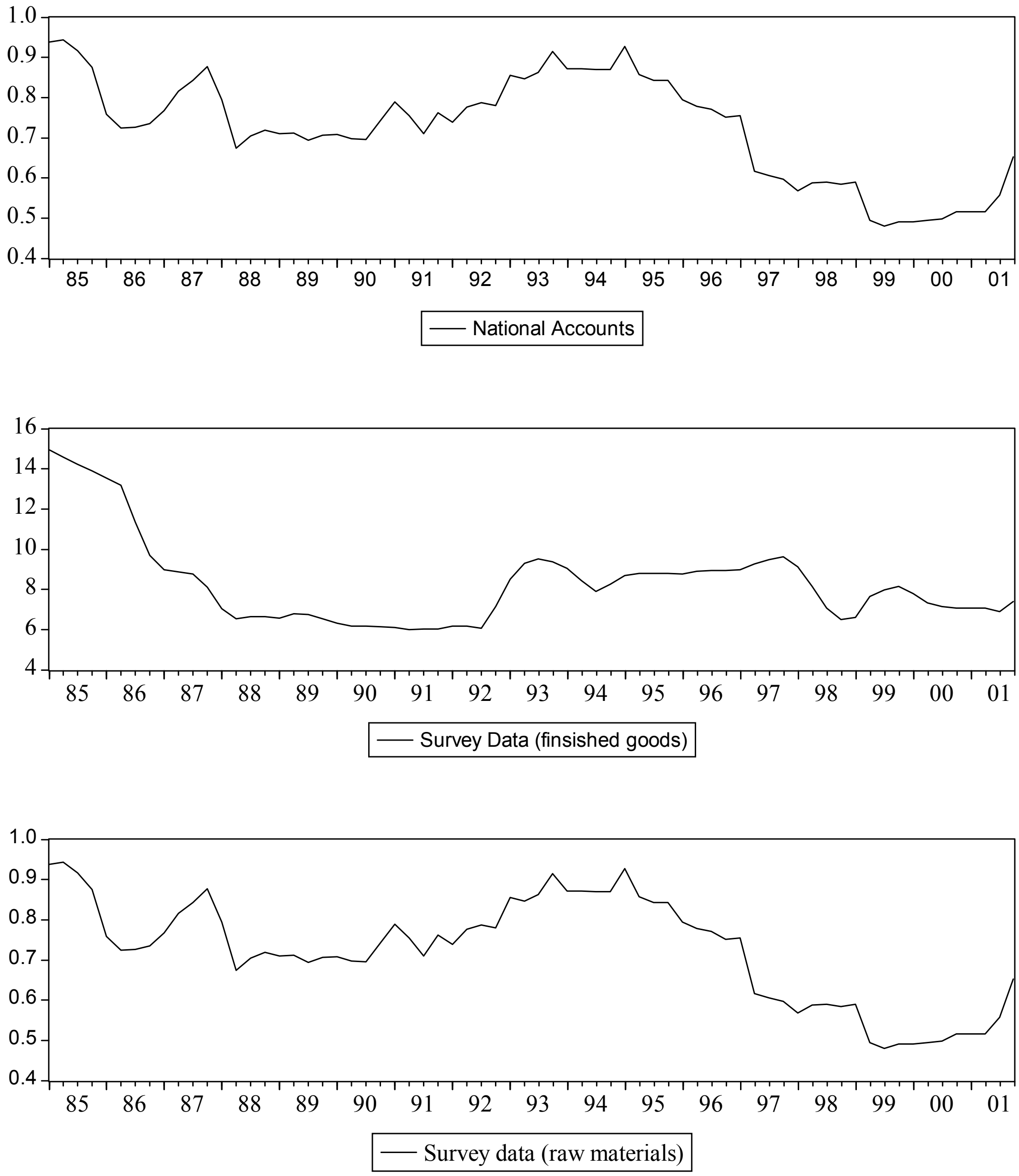


Table 1 — Is there a Trend in Output Volatility?

In this table, we give the estimation results for an AR(4)-ARCH(1) specified for the output gap in Germany. In the conditional variance equation of this model, we include a time-trend dummy variable to test the hypothesis that output volatility in Germany has experienced a trend decline. The sample period is 1971:1 2001:4. Convergence was achieved after 22 iterations. We use Bollerslev-Wooldrige robust standard errors to compute the *z*-statistics.

	Coefficient	Std. Error	z-Statistic	Prob.
C	–0.006101	0.070652	–0.086350	0.9312
BIP_HPGAP(–1)	0.705046	0.104733	6.731825	0.0000
BIP_HPGAP(–2)	0.007609	0.102454	0.074266	0.9408
BIP_HPGAP(–3)	0.079365	0.087878	0.903124	0.3665
BIP_HPGAP(–4)	–0.087868	0.073198	–1.200419	0.2300
		Variance Equation		
C	0.923551	0.261949	3.525696	0.0004
ARCH(1)	0.271334	0.123542	2.196282	0.0281
@TREND(1970.1)	–0.004471	0.002683	–1.666419	0.0956
R-squared	0.532120	Schwarz criterion		2.908225
Adjusted R-squared	0.503885	F-statistic		18.84666
Akaike info criterion	2.726272	Durbin-Watson stat		1.982139

Table 2 — Goldfeld-Quandt Test for Stability of the Variances in the VAR

In this table, we give the results of Goldfeld-Quandt *F*-tests (significance levels in brackets) for the temporal stability of variance for a VAR model containing the growth rate of output in Germany, the German inflation rate, and the change in the German short-term interest rate as endogenous variables.

Variable	Break date 1985:1	Break date 1990:1
Y	F(54,42) = 0.86367 (0.69656628)	F(34,62) = 0.48882 (0.98714799)
Dp	F(54,42) = 2.82000 (0.00034973)	F(34,62) = 3.21317 (0.00003272)
Dr	F(54,42) = 0.08071 (1.00000000)	F(34,62) = 0.06254 (1.00000000)

Table 3 — Chow Tests for the VAR

In this table, we give the results of Chow tests for the stability of the dynamics of a VAR model containing the growth rate of output in Germany, the German inflation rate, and the change in the German short-term interest rate as endogenous variables. Significance levels are given in brackets.

Null Hypothesis : The Coefficients Are Zero	Growth rate of output	Inflation rate	Change in the short-term interest rate
Growth rate of output	$F(4,97) = 1.04920$ (0.38601555)	$F(4,97) = 1.88329$ (0.11949461)	$F(4,97) = 1.29893$ (0.27589506)
Inflation rate	$F(4,97) = 2.91710$ (0.02513939)	$F(4,97) = 1.12193$ (0.35070594)	$F(4,97) = 3.22061$ (0.01579698)
Change in the short-term interest rate	$F(4,97) = 0.64741$ (0.63004748)	$F(4,97) = 1.32837$ (0.26489565)	$F(4,97) = 0.39221$ (0.81377687)

Table 4 — Results From a Counterfactual VAR Analysis

GDP growth is the four-quarter change in the HP-filtered BIP series. Inflation is the four-quarter change in the CPI. Financial openness has been defined as the average of capital in- and outflows (in absolute terms) of Germany. Gross capital flows are the sum of FDI, portfolio investments, and international bank lending. Data are in constant US$, deflated with the the US consumer price index. The different specifications *i_j* are defined as *i* = propagation mechanism, and *j* = shocks.

a) Baseline specification

Specification	I 1_1	II 1_2	III 2_1	IV 2_2
	Break 1984:4			
GDP growth rate	1.92	2.03	1.99	1.36
Inflation	1.57	2.19	1.99	1.67
Interest rate	3.15	2.76	3.25	1.30
	Break 1989:4			
GDP growth rate	1.81	1.24	3.62	1.34
Inflation	2.25	3.15	2.47	1.67
Interest rate	2.77	1.56	3.62	1.06

b) Including financial openness

Specification	I 1_1	II 1_2	III 2_1	IV 2_2
	Break 1984:4			
GDP growth rate	2.02	2.25	1.99	1.35
Inflation	1.59	2.48	1.92	1.64
Interest rate	3.20	3.86	2.91	1.30
	Break 1989:4			
GDP growth rate	1.88	1.37	3.06	1.32
Inflation	2.14	2.93	2.34	1.63
Interest rate	2.78	2.99	3.28	1.04