Patterns of co-movement between a developed and emerging market economy: The case of South Africa and Germany

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Working Paper Number 159

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December 11, 2009

Abstract

This article examines the co-movement between a leading first-world economy (Germany) and an emerging market economy (South Africa) by applying a dynamic factor model. These countries have been chosen as proxies to analyse the channels of transmission of positive supply and demand shocks in developed economies and the effects of these on emerging market economies. The study concludes that supply and demand shocks in developed economies do not necessarily have similar effects in emerging market economies. A German supply shock has more of a demand-shock effect on the South African economy, while a German demand shock has more of a monetary policy effect on the South African economy. This implies that the policy response in emerging market economies should not necessarily be the same as in developed economies. In the case of the transmission of a positive supply shock from a developed country to an emerging economy, the demand effect will lead to increase in prices, which will require a more restrictive monetary policy stance. Similarly, a positive demand shock from a developed economy is transmitted as a monetary policy shock in an emerging market economy, requiring the latter group of countries to stimulate demand through expansionary fiscal and/or monetary policy.

1 Introduction

General consensus exists that, within the context of a globalised world economy, open economies all tend to react to a greater or lesser extent to world economic stimuli or shocks. During periods of expansion or contraction in the business cycles of the developed world in particular, all trading countries tend to gain or lose to a certain extent. Since the group of emerging market economies is becoming more prominent in their roles as producers, suppliers and consumers in the world economy, it could be of interest to establish what the potential nature and extent of co-movement between the group of emerging market economies and the industrialised countries is. Taking cognisance of country differences, this article explores the co-movement between a leading first-world economy and an emerging market economy. Germany and South Africa have been chosen as proxies. The analysis will concentrate on the particular channels of transmission of positive demand and supply shocks in Germany and the effects of these on South Africa. These two countries have been chosen because of their strong historical trade and investment ties as well as the fact that both countries went through a transition and restructuring phase during the late 1980s and early 1990s.

A dynamic factor model will be used to analyse the extent of the co-movement between the two counties. Such a model tends to be more applicable because of the dynamic nature of the analysis and the fact that a common component is identified through which the response of the identified countries

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is captured. The model will also be able to establish to what extent the economies are synchronised. Since developed economies (in this case Germany) influence an emerging market economy (in this case South Africa), the model would be able to capture various macroeconomic linkages that could be of particular interest for policy makers in emerging market economies in particular. The model would, according to Kose, Otrok and Prasad (2008:9), be able to capture the degree of and changes in the patterns of co-movement between various selected macroeconomic aggregates – in this case the effect of positive supply and demand shocks – between these two countries.

In this article we argue that supply and demand shocks in developed economies do not have similar effects in emerging market economies and therefore require different policy responses.

The article is organised as follows. Section 2 provides an overview of the trade and investment links between South Africa and Germany. Section 3 presents a discussion of the methodology, the model and the data. The empirical results and the co-movement and correlation analysis are described in section 4, hereafter the number common components are estimated and the response to supply and demand shocks is discussed. The final section presents some policy implications and offers some concluding remarks.

2 Why South Africa and Germany?

Germany and South Africa have a long history of trade and investment ties. Germany is South Africa's largest import partner and its fourth largest export partner, measured in terms of share in value of imports and exports respectively. South Africa currently exports 7.5% of its total exports to Germany, which makes the country South Africa's fourth largest export partner after developed countries such as Japan, the USA and the UK (see Table 1).

On the import side, Germany has been the dominant supplier of imports to South Africa for the past five years. Developed economies such as the USA, Japan and the UK are amongst the country's top six import partners, while developing countries such as China and Saudi Arabia (predominantly oil) are also making significant inroads as trading partners (see Table 2 below). The fact that Germany is still a major exporting destination for South African goods and services illustrates the potential vulnerability of South Africa to supply and demand shocks in Germany.

The financial linkages between the two countries are determined by the synchronisation between the two currencies – the South African rand and the euro – as well as through investment linkages. This synchronisation is shown in Figure 1 below, and indicates a significant co-movement between the two currencies.

The investment linkages between the two countries are perhaps less pronounced. Table 3 shows the portfolio investment in- and outflows between the two countries. Portfolio investment inflows from Germany to South Africa increased in nominal terms between 2001 and 2004, declined in 2005 and increased again in 2006. Despite the low outlier in 2005, the flows have varied from between a high of 6.8% of all portfolio flows to South Africa, to a low of 2.4% in 2006. Germany is not a significant destination for South African portfolio investment outflows and less than 1% of all South African outflows are directed towards Germany. South African portfolio investment in Germany is insignificant in size, measured from the German perspective. Less than one percent of German portfolio outflows are directed towards South Africa.

Country-specific data on foreign direct investment (FDI) flows between the two countries is not available. South Africa's total net FDI for the period 2000 to 2007 tends to be extremely volatile and amounts to a mere 1.5 percent of GDP. Because of these relatively small flows, the assumption is made that German FDI has a negligible effect on the South African economy.

3 Methodology, the model and data

3.1 Methodology

The methodology used in this paper comprises two main steps: estimating the common components of a large panel of data and identifying a reduced number of structural shocks that explain the common components of the variables of interest. In a streamlined way, the estimation procedure requires the following: (1) A large panel of data fulfilling the condition that the number of time series is "much larger" than the number of observations (in a sense to be made clear below); and (1) The decomposition of each time series into two unobserved parts: its common component, driven by shocks common to all series, and its idiosyncratic component.

Then the following is done: (2) Write the common components of the series as a vector autoregression (VAR) of low order to represent the reduced form of the model; (3) Estimate the VAR to obtain the coefficients matrix and the *reduced-form residuals*; (4) Orthogonalise those residuals and obtain the impulse-response functions and forecast error variances; (5) Assume that the orthogonalised residuals are linearly correlated to a vector of "fundamentals" driving the variable of interest via a matrix such that the first shock explains as much as possible of the forecast error variance of the common components; the second one explains as much as possible of the remaining variance, and so on; (6) Concentrate on the first few *principal component shocks* (neglect others), e.g., the first two principal component shocks; (7) Compute the impulse-response functions and the variance decomposition of the few principal component shocks; (8) Recover the *structural shocks* that explain the principal component shocks by rotating a matrix such that orthogonal structural shocks produce impulse-responses satisfying a set of economically meaningful (sign) restrictions; (9) Construct confidence intervals for the impulse-responses using bootstrapping so as to account for biases in the VAR coefficients and the agnostic nature of the model.

The estimation procedure is explained in detail below. The reader not interested in technical details can skip the remainder of this section.

3.2 The Model

This paper uses a large-dimensional approximate dynamic factor model. As in Eickmeier (2007), Kabundi and Nadal De Simone (2007), and Kabundi (2007), this paper uses the static factor model of Stock and Watson (1998 and 2002). This model is related closely to the traditional factor models of Sargent and Sims (1977) and Geweke (1977), except that it admits the possibility of serial correlation and weakly cross-sectional correlation of idiosyncratic components, as in Chamberlain (1983) and Chamberlain and Rothschild (1983). Similar models have recently been used by Giannone, Reichlin, and Sala (2002), Forni *et. al.* (2005), and Eickmeier (2007).

The intuition behind the approximate dynamic factor model analysis is simple. A vector of time series $Y_t = (y_{1t}, y_{2t}, ..., y_{Nt})'$ can be represented as the sum of two latent components, a common component $X_t = (x_{1t}, x_{2t}, ..., x_{Nt})'$ and an idiosyncratic component $\Xi_t = (\varepsilon_{1t}, \varepsilon_{2t}, ..., \varepsilon_{Nt})'$

$$\begin{aligned} Y_t &= X_t + \Xi_t \\ Y_t &= CF_t + \Xi_t \end{aligned} \tag{1}$$

where $F_t = (f_{1t}, f_{2t}, ..., f_{rt})'$ is a vector of r common factors, and $C = (c_1', c_2', ..., c_N')'$ is a $N \times r$ matrix of factor loadings, with $r \quad << N$. The common component X_t, which is a linear combination of common factors, is driven by few common shocks, which are the same for all variables. Nevertheless, the effects of common shocks differ from one variable to another due to different factor loadings. In this framework, and in contrast to standard common component analysis, the idiosyncratic component is driven by idiosyncratic shocks, which are specific to each variable. The static factor model used here differs from the dynamic factor model in that it treats lagged or dynamic factors F_t as additional static factors. Thus, common factors include both lagged and contemporaneous factors.

The identification of the common components requires that the number of series is much larger than the number of observations. Stock and Watson demonstrate that, by using the law of large number (as T, $N \rightarrow \infty$), the idiosyncratic component, which is weakly correlated by construction, vanishes; and therefore, the common component can easily be estimated in a consistent manner by using standard principal component analysis. The first r eigenvalues and eigenvectors are calculated from the variance-covariance matrix $cov(Y_t)$.

$$X_t = VV'Y_t, \tag{2}$$

and since the factor loadings $C = V$, equation (1) becomes,

$$F_t = V'Y_t. \tag{3}$$

From (1), the idiosyncratic component is

$$\Xi_t = Y_t - X_t. \tag{4}$$

From all the more or less formal criteria to determine the number of static factors r, Bai and Ng's (2002) information criteria were followed. As in Forni and others (2005), F_t was approximated by an autoregressive representation of order 2:[1]

$$F_t = \sum_{l=1}^{p} B_l F_{t-l} + u_t \tag{5}$$

where B is a $r \times r$ matrix and u_t a $r \times t$ vector of residuals. Equation (5) is the reduced-form model of (1).

Once a decision has been taken on the process followed by the common components, structural shocks have to be identified. The identification of structural shocks is achieved by focusing on the reduced-form VAR residuals of (5). Following Eickmeier (2007), the identification scheme has three steps.

First, maximise the variance of the forecast error of the chosen variable and calculate impulse-response functions. As in Uhlig (2003), rather than identifying a shock as, say, a productivity shock, and calculating its contribution to the variance of the k-step ahead prediction error of, say, the German GDP, a few major shocks driving GDP are identified.[2] This implies maximising the explanation of the chosen variance of the k-step ahead forecast error of GDP with a reduced number of shocks.[3] To this end, k-ahead prediction errors u_t are decomposed into k mutually orthogonal innovations using the Cholesky decomposition. The lower triangular Cholesky matrix A is such that $u_t = Av_t$ and $E(v_t v_t') = I$. Hence,

$$cov(u_t) = AE(v_t v_t')A' = AA'. \tag{6}$$

The impulse-response function of y_{it} to the identified shock in period k is obtained as follows:

$$R_{ik} = c_i B^k A, \tag{7}$$

[1] VAR(**??**) provides a dynamic representation which is parsimonious and quite general (for more details, see Gianonne, 2005). The residuals u_t were white noise and thus an autoregressive process of order 2 was chosen.

[2] Uhlig (2003) shows that two shocks are sufficient to explain 90 percent of the variance at all horizons of real U.S. GNP.

[3] If, for example, two orthogonal shocks are identified, it is incorrect to identify the first shock as the one corresponding to the first eigenvalue and the second orthogonal shock as the one corresponding to the second eigenvalue (see Uhlig, 2003). The two orthogonal shocks identified *together* generate the total variation, the explanation of which is being maximised. However, there are multiple possible combinations of those orthogonal shocks all of which still will explain the total variation chosen: as an illustration, and measuring angles in degrees, the pairings of orthogonal shocks with rotation angles {0,90} or {10,100} or {80,170} would be equally acceptable. The grid of the angle of rotation can be different, of course. So the number of possibilities is vast. This paper uses a grid of 30 degrees.

with c_i the *ith* row of factor loadings of C and with a corresponding variance-covariance matrix $\sum_{j=0}^{k} R_{ij}R'_{ij}$.

Second, the identified shocks are assumed to be linearly correlated to a vector of fundamentals. The fundamental forces $\omega_t = (\omega_{1t}, \omega_{2t}, ..., \omega_{rt})'$behind the German GDP are correlated to the identified shocks through the $r \times r$ matrix Q. Thus,

$$v_t = Q\omega_t. \tag{8}$$

The intuition of the procedure is to select Q in such a way that the first shock explains as much as possible of the forecast error variance of the German GDP *common component* over a certain horizon k, and the second shock explains as much as possible of the remaining forecast error variance. Focusing on the first shock, the task is to explain as much as possible of its error variance

$$\sigma^2(k) = \sum_{j=0}^{k} (R_{ij}q_1)(R_{ij}q_1)', \tag{9}$$

where i is, in our example, Germany's GDP, and q_1 is the first column of Q. The column q_1 is selected in such a way that $q_1'\sigma^2 q_1$ is maximized, that is

$$\begin{aligned}\sigma^2(k) &= \sum_{j=0}^{k} (R_{ij}q_1)(R_{ij}q_1)' \\ &= q_1' S_{ik} q_1\end{aligned}$$

where $S_{ik} = \sum_{j=0}^{k} (k+1-j)R'_{ij}R_{ij}$.

The maximization problem subject to the side constraint $q_1'q_1 = 1$ can be written as the Lagrangean

$$L = q_1'S_{ik}q_1 - \lambda(q_1'q_1 - 1) \quad , \tag{10}$$

where λ is the Lagrangean multiplier. From (10), q_1 is the first eigenvector of S_{ik} with eigenvalue λ and, therefore, the shock associated with q_1 is the first principal component shock. Q is the matrix of eigenvectors of S, (q_1,q_2, …, q_r), where q_l (l = 1, ..., r) is the eigenvector corresponding to the l^{th} principal component shock. Along the lines of Uhlig (2003), Eickmeier (2007), Kabundi and Nadal De Simone (2007), Kabundi (2007), and Altig *et al.* (2002), the following is posed: $k = 0$ to $k = 19$, i.e., five years, which covers short- as well as medium-run dynamics.

Finally, orthogonal shocks are identified by rotation. If two shocks are identified, following Canova and de Nicoló (2003), the orthogonal shocks vector $\omega_t = (\omega_{1t}, \omega_{2t})'$ is multiplied by a 2×2 orthogonal rotation matrix P of the form:

$$P = \begin{pmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{pmatrix},$$

where θ is the rotation angle; $\theta \in (0, \pi)$, produces all possible rotations and varies on a grid. If θ is fixed, and $q = 5$, there are $q(q-1)/2$ bivariate rotations of different elements of the VAR. Following the insights of Sims (1998), and as in Peersman (2005), Canova and de Nicoló (2003), Eickmeier (2007), Kabundi and Nadal De Simone (2007), and Kabundi (2007), the number of angles between 0 and π is assumed to be 12: this implies 6,191,736,421x10^{10} (12^{10}) rotations. Hence, the rotated factor $w_t = Pw_t$ explains in total all the variation measured by the first two eigenvalues. This way, the two principal components ω_i are associated to the two structural shocks w_i through the matrix P, and the impulse-response functions of the two structural shocks on all the fundamental forces can be estimated.

A sign-identification strategy is followed to identify the shocks. The method was developed by Peersman (2005). This strategy imposes inequality sign restrictions on the impulse response functions of variables based on a typical aggregate demand and aggregate supply framework.[4] Only those rotations among all possible $q \times q$ rotations that have a structural meaning are chosen. Table 5 displays the sign restrictions for the identification of shocks that are imposed contemporaneously and during the first year after the shock.[5]

As in major standard macroeconomic models, a positive supply shock has a non-negative effect on output and a non-positive effect on prices during the estimated first four quarters following the shock.[6] A positive demand shock has a non-negative effect on both output and prices during the initial period following the shock.

3.3 Data Discussion

This paper uses a large panel data containing 135 quarterly series ($N = 135$) for Germany and South Africa, observed from 1985Q1 to 2006Q4 ($T = 88$).[7] The dataset contains real and nominal variables: for example, GDP, consumption, investment and prices; as well as the external side of each country. Furthermore, the panel also comprises portfolio flows and FDI flows, financial variables and confidence indices. Included in the 135-panel dataset are the following four global variables: crude oil prices, the commodity industrial inputs price index, world demand, and world international reserves. In order to isolate world economic shocks from German shocks, two series from the United States, namely US short-term interest rates (Fed Fund rates) and the Standard and Poor stock price index, have been included. The data have been obtained from the International Monetary Fund, OECD data, the Bundesbank and the South African Reserve Bank.

Outliers have been removed and all series have been transformed into natural logarithms, except those in percentages and those containing negative values. All series are seasonally adjusted and covariance stationary. The more powerful Dickey–Fuller generalised least squares (DFGLS) test of Elliot, Rothenberg, and Stock (1996), instead of the most popular augmented Dickey–Fuller (ADF) test[8], is used to assess the degree of integration of all series. All non-stationary series are made stationary through differencing. The Schwarz information criterion is used in selecting the appropriate lag length so that no serial correction is left in the stochastic error term. Where there were doubts about the presence of unit root, the KPSS test (Kwiatowski *et. al.*, 1992), with the null hypothesis of stationarity, was applied. All series are standardised to have a mean of zero and a constant variance.

4 Empirical results

4.1 Co-movement and correlation analysis

Figure 2 depicts the co-movement between growth in output of Germany and South Africa. In general, the two countries have distinct periods of co-movement, which seems more dominant than the shorter periods of diversion. During the initial period between 1985:1 and 1986:4, a divergent growth path is evident, followed by a period of co-movement until 1990:4. During the early 1990s the two economies were on a divergent growth path. This was just after the unification of Germany,

[4] See Peersman (2005) for more technical details.

[5] Notice that inequalities include zero responses, some of which are usually excluded in the VAR literature. As shown by Peersman (2005), this may sometimes be unduly restrictive. Peersman shows, for example, that oil prices do react within one quarter to demand and monetary policy shocks. In contrast, imposing the standard contemporaneous zero restriction on oil prices, makes them appear as exogenous rather than as endogenous responses of an asset price to demand disturbances and monetary policy shocks.

[6] Clearly, a set of restrictions based on neoclassical model features would produce different results.

[7] The data set contains 63 series for Germany and 66 variables for South Africa.

[8] See Phillips and Xiao (1998) for more details on the weaknesses of using standard ADF test.

where unprecedented growth was experienced due to initial inflow of foreign funds to assist in the restructuring. In contrast, South Africa was still experiencing a declining growth trend during the last days of apartheid. In 1992:1 Germany followed in a co-moving downward trend with South Africa until 1993:1, as the costs of unification started to set in, coupled with a downswing in the world business cycle. Both countries reversed the downward cycle and moved to a more generalised positive co-moving cyclical trend until mid- to late 1997, when South Africa was affected severely by the Asian emerging market meltdown, which lasted until 1998:4. The co-movement resumed and lasted until 2001:4. The divergence in output patterns between 2001 and 2005:3 is primarily due to the bursting of the IT bubble in 2000, which had more significant effects on developed countries than on emerging market economies. The pattern of co-movement between the two countries resumed again in 2006. It is important to note that, although Figure 2 illustrates a pattern of co-movement between the two cycles, it does not in fact present a detailed analysis of synchronisation.

In addition to the graphical representation of the co-movement in the pattern of the output growth rates, this study uses the dynamic correlation technique as proposed by Croux, Forni, and Reichlin (2001). A dynamic correlation coefficient varies between -1 and 1, and reveals that series with a negative long-term correlation could have a positive cycle correlation and also a positive short-term correlation.

Table 5 and Figure 3 report results obtained from the dynamic correlation technique applied to the German and South African GDP. Based on contemporaneous correlation, the two series show a weak and negative correlation of 9 percent over the entire period. For detailed analysis of dynamic correlation, we divide our series into three frequency bands, which reveals asymmetry in correlation. The first band $[0, \pi/16]$ corresponds to cycles with periods longer than eight years. This period is a low-frequency band and represents the long-run relation between the two series, indicating that Germany and South Africa are negatively correlated. The second band $[\pi/16, \pi/3]$ represents a high-frequency period and corresponds to cycles with a period between 1.5 and 8 years, according to the NBER representative of a complete business cycle period. The correlation between the two countries over the business cycle period is around 13 percent, illustrating a positive but weak correlation. It reaches the maximum of 32 percent near the frequency of $\pi/5$ or approximately 11 quarters. Finally, the frequency band $[\pi/3, \pi]$ represents cycles over the short horizon, which is less important.

Despite the pattern of co-movement, the dynamic correlation between the German and South African GDP growth pattern seems to be weak. To gain further insight, a dynamic factor model is applied to assess whether empirical evidence exists of synchronisation between the two economies and what the possible channels of transmission of German shocks to the South African economy are.

4.1.1 The Dynamic Factor Model Analysis

As discussed earlier in section 3.2, the first step of dynamic factor modelling is the determination of the number of factors to include. In the absence of a formal statistical procedure to determine the number of factors, two methods typically are used: the Bai and Ng (2002) approach and the static principal component method. Table 6 represents various results flowing from these two methods. Following Bai and Ng (2002), there is no consensus as to the choice of the number of factors to include. This is illustrated in the table below, showing PC_{p1} and PC_{p2}suggesting six factors, $PC_{p3}$and IC_{p3}suggesting no minimum, and IC_{p1} and IC_{p2}proposing three and two factors, respectively.

The last column in Table 6 reports the cumulated variance shares by ten principal components (CVSPC), respectively, using the static principal component approach. The first five principal components explain approximately 33 percent of the total variance. The variance explained by the sixth principal component (0.044) is less than the generally accepted five-percent benchmark. For the purpose of this analysis we accept five factors based on static principal component analysis.

Following the identification procedure of Uhlig (2003) on the common component of German GDP, a reduced number of structural shocks that maximises the explanation of its forecast error variance over 20 periods is computed. It results in the identification of only two structural shocks which explain 96 percent of the forecast error variance of the common component of German GDP.

4.2 Supply and demand shocks

To avoid commonly used zero restrictions, which are sometimes very restrictive, the study uses sign restrictions as proposed by Peersman (2005) – see Table 5 discussed earlier. The angle of rotation is applied on the first two principal component shocks taking first a supply shock, then a demand shock, and finally a supply shock together with a demand shock. To account for uncertainty in the factor estimation, a bootstrap technique based on Kilian (1998) is implemented, which is necessary in constructing confidence bands. This study uses a 90 percent confidence interval. The draws recover a set of shocks that satisfy the restrictions. In total, the bootstrap was made up of 500 shocks.[9]

The results of the positive supply and demand shocks are presented in the form of variance decomposition and impulse-response functions.

4.2.1 German supply and demand shocks

Table 7 shows the variance decomposition and the forecast error variance of the common components (henceforth, error variance) of German variables as explained by the two identified shocks.[10] From the table it is evident that the supply (42 percent) and demand (54 percent) shocks account for 96 percent of the error variance of the German GDP common component over the period of 20 quarters (or five years), respectively. The German demand shocks are relatively more important than supply shocks. The nature of the demand shock is driven mainly by consumption expenditure (89 percent) and government expenditure (85 percent) cycles and less commonly by investment cycles (24 percent). The business cycle literature suggests that the supply shocks are labour productivity-driven. This corresponds with the evidence of Kabundi and Nadal De Simone (2008), who attribute the difference in competitiveness between France and Germany to the productivity of the latter country.

The main channels of transmission of the German economy are the short-term interest rate (66 percent), followed by the real effective exchange rate (64 percent), long-term interest rate (58 percent), and business confidence (52 percent). Of these channels, only business confidence is driven by supply shock, while the remaining three are primarily driven by demand shock, illustrating the dominance of the latter shock.

Figure 4 shows the impulse-response functions of the German shocks and their impact on German variables. Positive supply shocks in Germany have positive and long-lasting effects on output, consumption and employment. Productivity increases and remains high; similarly, consumer confidence and business confidence also increase. Stock prices increase gradually and remain positive and high. However, price-level decreases follow an increase in productivity, forcing the monetary authority to decrease the short-term interest rate. The drop in interest rate is, however, short-lived.

German real variables, i.e. output, consumption and employment, increase briefly following a positive demand shock. Similarly, consumer and business confidence increase for a short period and then decrease. The demand shock triggers prices; CPI increases gradually and remains high. The rise in prices forces the monetary authority to adopt a more stabilising policy by increasing short-term interest rates to curb inflationary pressure. Unlike the case of supply shocks, stock prices in Germany do not increase permanently following a demand shock: instead they increase over the short term and tend to stabilise over the long term.

[9] 504 draws were needed.

[10] A measure of the explanatory power of each variable can be obtained by weighing the median forecast error variance of the common components explained by the shock, by the variance share of the common components of the variable. To help the reader, for each variable, the last column of each table displays the percentage of the forecast error variance of the common components explained by the sum of the two shocks.

4.2.2 Channels of transmission of German supply and demand shocks to South Africa

The variance shares of common components explained by supply and demand shocks from Germany to South Africa are shown in Table 8. Seventy-one percent of the variation in South African GDP is explained by the common components, representing a strong co-movement between the South African and German economies. It is evident from Table 8 that a German demand shock (47 percent) has more influence on the South African economy than a German supply shock (14 percent). The most important channels of transmission are short- and long-term interest rates, followed by confidence levels (through business and consumer confidence), the inflation impact, real effective exchange rates, and imports from Germany. In all these channels of transmission, the German demand shock is dominant. Overall, it seems that financial linkages and confidence levels constitute important channels of transmission. The significance of the inflation impact could be explained by the real effective exchange rate and German imports as channels of transmission. The most recent literature emphasises the critical role that foreign direct investments play as catalysts of financial linkages between countries. The variance shares of outward and inward FDI indicate no evidence of the contribution of FDI in the synchronisation process. The same applies to South African exports to Germany.

The impulse response of South African variables to German supply and demand shocks are asymmetrical compared to the response of German variables – see Figure 5. Real variables (output, consumption and employment) react positively to German supply shocks, but the positive effect is only temporary. A positive supply shock from Germany does not trigger labour productivity in South Africa. Consumers and businesses react positively, as depicted by a short-term increase in consumer and business confidence. Prices react gradually followed by a subsequent restrictive monetary policy stance by the South African Reserve Bank through a gradual increase in short-term interest rates. Finally, stock prices increase gradually and remain at a higher level.

However, the response of South African variables to a demand shock from Germany is quite significant, taking into account the dominance of the German demand shocks. The reaction of South Africa to a German demand shock is quite contrary to the expected reaction to such a demand shock. Theoretically, a positive demand shock would increase output, consumption and employment over the short term. However, quite contrarily, a German demand shock leads to a decrease in all these variables in South Africa. This pattern is more illustrative of a monetary policy shock than of a positive demand shock. A possible explanation could be found in the dominance of short- and long-term interest rates as channels of transmission. The German monetary policy authority reacts strongly to curb inflationary pressure caused by a domestic demand shock. A German demand shock causes upward pressure on the price level. The South African Reserve Bank, which has adopted inflation rate targeting as its sole mandate since 2000, reacts strongly by increasing the short-term interest rate to fight inflation. Consequently, this restrictive monetary policy stance affects the real economy negatively, pushing down output, consumption and employment. The negative impact on the real economy, in turn, creates pessimistic perceptions among consumers and businesses about the economy at large. Finally, stock prices plummet, reflecting the negative perceptions in the economy.

5 Conclusions and policy implications

Despite the co-movement pattern in output growth between Germany and South Africa, the dynamic correlation demonstrates a negative and weak correlation between the countries over the long term. In contrast, the correlation over the business cycle period is positive, but still weak. However, the analysis based on a dynamic factor model within a data-rich environment reveals more detailed and significant results on the synchronisation between these two countries.

In the identification of German supply and demand shocks, the analysis reveals that the latter shock is the more dominant one in Germany. Furthermore, the study assesses the impact and transmission channels of German supply and demand shocks on the South African economy. The analysis reveals that 71 per cent of the variation in South African GDP is explained by the estimated common components, indicating a strong co-movement between the two economies. As in the case of Germany, a German demand shock is the more dominant shock on the South African economy. The South African reaction to German demand and supply shocks is contrary to what generally is expected. A positive German supply shock has more of a demand shock effect on the South African economy, while a positive German demand shock has more of a monetary policy effect on the South African economy. The explanation could be the fact that financial linkages and confidence levels in emerging market economies such as South Africa constitute important channels of transmission, in contrast to trade and FDI linkages, as would be commonly expected.

This study concludes that supply and demand shocks in developed countries do not necessarily have similar effects in emerging market economies. Given this, the policy response in emerging market economies should not necessarily be the same as in developed economies. In the case of the transmission of a positive supply shock from a developed country to an emerging economy, the demand effect will lead to an increase in prices, which will require a more restrictive monetary policy stance. Similarly, a positive demand shock from a developed economy is transmitted as a monetary policy shock in an emerging market economy. The policy response in the latter group of countries should be to stimulate demand through expansionary fiscal and/or monetary policy.

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Table 1: Share in value of South African exports as percentage of total exports, 2002-2006 (%)

Rank	Importing country	2002	2003	2004	2005	2006
1	Japan	6.5	9.9	10.2	11	11.9
2	USA	10.6	12.2	11.6	10.4	11.5
3	UK	10.9	10.1	10.5	10.6	8.8
4	**Germany**	**8.2**	**7.7**	**8**	**7.1**	**7.5**
5	Netherlands	5.2	4.8	4.6	5	5.2
6	China	2	2.8	2.6	2.9	4

Note: Ranked according to the 2006 export share
Source: SA Trade Map

Table 2: Share in value of South African imports as percentage of total imports, 2002-2006 (%)

Rank	Exporting country	2002	2003	2004	2005	2006
1	**Germany**	**15.6**	**14.8**	**14.2**	**14**	**12.5**
2	China	5.2	6.4	7.5	9	10
3	USA	11.8	9.9	8.6	7.9	7.6
4	Japan	6.9	7	6.8	6.8	6.5
5	Saudi Arabia	5	5.7	5.6	5.5	5.3
6	UK	9	8.7	6.8	5.5	5

Note: Ranked according to the 2006 import share
Source: SA Trade Map

Table 3: Total portfolio investment (PI) flows between Germany and South Africa, 2001-2006 (US$ million)

Portfolio Investment Flows	2001	2002	2003	2004	2005	2006
PI inflows from Germany to SA	1 039	1 623	2 191	2 746	1 103	2 066
Total SA PI inflows	19 908	23 759	40 073	57 541	80 733	84 815
As % of total SA PI inflows	5.20%	6.80%	5.50%	4.80%	1.40%	2.40%
PI outflows from SA to Germany	80	64	188	161	211	128
Total SA PI outflows	29 741	30 068	40 752	47 304	64 686	70 637
As % of total SA PI outflows	0.30%	0.20%	0.50%	0.30%	0.30%	0.20%

Source: IMF, Coordinated Portfolio Investment Survey
Note: Data only available from 2001 onwards

Table 4: Identification Inequalities

	Positive Supply Shocks	Positive Demand Shocks
GDP	≥ 0	≥ 0
Prices	≤ 0	≥ 0
Interest Rates	≤ 0	≥ 0

Table 5: Dynamic correlation coefficients over the frequency λ

	Frequency Band			
	0-π	0-$\pi/16$	$\pi/16$-$\pi/3$	$\pi/3$-π
Correlation	-0.09	-0.25	0.13	-0.23

Table 6: Determining the number of common factors

k	*PCp1*	*PCp2*	*PCp3*	*ICp1*	*ICp2*	*ICp3*	CVSPC
1	0.938	0.943	0.927	-0.030	-0.020	-0.053	0.089
2	0.902	0.911	0.878	-0.040	**-0.021**	-0.088	0.163
3	0.878	0.892	0.842	**-0.043**	-0.014	-0.114	0.225
4	0.865	0.883	0.817	-0.036	0.001	-0.131	0.276
5	0.853	0.877	0.794	-0.032	0.015	-0.151	**0.326**
6	**0.847**	**0.875**	0.776	-0.025	0.031	-0.168	0.370
7	0.848	0.881	0.765	-0.011	0.055	-0.177	0.407
8	0.853	0.890	0.758	0.007	0.083	-0.183	0.439
9	0.862	0.904	0.755	0.030	0.114	-0.184	0.468
10	0.872	0.920	0.754	0.052	0.147	-0.185	0.495

Table 7: Forecast Error Variance of the Common Components of Germany Variables Explained by the Supply and Demand Shock, 1985-2006 1/

	Variance Shares of the Common Components	Supply Shocks	Confidence Intervals Lower Bound	Confidence Intervals Upper Bound	Demand Shock	Confidence Intervals Lower Bound	Confidence Intervals Upper Bound
1 Gross domestic product	0.23	0.42	0.12	0.94	0.54	0.03	0.70
2 Investment	0.73	0.37	0.11	0.86	0.24	0.01	0.55
3 Private final consumption expenditure	0.38	0.01	0.02	0.88	0.89	0.05	0.91
4 Total employment	0.48	0.26	0.15	0.95	0.70	0.02	0.74
5 Labour productivity of the total economy	0.43	0.17	0.05	0.77	0.27	0.01	0.59
6 Capacity Utilisation	0.38	0.57	0.03	0.88	0.06	0.02	0.65
7 Government current disbursements	0.25	0.05	0.02	0.85	0.85	0.05	0.89
8 Government current receipts	0.05	0.70	0.08	0.93	0.14	0.01	0.57
9 Consumer confidence	0.22	0.51	0.14	0.94	0.44	0.03	0.64
10 Business confidence	0.52	0.58	0.10	0.92	0.31	0.02	0.57
11 CPI	0.11	0.53	0.03	0.81	0.05	0.02	0.62
12 Short-term interest rate	0.66	0.22	0.00	0.42	0.41	0.21	0.90
13 Long-term interest rate on government bonds	0.58	0.20	0.00	0.37	0.44	0.23	0.90
14 Stock prices	0.19	0.18	0.14	0.93	0.72	0.02	0.74
15 Wages	0.28	0.05	0.02	0.64	0.72	0.06	0.83
16 Exports	0.35	0.65	0.04	0.91	0.04	0.02	0.66
17 Imports	0.38	0.68	0.05	0.92	0.07	0.02	0.62
18 M3	0.12	0.11	0.00	0.48	0.56	0.20	0.91
19 Real Effective exchange rate	0.64	0.30	0.00	0.56	0.32	0.07	0.85
20 FDI out	0.22	0.53	0.01	0.81	0.13	0.02	0.84
21 FDI in	0.15	0.48	0.01	0.78	0.18	0.02	0.85

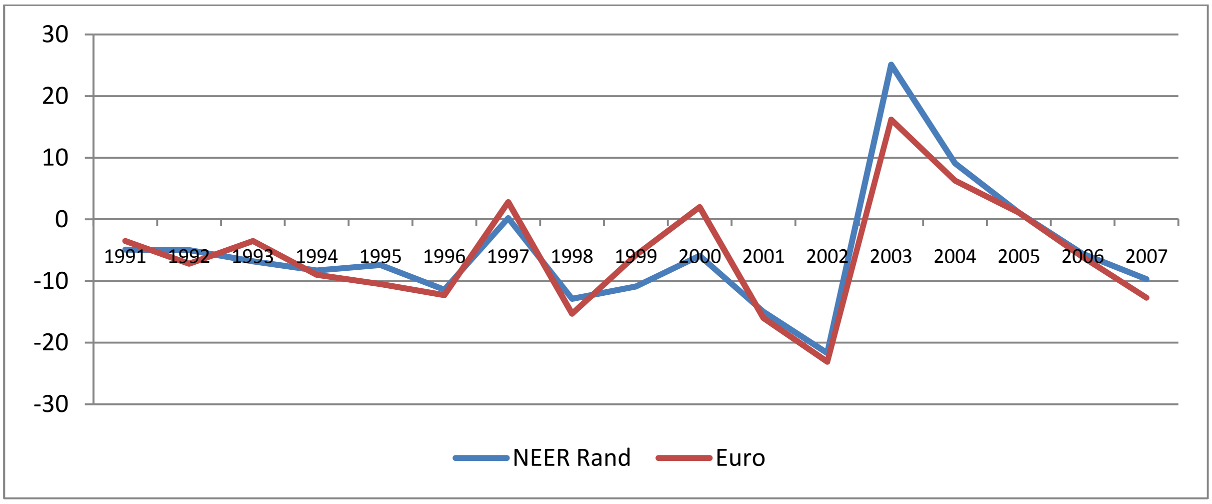
1/ Forecast horizon is 20 quarters and refers to the levels of the series. Confidence intervals are constructed using bootstrapping methods.

Table 8. Forecast Error Variance of the Common Components of SA Variables Explained by the Supply and Demand Shock From Gernany, 1985-2006 1/

	Variance Shares of the Common Components	Supply Shocks	Confidence Intervals Lower Bound	Confidence Intervals Upper Bound	Demand Shock	Confidence Intervals Lower Bound	Confidence Intervals Upper Bound
1 Gross domestic product	0.71	0.14	0.00	0.39	0.47	0.16	0.86
2 Investment	0.35	0.05	0.01	0.61	0.35	0.01	0.44
3 Final consumption expenditure by households	0.48	0.18	0.00	0.40	0.38	0.11	0.83
4 Total employment in the private sector	0.12	0.01	0.01	0.66	0.43	0.01	0.58
5 Labour productivity	0.31	0.03	0.00	0.58	0.02	0.00	0.31
6 Capacity Utilisation	0.33	0.11	0.00	0.41	0.44	0.07	0.77
7 Final consumption expenditure by general government	0.06	0.01	0.01	0.71	0.36	0.01	0.57
8 Consumer confidence	0.44	0.28	0.01	0.57	0.30	0.09	0.85
9 Business confidence	0.55	0.21	0.00	0.40	0.37	0.10	0.84
10 CPI	0.52	0.12	0.00	0.44	0.58	0.26	0.93
11 Short-term interest rate	0.59	0.06	0.00	0.59	0.57	0.07	0.86
12 Long-term interest rate on government bonds	0.53	0.10	0.00	0.53	0.55	0.13	0.90
13 Stock prices	0.05	0.59	0.02	0.85	0.04	0.01	0.69
14 Total remuneration per worker	0.14	0.07	0.00	0.58	0.61	0.19	0.90
15 Imports from GER	0.24	0.01	0.01	0.72	0.54	0.02	0.67
16 Exorts to GER	0.05	0.03	0.01	0.60	0.16	0.01	0.44
17 M3	0.15	0.38	0.02	0.79	0.16	0.02	0.76
18 Real Effective exchange rate	0.33	0.12	0.01	0.53	0.16	0.01	0.35
19 FDI out	0.11	0.07	0.00	0.62	0.73	0.22	0.93
20 FDI in	0.08	0.58	0.06	0.87	0.05	0.02	0.59
21 Total car & commercial vehicle sales incl AMH	0.33	0.03	0.01	0.58	0.58	0.06	0.79
22 Production in total mining	0.34	0.25	0.10	0.88	0.37	0.01	0.51

1/ Forecast horizon is 20 quarters and refers to the levels of the series. Confidence intervals are constructed using bootstrapping methods.

Figure 1: Synchronisation between the SA rand and the euro, 1991-2007



Source: South African Reserve Bank, Quarterly Bulletins

Figure 2: Output growth of Germany and South Africa

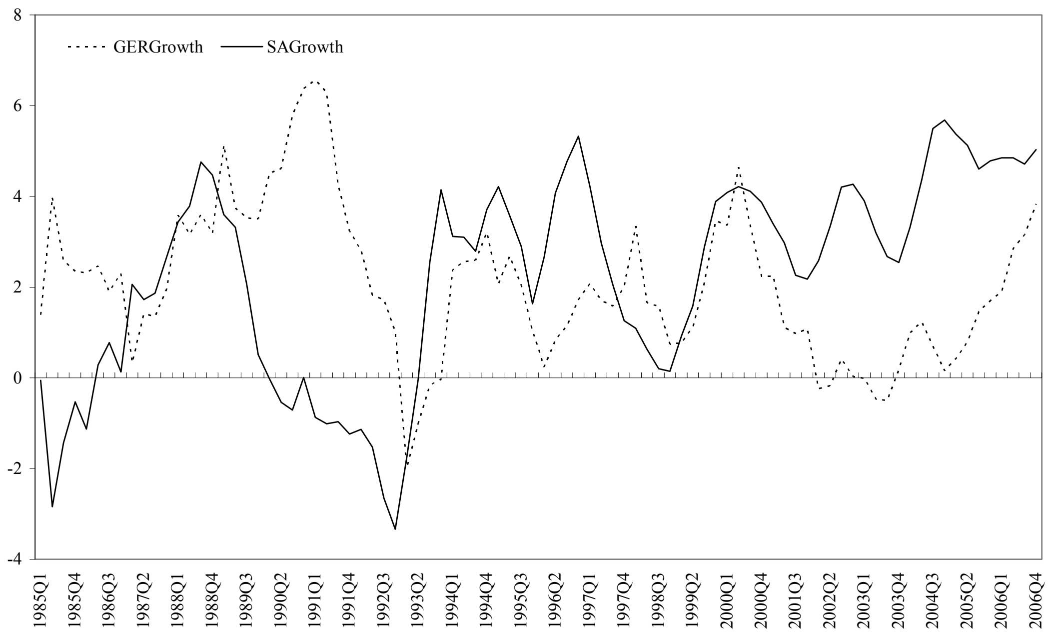


Figure 3: Dynamic correlation GER GDP and SA GDP 1980:1-2006:4

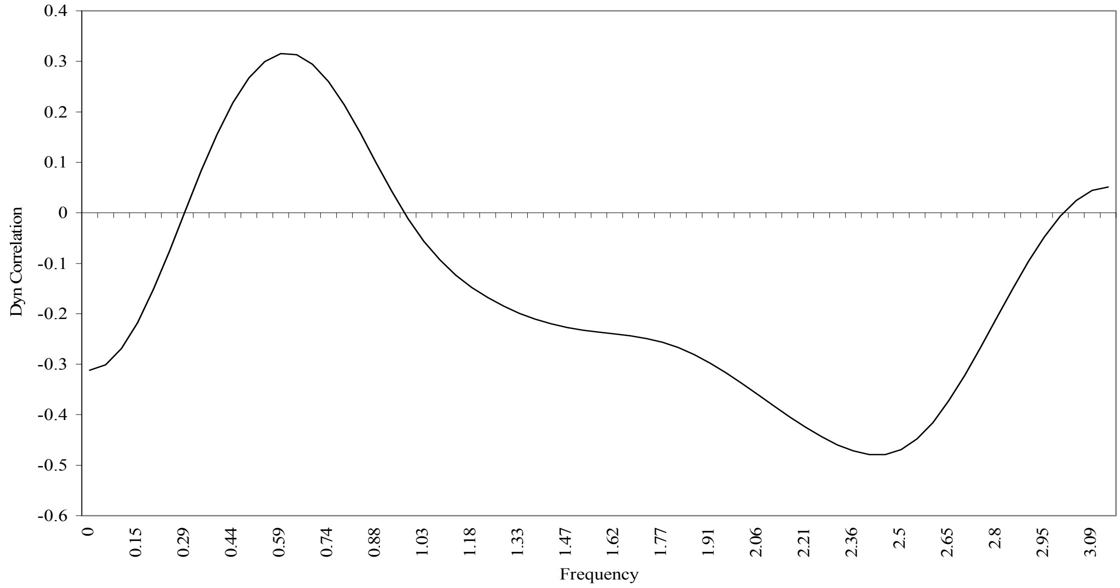
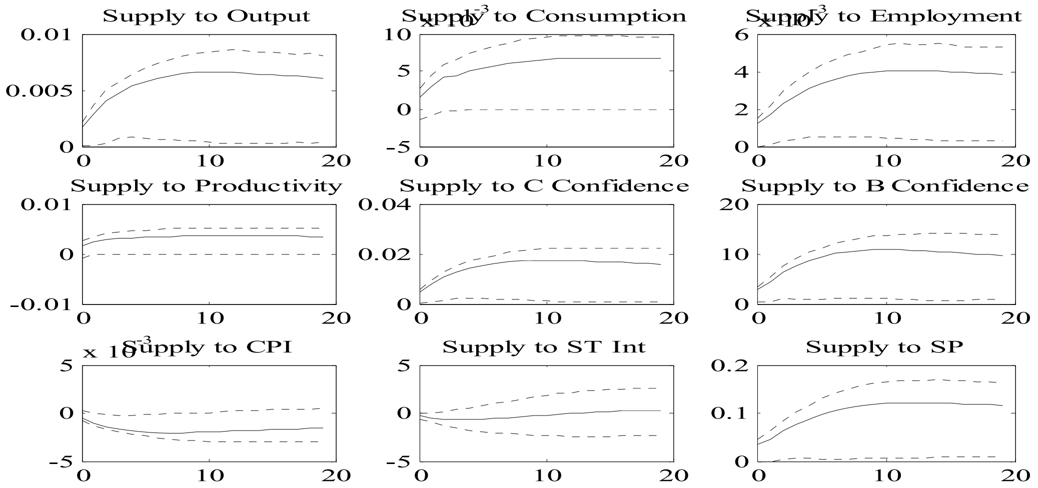


Figure 4: Impulse-response functions to GER shocks

GER Supply Shocks → GER variables



GER Demand Shocks → GER variables

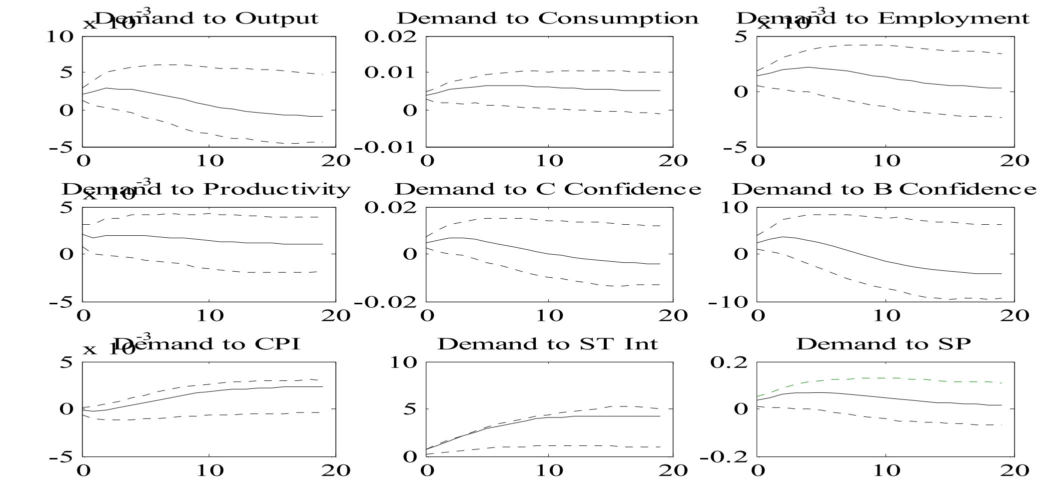
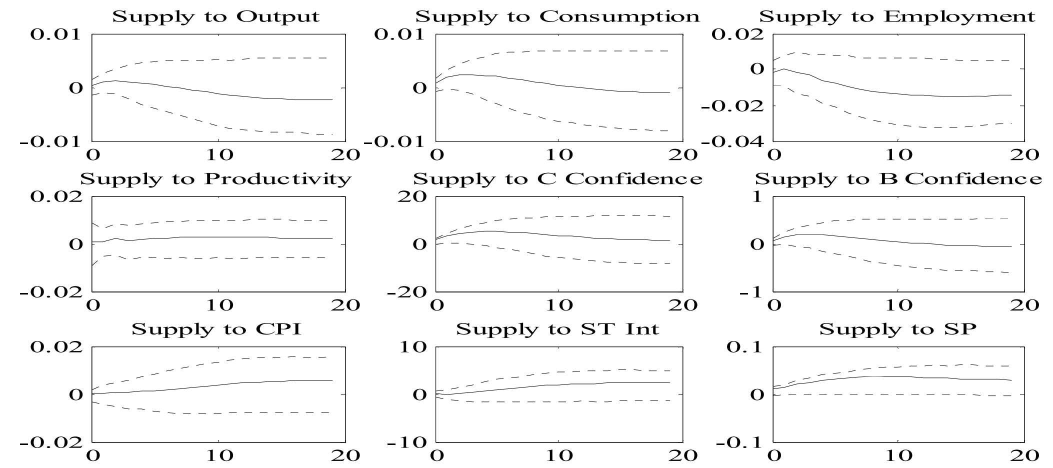


Figure 5: Impulse-response functions of German shocks to South Africa

GER Supply Shocks → SA variables



GER Demand Shocks → SA variables