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Fiscal Policy and Business Cycles in an Oil-Producing Economy: The Case of Venezuela

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Fiscal Policy and Business Cycles in an Oil-Producing Economy: The Case of Venezuela[1]

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Abstract

This paper analyzes the fiscal policy in Venezuela during 1991–2003, by using a number of statistical approaches to analyze trends and cycles of economic output and fiscal outcomes. The business cycle features a strong dominance of short-term cyclical components—each cycle having an average duration of about two to three years. However, the cyclical volatility of non-oil sector GDP is more than two times as large as the volatility of oil sector GDP. On the fiscal side, while oil revenues are independent of the business cycle, all the other main fiscal variables exhibit strong procyclicality. In particular, fiscal procyclicality is higher during good times than bad times, which could be related to the existence of "voracity effects." The discretionary component of fiscal policy is as volatile as the component induced by the business cycle.

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I. INTRODUCTION

Fiscal outcomes in developing countries tend to be both volatile—much more volatile than in the industrial economies—and highly procyclical, that is, expansionary in "good" times and contractionary in "bad" times. There are several reasons why these patterns emerge in developing countries, including: the limited and volatile access to international financial markets, especially during recessionary periods; frequent changes in the discretionary component of public spending responding to political cycles; and the high dependence on cyclically sensitive revenue sources such as indirect taxes and transfers from state-owned natural resource industries.

In particular, countries with strongly cyclical revenue flows stemming from oil exports seem to have a strong volatile and procyclical response of fiscal policy. In connection with these issues, this paper looks at the recent experience of Venezuela, a major oil-producing and emerging market economy.

The oil sector plays a dominant role in Venezuela as it contributes (in real terms and based on the period 1991–2002) to about 25 percent of its total GDP, 50 percent of public sector revenues, and about 80 percent of exports. As a result, Venezuela's macroeconomic stability is highly dependent on—and therefore vulnerable to—the oil sector.[2] The oil sector component of the GDP of Venezuela is also highly correlated to oil price fluctuations: Figure 1 shows that, during 1991–2002 the correlation ration between the oil price—as measured by the Venezuelan basket—and the oil sector nominal GDP was 0.80.[3]

This paper aims at making three main contributions: first, it analyzes the business cycle in a single country time series study and focuses on an oil-producing emerging market economy.[4] In order to do so, we disaggregate the cyclical components of the output in the oil economy and the non-oil economy. A disaggregated approach is potentially useful in highlighting the cyclical components of output which are more prone to volatility and procyclicality.

Second, it compares the behavior of fiscal policy in Venezuela to a group of selected emerging market economies and measures the country's discretionary and cyclical indicators

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[2]In February 2003, in order to halt foreign exchange reserve depletion caused by a deep economic recession, Venezuelan authorities introduced wide-ranging foreign exchange (FX) controls covering current and capital account transactions and switched from a floating exchange rate regime to a fixed exchange rate regime. Initially set at Bolívares (Bs) 1,600 per US$, the official exchange rate was devalued again in February 2004 and March 2005 at, respectively, Bs 1,920 and Bs 2,150 per US$. However, the Bolívares are currently exchanged in the parallel market at 2,750 Bs per US$.

[3] During the same period, the correlation between the oil price (Venezuelan basket) and the total nominal GDP of Venezuela was 0.60.

[4] Kydland and Zarazaga (1997), Franken, Le Fort, and Parrado (2004), Restrepo and Reyes (2002), Torres (1999), and Sáez (2004) also investigate the business cycles of, respectively, Argentina, Chile, Colombia, Mexico, and Venezuela. Using annual and quarterly data, Sáez (2004) finds evidence that total public sector expenditure in Venezuela is strongly procyclical.

for several components of public sector revenues and spending. To do so, fiscal and macroeconomic variables are measured over the business cycle to assess whether a cyclical increase in the output—for example, caused by a temporary rise in the oil price—is associated with either a cyclical or a discretionary change in public spending. With respect to the overall primary balance, the non-oil primary balance is selected as a more reliable indicator for the fiscal stance. This is due to the fact that oil revenues are mostly dependent on the oil price, which is largely exogenous and also highly erratic.

Third, the paper assesses how fiscal policy is conducted over the business cycle by applying four different econometric approaches. The reason to use four approaches is that measuring business cycle components involves a certain degree of arbitrariness as to which particular type of filtering approach is to be used (Canova, 1998). Moreover, the application of several approaches helps to comply with robustness checks.

The first approach uses a Hodrick-Prescott (HP) filter to study the business cycle in standard time domain analysis. The second approach is based on a two-step procedure which identifies an ARIMA model for the observed series, and then uses frequency-domain analysis to estimate the cyclical component.[5] The third approach is a mixture of the two and is called the "modified HP filter."[6] The fourth and last approach uses frequency-domain analysis by estimating a band-pass filter which eliminates frequencies outside a specified range, thus allowing targeting of specific business cycle frequencies.[7] To gauge the thrust of fiscal policy, these four filtering approaches are used to estimate the "output gap," which is an important input to measuring the structural or underlying fiscal balance.[8]

The plan of the paper is as follows: Section II highlights some stylized facts on volatility of public revenue and expenditure, based on a cross-section analysis of fiscal outcomes in selected emerging market economies. Section III provides an overview of past trends of macroeconomic and fiscal variables in Venezuela during the period 1991–2003. Section IV describes the methodology used to measure unobserved components, such as trends and cycles, as well as Venezuela's output gap. Section V applies these methodologies to show how the Venezuelan authorities conducted fiscal policy over the business cycle in the period 1995–2003. Section VI estimates the fiscal stance in Venezuela by using fiscal impulse and output gap analysis. The last section provides some concluding remarks.

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[5] Kaiser and Maravall (2000) define this approach as ARIMA Model-Based (AMB) Approach. The Frequency-domain approach represents cyclicality in stochastic processes by using the spectral density function or spectrum.

[6] The modified HP filter approach has been proposed recently in Kaiser and Maravall (2004).

[7] In particular a band-pass filter constructed by Ouliaris and others (2002) is applied here. I wish to thank Andreas Billmeier for having suggested use of this specific filter.

[8] Output gap analysis is also relevant for assessing whether variations in actual growth are of cyclical or more permanent nature, as well as to gauge inflationary pressures.

II. Stylized Facts about the Volatility of Revenues and Expenditures

It is only recently that empirical and theoretical studies pointed out that growth and business-cycle volatility might be related. The evidence shows that countries with more volatile fluctuations display lower long-term output growth rates.[9] Moreover, there is also extensive evidence on the behavior of fiscal policy over the business cycle which shows that fiscal outcomes are far more volatile and procyclical in developing economies than in industrial countries.[10]

Figure 2 shows the simple correlations between output growth and its volatility between 1960 and 2000 in a group of selected middle-income and emerging economies, while Figure 3 shows the correlations between volatilities of public revenues and expenditures in percent of GDP between 1990 and 2002 for the same group.[11] In Figure 2, output growth and volatility are measured by, respectively, the average annual growth rate of real per capita GDP and the standard deviation of real per capita GDP growth. In Figure 3, the volatility of fiscal outcomes is measured by the annual standard deviation of total public expenditures and revenues over the sample period 1990–2002.

The result of an ordinary least squares (OLS) regression of annual mean growth of GDP per capita (Δy_i) on its standard deviation, $\sigma(\Delta y)_i$, for the 26-country sample from 1960 to 2000 is

$$\overline{\Delta y_i} = \underset{(4.60)}{3.81} - \underset{(-2.17)}{0.39}\,\sigma(\Delta y)_i \tag{1}$$

($R^2 = 0.165$, t-statistics in parentheses). The regression equation (1) indicates that volatility is harmful for growth since there is a negative and statistically significant relationship between growth and volatility. The negative relationship suggests that a percentage point increase in output volatility decreases output growth by 0.4 percent. However, the low value of the R-squared coefficient indicates that growth volatility alone explains only up to 16 percent of variation in negative growth. It is also noteworthy that the two major oil-producing economies of the sample—Nigeria and Venezuela—have experienced average negative

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[9] Ramey and Ramey (1995), Gavin (1997), and Kose, Prasad, and Terrones (2005) all found a negative correlation between volatility and growth for a wide cross-section of developing and industrialized economies, including Latin America.

[10] Evidence on Latin America includes Gavin and others (1996), and Gavin and Perotti (1997). Further evidence showing procyclicality of fiscal policies in a broader cross-section of developing and emerging markets economies than Latin America are documented in Talvi and Vegh (2000), Lane (2003) and, more recently, in Kaminsky, Reinhart, and Vegh (2004).

[11] The countries are: Argentina, Brazil, Bulgaria, Chile, China, Colombia, Costa Rica, Cote d'Ivoire, Croatia, Ecuador, Egypt, Hungary, India, Indonesia, Jordan, Korea, Lebanon, Malaysia, Mexico, Morocco, Nigeria, Pakistan, Panama, Peru, Philippines, Poland, Russia, South Africa, Thailand, Turkey, Ukraine, Uruguay, Venezuela. Due to lack of data, countries from Eastern Europe and the former Soviet Union are omitted in the top panel on output growth and volatility.

output per capita growth during the period 1960–2000. However, the output growth average volatility of Nigeria was two times as large as in Venezuela.

To see if the volatility of public spending is correlated to revenue volatility, the annual average of public expenditure volatility in percent of GDP, $\sigma_i(g)$, is regressed against the annual average of public revenue volatility in percent of GDP $\sigma_i(\tau)$ for the 33-country sample from 1990 to 2002. The estimation results of this OLS regression are

$$\overline{\sigma_i(g)} = \underset{(1.92)}{1.03} + \underset{(5.79)}{1.09}\,\overline{\sigma_i(\tau)} \tag{2}$$

($R^2 = 0.52$, t-statistics in parentheses). This suggests the following facts: first, there is a strongly positive correlation between revenue and expenditure volatility, whereas a percentage point increase in revenue volatility increases expenditure volatility by almost 1.1 percent.[12] Moreover, the R-squared coefficient of 0.52 indicates that the volatility of revenues alone explains up to 52 percent of variation in expenditure volatility.

Secondly, oil countries and countries with main export commodities—like Brazil, Costa Rica, Nigeria, and Venezuela—do tend to exhibit the highest volatility in both revenues and expenditures.[13] Venezuela has recorded both high public sector revenue and expenditure volatility, with an annual average standard deviation of around 4 percent of GDP during the period 1990–2002.

Why is it that a country may experience revenue volatility? And why does revenue volatility seems to enhance expenditure volatility as well? Oil prices tend to be very volatile in an uncertain and unpredictable environment for several reasons—reflecting a combination of factors such as time-varying excess capacity (discrete jumps in technological innovation changing levels of excess capacity over time and creating cycles of high and low production capacity) and uncertain demand for oil and investment activity in the oil sector due to changing geopolitical reasons. Therefore, in the absence of strategies to hedge against oil price risk, the volatility of oil prices will directly affect oil revenues which, for oil-producing countries like Venezuela, historically account for a large share of total revenues.[14] To reduce revenue volatility associated with oil price volatility, a number of recommendations have been proposed: (i) the authorities should adjust the non-oil balance of the public sector in line with oil price movements to guarantee a sustainable level of non-oil primary deficit; (ii) the authorities should accumulate substantial financial assets over the period of high oil

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[12] The same results hold after taking outliers out of the sample like Nigeria, Turkey, and Ukraine. The median values for expenditure and revenue volatility of this sample are, respectively, 1.9 percent and 2.9 percent of GDP.

[13] Hausmann and Rigobon (2002) provided a rationale as to why an oil-dependent economy or a country with a large resource-tradable sector may be vulnerable to higher price volatility and larger decline in welfare than less specialized economies.

[14] See Daniel (2001) for a critical assessment and review on how to hedge against oil price risk.

production; and (iii) the authorities should formulate accurate oil price assumptions.[15] However, in the absence of corrective measures and accurate budget forecasting and planning, revenue volatility is detrimental to budget execution, and this in turn enhances expenditure volatility.

The third fact related to the volatility of fiscal outcomes is that—at least for the period 1990–2002—some differences have started to emerge within developing economies. Several countries of the sample continued in the 1990s to exhibit a volatility above the sample average of 2 percent and 3 percent of GDP, respectively, for revenue and expenditure volatility. However, other countries of the sample started to lower their revenue and expenditure volatility below the sample average. In particular, despite Latin America's high dependence upon cyclically sensitive revenue sources such as indirect taxes and transfers from state-owned natural resource industries, countries such as Chile, Ecuador, Mexico, Panama, Peru, and Uruguay are included within the group of countries with lower fiscal outcome volatility. However, other countries of the same region, such as Brazil, Costa Rica, Venezuela, and Nigeria, have instead continued to exhibit higher fiscal outcomes volatility.[16] Some other countries of the sample, such as Bulgaria, Lebanon, Côte d'Ivoire, Turkey, and Ukraine, experienced instead high revenue volatility but kept their expenditure volatility in line or below the sample average.

A number of factors other than volatility in the main commodity price have been indicated to explain as to why fiscal outcomes in developing or emerging market economies tend to be volatile and strongly procyclical— that is a fiscal policy which tends to be expansionary in "good" times and contractionary in "bad" times. Most notably, as has also been argued in Talvi and Vegh (2002), the consumption of the private sector tends to be much more unstable and volatile in developing countries than in developed countries. Since in developing countries the tax administration is weak and therefore largely dependent on indirect taxation, the volatility of private consumption is directly reflected in the volatility of revenues. Gavin and Perotti (1997) highlighted three other main factors: (i) the implementation of misguided discretionary policies which causes recessions instead of sustaining the cycle; (ii) the existence of political incentives which may lead governments to enact discretionary increases in government spending during periods of revenue windfall; (iii) in connection with the political or institutional incentives, Lane and Tornell (1999) and, similarly, Talvi and Vegh (2000) also provided a rationale as to why the existence of multiple power blocs within the government competing for a share in fiscal revenues causes the existence of so-called "voracity effects." These voracity effects lead the government to increase spending more than proportionally to increases in revenues. Finally, the presence of international credit constraints can prevent developing countries from borrowing during recessions and force them to curb spending in bad times.

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[15] See Barnett and Ossowski (2003) on the operational aspects of managing fiscal policy in oil-producing countries.

[16] Alesina and others (1996) classified budget institutions of Latin America in the period 1980–92 and showed that "hierarchical" and transparent budgetary procedures are associated with more fiscal discipline.

All these economic factors therefore may increase the volatility of output, which in turn affects fiscal policy volatility and increases the likelihood of running a procyclical fiscal policy. However, reverse causality holds, as a procyclical fiscal policy would also contribute to exacerbating the amplitude and persistence of economic fluctuations.[17] As a result, there is more aggregate macroeconomic instability, which in turn increases the risk of having more prolonged recessions.

III. Fiscal Trends in Venezuela

In this section, the fiscal trends of Venezuela are compared with a selected group of emerging market economies during the period 1990–2002. Figures 4 and 5 show, respectively, the average external public debt in percent of GDP and the primary balance in percent of GDP. The variance of fiscal outcomes within a group of 33 emerging market economies is remarkable: for instance, within the period 1990–2002, the average external public-debt-to-GDP ratios ranged from more than 120 percent in Côte d'Ivoire to about 3 percent in South Africa. Venezuela, with an average external debt-to-GDP ratio above 40 percent, was in the upper range of the sample. Primary balances varied from an average surplus of 5 percent of GDP in Malaysia to an average deficit of more than 6 percent of GDP in Lebanon.[18] Venezuela, with an average primary surplus around 1 percent of GDP, is in line with the sample average. However, on the revenue side, during the period 1996–2003, there was a clear downward trend in non-oil revenues, with a reduction of more than 20 percent in real terms, while oil revenues were also slightly decreasing in real terms despite the rise in oil prices. Total revenues declined for about 15 percent in real terms since 1996.

During this period, Venezuelan authorities have also benefited both from seigniorage and the impact of foreign exchange controls as important sources of implicit revenues to finance the growing deficits and reduce debt service payments.[19] The average annual revenue from seigniorage during the 1995–2003 period was 1.5 percent of GDP. More recently, the implementation of the capital controls since February 2003 caused domestic interest rates to decline. As a result, the government's domestic debt service declined and money holdings increased, thereby increasing the seigniorage revenue base.[20] On the expenditure side, a main

[17] The literature on the macroeconomic effects of fiscal policy is extensive. The seminal research in Blanchard and Perotti (2002) uses a structural VAR approach to estimate the dynamic effects of shocks to government spending and taxes on output in the United States in the postwar period.

[18] The coverage of these data on fiscal outcomes is based on the consolidated nonfinancial public sector, while debt is measured on a gross basis.

[19] Seigniorage and financial repression were also related to the presence of high and persistent inflation as well as various forms of foreign exchange controls in Venezuela. Fischer (1982), and Giovannini and de Melo (1993), respectively, measured revenues from seigniorage and financial repression for a large sample of developing countries and underlined how these implicit forms of taxation could be quite substantial. Giovannini and de Melo (1993) also show the potential complementarities between the financial repression tax and revenues from seigniorage.

[20] Seigniorage is measured as the change in nominal base money in percent of GDP, that is $[M(t) - M(t\text{-}1)] / GDP(t)$, where M is nominal base money, and GDP is nominal GDP.

source of vulnerability remains the large share of mandatory spending, which accounts for more than 60 percent of total expenditure. While the trend of no interest expenditure was rather stationary throughout the period, interest expenditure decreased until 1996 and then rebounded.[21]

In summary, these results seem to indicate that the fiscal stance in Venezuela was fragile as it was relying on volatile oil revenues and implicit forms of taxation such as seigniorage and financial repression. However, it would also be important to assess whether the fiscal outcomes observed during this period were due to the effect of the business cycle and therefore of transitory nature or to discretionary action by the government. In order to do so, it is necessary to measure and distinguish between the discretionary and cyclical components of macroeconomic and fiscal variables. The next section—which is devoted to this task—applies several econometric and statistical methods.

IV. Detrending and Business Cycles: The Methodology

Measuring business cycle components involves a certain degree of arbitrariness since filtering approaches generate different conclusions (Canova, 1998). Hence, we use four types of detrending methods in order to extract different types of information from the data. These detrending techniques are based on the following main filtering methodologies: (i) the *standard* approach of Hodrick-Prescott (HP); (ii) the ARIMA model-based approach (AMB); (iii) a procedure defined in Kaiser and Maravall (2004) as “modified” Hodrick-Prescott filter (MHP), which is a mixture between the AMB and the HP filtering approaches; and (iv) the frequency-domain approach as applied by a band-pass filter developed by Corbae, Ouliaris, and Phillips (2002). These techniques are briefly described in the appendix and compared in the following sections. The dataset on Venezuela consists of quarterly data for several macroeconomic and fiscal variables during the period 1990–2003. In particular, 13 economic time series are analyzed. The first three are total GDP, and its subcomponents of non-oil GDP and oil GDP. The next two are the oil price as measured by the World Economic Outlook (WEO) and by the Venezuelan basket. The rest are key fiscal variables, which include total revenues, oil and non-oil revenues, seigniorage, total expenditures, non-oil expenditures, non-oil primary expenditures, and the non-oil primary balance. All data were provided by the Venezuelan authorities, and—to control for inflation—are expressed in real terms by using a GDP deflator. For the GDP, quarterly data are available from 1991 to end-2004, but fiscal data are available only from 1995 to end-2003.

A. The Hodrick-Prescott Filter

The HP filter is a moving average filter widely used by macroeconomists to obtain a smooth estimate of the long-term trend component of a series. Since it is independent of the

[21] Nondiscretionary spending is here defined as spending for which there is a legal or strong obligation of the government to meet. It includes: interest payments on public debt, transfers to nonfinancial public enterprises, transfers to lower levels of governments, and public pensions.

particular series to which it is applied, this filter is also defined as an ad hoc filter. However, one of the drawbacks pointed out by the literature on business cycles (Nelson and Plosser, 1982; Baxter and King, 1999), is that HP filtering may yield a cycle containing contributions from noncyclical frequencies. That is, even if the HP filter is applied to a seasonally adjusted series, the HP filter will still attribute to the cycle highly transitory variations, which should not be included in a cyclical component.[22]

By using the HP filter, Figure 6 plots the cyclical component for, respectively, real GDP, the GDP of the non-oil sector, and the GDP of the oil sector.[23] By looking at these cycles, the GDP of the non-oil sector appears to be more volatile than the GDP in the oil sector economy: the amplitude of the business cycle of the non-oil sector economy is much larger than the amplitude of the oil sector GDP. Most notably, non-oil sector GDP volatility—measured by the standard deviation of the cyclical component—is more than twice as large than the volatility in the oil sector GDP. As this evidence suggests, macroeconomic volatility in Venezuela is also exacerbated by factors other than those related to the oil sector economy.

B. The ARIMA Model-Based Approach

An alternative method for estimating a trend and cyclical component is to apply the ARIMA Model-Based Approach (AMB method) or Beveridge-Nelson procedure. Because ARIMA models are designed to fit the short-run properties of the data, the trend estimator obtained with this procedure will include a large amount of short-term variation. That is why this trend is also referred to as a trend-cycle component as it includes frequencies belonging to trend and cyclical components. The properties of this estimation approach could be usefully applied on the Venezuelan case, since its output trend is expected to be largely subject to both structural and cyclical shocks.

Similarly to the previous section, Figure 7 shows the cyclical component for real GDP, the GDP of the non-oil sector economy, and the GDP of the oil sector economy. The time series for each of the GDP series is decomposed into a trend-cycle component by applying the AMB model-based approach.[24] The underlying derived 'optimal' model for total GDP is an ARIMA (2,2,0), which is an autoregressive component of the second order applied to the

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[22] HP filtering is also likely to produce spurious cycles in a white-noise series (Kaiser and Maravall, 2004)

[23] The HP trend was estimated for $\lambda = 1600$, since there is general agreement among researchers at setting the parameter λ =1600 when working with quarterly data. However, there is less agreement for other frequencies (Ravn and Uhlig, 2001). The cyclical component is the difference between the series and its HP trend.

[24] The model is estimated using the program "TRAMO-SEATS." The TRAMO (Time Series Regression with ARIMA Noise, Missing Observations, and Outliers) program performs estimation, forecasting, and interpolation of regression models with missing observations and ARIMA errors, in the presence of possibly several types of outliers. The SEATS (Signal Extraction in ARIMA Time Series) program performs an ARIMA-based decomposition of an observed time series into unobserved components using spectral analysis. These programs were developed by Victor Gomez and Agustín Maravall.

second differences of the series.[25] However, when considering the oil GDP series, the derived estimated model is an IMA (0,1,1) that is a moving average process applied to the first-difference of the series. For the non-oil GDP series the optimal model fitted is an IMA (0,1,3) or a moving average of the third order applied to the first difference of the series.

C. The Frequency-Domain Approach

Another way to analyze the cyclical variability of a time series Y_t is by applying the spectral analysis in a *frequency domain approach*.[26] To study the characteristics of the trend-cycle under this approach, we compute the "squared gain" function of the trend-cycle—a function that includes only mid and low frequencies which contribute to the trend-cycle component and filters out the seasonal high frequencies. Figures 8a and 8b plot the "squared gain" of the trend-cycle component respectively for the non-oil GDP and the oil GDP of Venezuela. The area underlying the trend-cycle gain for the oil GDP is smaller than that for the non-oil GDP for every frequency and drops to zero for frequencies around 1.57, which corresponds approximately to a time period of four quarters. This implies that the oil GDP exhibits overall less variability than the non-oil GDP. Moreover, while the oil GDP trend-cycle declines smoothly to zero for frequencies around 1.57, the squared gain function for the non-oil GDP exhibits a cyclical peak for frequencies around 1.77, which correspond to a duration of almost a year (3.6 quarters). This short-term cyclical peak seems to suggest a mean reverting behavior of the non-oil GDP in relatively short-term periods.

This preliminary evidence seems to indicate that Venezuela's output tends to be characterized by short-term business cycles. To test this hypothesis, however, one can apply the frequency-domain approach to estimate a band-pass filter—developed in Corbae, Ouliaris, and Phillips (2002)—which eliminates frequencies outside a prespecified range, thus allowing to target specific business cycle frequencies.[27] In the case of Venezuela, where—as noted above—the observed presence of short-term cyclical components in the business cycle stems from fluctuations in both the oil GDP and the non-oil GDP, a business cycle frequency between 0.31 and 1.05 is chosen. This frequency band—which corresponds to a time duration ranging between 6 and 20 quarters—is shorter than the standard business cycle duration of 8 to 32 quarters. However, the choice of this narrow band-pass filter is made to reflect both the short-term characteristics of the business cycle of the non-oil GDP,

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[25] The model derived is defined to be 'optimal' in the sense that the AMB estimators for the trend, seasonal and irregular component are Mean Minimum Square Errors (MMSE) estimators based on the observed series. See the Appendix and Kaiser and Maravall (2000) for details.

[26] For a detailed analysis of spectral analysis in frequency domain, see Watson (2001), and Hamilton (1994). A brief description of this approach is provided below in the appendix.

[27] Hamilton (1994) suggests to target a specific frequency range based on visual inspection of the spectral density function. The choice of specifying a certain frequency band remains arbitrary, however.

as well as the oil price fluctuations which affect the business cycle of the oil GDP with a mean-reverting behavior in relatively short-periods of time.[28]

Figure 9 shows the cyclical component, respectively for the real GDP, the GDP of the non-oil sector economy, and the GDP of the oil sector economy by using the band-pass filter developed by Corbae, Ouliaris, and Phillips (2002). The observed stochastic behavior of non-oil GDP could reflect the rapid alternance between periods of weak and strong economic growth which occurred in Venezuela during the period 1995–2002. In particular, the banking crisis of 1995, whose recessionary effects were felt until 1997; a period of relatively strong growth during 2001–02 followed by the political stalemate of early 2002; and the work stoppage in the oil sector at the end of 2002 which moved the country again in a strong contractionary growth period.

D. The Modified Hodrick and Prescott Filter

The cyclical component estimated under the standard HP filter and the AMB approaches tends to be more volatile and less persistent than the business cycle estimated by the band-pass filter.[29] An alternative strategy would be to take the first difference of the series and then extract the cyclical component. However—as noted in Baxter and King (1999)—despite the benefit of removing unit root components, the first difference filter is asymmetric and reweighs strongly the higher frequencies while down weighting the lower frequencies. To overcome these shortcomings, Kaiser and Maravall (2004) suggest an alternative filtering procedure defined as a "modified HP" filter (MHP) which combines the properties of an ad hoc filter, such as the HP filter with the properties of the ARIMA-Model Based filtering approach. With the MHP filtering procedure, the trend-cycle component is first extracted by using the AMB approach; the second step is to de-trend the estimated trend-cycle function by applying the HP filter. By applying this procedure, one obtains a cycle which removes the seasonal frequencies with associated periods of roughly two years, as well as the low frequencies removed out through the HP filter.[30] As a result, the erraticism observed in the "standard" HP and AMB cyclical components is greatly reduced.

[28] By analyzing the spectrum of the oil price (Venezuelan basket, quarterly data), most of the variability in the oil price comes from two main sources: (i) cyclical variation over two-year periods (first peak at $\omega = 0.26$ or 8 quarters); (ii) seasonal variation, with peaks occurring at seasonal frequencies 1.05, 1.57, 2.09, 2.62, and 3.14, which correspond to, respectively, 6, 4, 3, 2.4, and 2 months. These estimates are not shown in the paper but are available upon request.

[29] Cyclical variation or volatility is measured by its standard deviation, while persistence is measured by the first-order autocorrelation. Two strictly periodic function or business cycles of same periodicity can therefore be more or less volatile or persistent depending on their respective variance or autocorrelation. This concept would be better understood by applying the definition of spectral density in frequency domain analysis (see the Appendix).

[30] This procedure—developed by Kaiser and Maravall (2004)—targets a business cycle frequency between two and eight years, which corresponds to a range of 8 to 32 quarters.

This is evident in Figures 6, 7, 9, and 10 which compare these four different decompositions for quarterly real GDP, non-oil GDP, and oil-GDP of Venezuela during the period 1991–2002. Figures 9 and 10 show that the GDP business cycle estimated with respectively the MHP and the band-pass filter, crosses the horizontal zero line only seven times, compared to about 16 times for the business cycle estimated with the “standard” HP and 28 times with the short-term cycle computed by the AMB filter. As a result, the erraticism of the business cycle is much reduced when using a band-pass filter, such as the MHP and the frequency-domain filter by Corbae, Ouliaris, and Phillips (2002).

V. Business Cycle Properties of Fiscal Variables in Venezuela

This section applies the previous filters to measure how fiscal policy in Venezuela has been conducted over the cycle. We use quarterly data for several macroeconomic and fiscal variables during the period 1990–2003 and examine 13 economic time series: total GDP, and its subcomponents of non-oil GDP and oil GDP; the oil price as measured by the WEO and the Venezuelan basket; and a group of key fiscal variables, which include: total revenues, oil and non-oil revenues; total expenditures, non-oil expenditures; the non-oil primary balance, and seigniorage.

Since we are interested in studying the business-cycle properties of Venezuela’s fiscal policy, we focus on three sets of moments: (i) the standard deviation is used as a proxy of volatility; (ii) the first-order correlation as a proxy for persistence; and (iii) the contemporaneous correlations with GDP to capture the cyclicality of the series.[31] For each series, the standard HP filter, the modified HP filter, the AMB model-based filter, and the frequency-domain filter approach are used.[32] Tables 1, 2, and 3 summarize the results.

A. Volatility

Table 2 presents volatility statistics, with volatility measured by using the quarterly average standard deviation for each variable. Every variable has been decomposed in its trend and cyclical component to indicate how its volatility varies with the output.

By normalizing the volatility of the cyclical component of real GDP to its corresponding trend, the former is more volatile than its trend by a factor of 1.2. It is to be noted that the cyclical component of non-oil GDP exhibits a volatility two times as high as the oil GDP component independently of which filter is applied. However, the trend component of oil GDP is more than twice volatile as its cycle. This, in turn seems to suggest that in the oil sector there are frequent policy regime switches—perhaps due to the high volatility of the oil

[31] Baxter and King (1999) apply this methodology to study business-cycle properties for the U.S. time series.

[32] However, the results under the frequency-domain filter are omitted since they are very similar to the Modified HP filter.

price in its trend level. Consequently, the shocks to the trend seem to be the primary source of fluctuations in the oil GDP rather than the cyclical fluctuations around a stable trend.[33]

On the fiscal side, the variable with the highest volatility is oil revenue which, under the standard HP cyclical component, exhibits a standard deviation of 6.3 billions of Bolívares (in real terms). Oil revenue is more volatile than its HP trend by a factor of 3. Similarly, under the AMB approach, oil revenue is very volatile since its optimal estimator is identified as a moving average (MA) process of the second order *MA(2).* This implies that the value in real terms of oil revenues is influenced only by events that take place up to two quarters.[34]

Interestingly, and in connection with the positive correlation between expenditure and revenue volatility discussed in Section II, non-oil primary expenditures are up to twice as volatile as non-oil revenues. Comparing volatility measures across the filters, the standard HP filter produces volatility statistics that are larger than under each of the other filters: on average the standard HP is more volatile by a factor of 2 if compared with the modified HP filter and by a factor of 3 with the AMB filter. This is because the HP standard filter and to a lesser extent the AMB filter are a rough approximation to high-pass filters which retain some high-frequency volatility removed by the Modified HP band-pass filter.

B. Persistence

Table 2 presents persistence statistics measured by the first-order autocorrelation for, respectively, the series (column 1), the trends (columns 2, 3, and 4) and the cyclical components (columns 5, 6, and 7). Since the most persistent components of macroeconomic time series occur at the lower frequencies, an obvious result is that trends are more persistent than their respective cyclical components. The persistence of the cyclical component is a relevant indicator since a value of substantial persistence—around 0.9—implies business cycle predictability. Taking the modified HP filter as a benchmark, GDP, total expenditure and the non-oil primary balance exhibit substantial persistence with values of, respectively, 0.92, 0.93, and 0.90. Oil GDP, with a value of 0.88, is more persistent than non-oil GDP which records a value of 0.73.While total expenditures are more persistent than total revenues, non-oil primary expenditures are slightly less persistent than non-oil revenues with, respectively, values of 0.88 and 0.92. This difference could be explained by the increasing share of interest payments which tend to be highly persistent.

The difference of persistence across the three filters is striking. The band-pass filters estimated with the modified HP filter exhibit the cyclical component with the most persistent behavior, because it includes low-frequency components which are instead removed under the standard HP cycle and AMB approach. The difference in persistence between the

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[33] In a standard real business cycle model, Aguiar and Gopinath, (2004) apply a VAR methodology to identify permanent shocks which supports the notion that the “cycle is the trend.”

[34] When a time-series is estimated to be a MA process, the model is noninvertible and therefore no cyclical decomposition is provided by TRAMO/SEATS.

modified HP filter and the standard HP filter is on average a factor of 1.6 (except seigniorage, where the difference is much larger). However, the AMB cycle—due to its high short-term erraticism—exhibits negative persistence for all the 13 variables except for non-oil revenues and expenditures (and therefore non-oil primary balance). Once again, this is due to the fact that the AMB short-term cycle removes more of the highly persistent, low-frequency components, and emphasizes the much less persistent, high-frequency components.

C. Cyclicality of Fiscal Policy

Table 3 provides the simultaneous correlation rates between each of the variables of the sample and real GDP. As for the previous statistics, every variable has been decomposed in its trend and cyclical component to indicate how it varies with output. In particular, the table provides the correlations between GDP and several categories of fiscal variables to test whether fiscal outcomes are procyclical—that is, expansionary in "good" times and contractionary in "bad" times.

A procyclical fiscal outcome is associated with positive correlations between real GDP and the cyclical component of expenditures.[35] The main findings reported in Table 4 are the following: the cyclical component of non-oil primary expenditures exhibits strong procyclicality with correlation ratios ranging between 0.41 and 0.52, while non-oil expenditures exhibit a mild, albeit still positive correlation with real GDP. Non-oil primary expenditures are more procyclical than non-oil expenditures due the fact that the interest component tends to be counter-cyclical.[36] Also total expenditures are weakly procyclical, with positive ratios ranging between 0.21 and 0.44. This is due to the inclusion of oil-related expenditures which are not depending on the GDP cycle—the simple correlation ratio between real GDP is close to zero—and account for about 20 percent of total expenditure in the considered sample.[37]

Procyclicality is also confirmed when looking at the correlation between GDP and the cyclical component of the non-oil primary balance. This fiscal aggregate is negatively correlated with GDP with a ratio of 0.37 and 0.39, when using, respectively, the HP and the

[35] The cross-correlation ratios between one fiscal variable and the GDP are numbers ranging between -1 and +1. With a ratio around zero, fiscal policy would be considered independent on the cycle (acyclical), while a ratio close to -1 or +1, fiscal policy would be interpreted as, respectively, very strongly countercyclical or procyclical.

[36] Especially for an emerging market economy, the interest component tends to be declining in "good" times while increasing in "bad" times as the country's creditworthiness, and therefore the cost of servicing its debt, is positively related to the output. In real terms, interest expenditure of the non-oil sector in Venezuela is negatively correlated with real GDP with a correlation ratio of -0.26.

[37] Correlation ratios of the unadjusted series quoted in this section but not reported in Table 4 are available upon request.

modified HP cyclical component.[38] This implies that, for each percentage point increase in real GDP, there is actually a worsening in the non-oil primary balance of about 0.4 percentage points. On the revenue side, total revenues appear to be independent on GDP business cycle with correlation ratios close to zero or weakly negative. However, once revenues are disaggregated in oil and non oil sector revenues, non-oil revenues exhibit stronger procyclicality with a coefficient between 0.40 and 0.50, while oil revenues are weakly negatively related to the GDP cycle with a correlation ratio of -0.18.

Summarizing, these results indicate that during the period 1995–2003, non-oil primary expenditures, which account for about 80 percent of total public expenditures, were procyclical, with highly positive correlation ratios with total GDP up to 0.50. Interest expenditures, on the other hand, were countercyclical as expected for an emerging market economy. One step further with respect to this analysis, would be to differentiate between cyclical and discretional components of the main fiscal aggregates. This is the aim of the next section, which analyses the fiscal stance and impulse of fiscal policy in Venezuela during the same period.

VI. Fiscal Policy Behavior: Discretionary versus Cyclical Component

The aim of this section is to assess the behavior of fiscal policy of Venezuela during the period 1995–2002, by using the non-oil primary balance as the main fiscal indicator. The reason why the non-oil primary balance is preferred to the overall primary balance is related to the fact that, in an oil-producing economy, oil revenues are usually a large share of total revenues but mostly dependent on the oil price which is exogenous and highly erratic. The non-oil primary balance is also a more reliable indicator in terms of longer-term fiscal policy sustainability analysis (Barnett and Ossowski, 2003).

There are a number of approaches to gauge how fiscal policy responds to the cycle and to the discretionary action of the government. A standard approach to do this is to decompose the main fiscal indicator—in this case the non-oil primary balance—into its discretionary and cyclical components. We do this by applying two approaches: (i) the ARIMA based model estimation; and (ii) the structural fiscal balance, which is based on an underlying measure of potential output.[39] Under both approaches, we estimate the underlying discretionary component and the potential output by using the Modified HP filter, which has some desirable properties as noted above—lower erraticism and more balanced volatility through bust and booms.

[38] The negative correlation implies that in bad times a procyclical fiscal policy would improve the balance. There is large evidence showing procyclicality of fiscal policies in Latin America and other non-OECD member countries (Talvi and Vegh, 2000; Gavin and others 1996; Gavin and Perotti, 1997; and Lane, 2003).

[39] The discretionary component is simply defined as the component which removes the cyclical component of the fiscal balance.

Moreover, we also measure the fiscal stance and the fiscal impulse to evaluate the impact of the fiscal budget on aggregate demand (Blejer and Cheasty, 1993).[40] In connection with the positive correlation between expenditures and revenues volatility highlighted in Figure 3, we measure how the increase in the discretionary component of government spending is related to an increase in the discretionary component of revenue. This is also to test for the existence of the so-called “voracity effects”.[41]

In an oil-producing economy, to maximize welfare over the long run, the government should try to smooth consumption and oil-related taxation over the long run. (Barnett and Ossowski, 2003). To do so, the oil-revenues should be first accumulated and then used after the depletion of the exhaustible natural resource. As a result, non-oil primary balances would remain constant over time, and independent on oil revenues. This, in turn implies two policy implications both empirically testable: (1) zero or very low volatility of the non-oil primary balance; and (2) no correlation between the non-oil primary balance and oil-revenues.[42, 43]

Table 4 summarizes fiscal policy performance behavior in Venezuela under these two conditions. Under the first column, are reported the volatilities for oil-revenues and non oil-revenues, as well as non-oil primary expenditures, and the non-oil primary balances. Under the second column, are reported the correlation ratios of the same variables with oil-revenues. The volatilities and the correlation ratios are computed for both the unadjusted series and for the discretionary component.

Regarding the volatility of fiscal policy, during the period 1995–2003, the non-oil primary balance, at almost 7, is more than twice as volatile as non-oil revenues. In particular, non-oil primary expenditures, at 6.4, were almost as volatile as oil revenues, whose volatility was 6.9. When considering the discretionary components, the volatility of non-oil primary balances and primary expenditures are reduced by more than half, indicating that the volatility of these fiscal aggregates was largely due to the cyclical component.

Regarding the second fiscal policy implication, that is on the independence of non-oil primary balances on oil-revenues, results are somewhat mixed: when the unadjusted component of the non-oil primary balance is used, the correlation between oil-revenues and the non-oil primary balance is close to zero, thereby indicating that the fiscal policy was

[40] Other approaches include the debt-stabilizing primary surplus, to gauge the sustainability of public debt in the long run, and the constant oil price balance to evaluate how fiscal policy is affected by the oil price cycle.

[41] Lane and Tornell (1999) analyze the negative effects on growth due to so-called voracity effects in fiscal policy. Due the presence of weak institutions and powerful interest groups, a shock, such as a terms of trade windfall could generate a more than proportionate increase in fiscal redistribution. As a result, fiscal policy becomes strongly procyclical and fiscal balances may even worsen in good times with harmful effects on economic growth.

[42] For a similar exercise on the Russian Federation case, see Spilimbergo (2005).

[43] The discretionary component is computed as the extracted Modified HP trend after applying the ARIMA based model (AMB) estimation as explained above.

following an optimal path. However, when the discretionary component of the non-oil primary balance is used, the correlation between oil-revenues and the non-oil primary balance shows a positive value of 0.24. In particular, the discretionary component of non-oil primary expenditure is negatively correlated to oil revenues with a value of -0.27. This seems to indicate that, in real terms, the discretionary component of non-oil primary expenditures increased despite declining oil revenues. Summarizing, the occurrence of relatively high volatility of non-oil primary expenditures and balances and a mild correlation with oil revenue seem to indicate that fiscal policy in Venezuela during the 1995–2003 period, was deviating from an optimal path.

As an alternative way to gauge the thrust of fiscal policy, the structural fiscal balance is also computed, by using the following standard definition

$$B_{str} = B - \eta \times Y^{Gap} \tag{3}$$

where B_{str} is the non-oil primary structural balance; B is the actual non-oil primary balance, η is the non-oil primary balance elasticity to output, and Y^{Gap} is the output gap defined as the output cyclical component in percent of the potential output. All the variables are expressed in real terms. The potential output is defined here as the trend output extracted with the modified HP filter, using the ARIMA based-model estimation procedure. For a proxy value of η, a value of 0.39 is used, which is the correlation ratio between the non-oil primary balance and the real GDP.[44]

Table 5 presents the fiscal stance and fiscal impulse of Venezuela during the period 1995–2003, and on an annual basis. Estimates for the output gap and the structural balance are also reported at the bottom of the table. The main results are as follows. The discretionary component of the non-oil primary balance shows a progressive worsening throughout the period: by end-2003, the non-oil primary deficit is almost four times as large as at the end of 1995. However, during 1996–2001, the fiscal impulse is positive, reflecting a strong increase in expenditure with an annual average growth of about 5 percent change in real terms, while non-oil revenues are mainly stationary.

During 2002 and 2003, however, primary public expenditure growth becomes negative by falling by about 1–2 percentage points each year. However, since also non-oil revenues fall by about 4 percentage points each year, this allows a still positive fiscal impulse of about 3 and 2 percentage points in real terms, respectively, in 2002 and 2003. This fiscal impulse, however, was almost entirely stemming from the sharp fall in revenue and was half the size of the annual average fiscal impulse recorded during 1996–2001.

[44] This value is also reported in Table 4.

Fiscal outcomes were more negative in 2002 and 2003, because during this period the real GDP of Venezuela fell by 9 percent each year. As a result, the output gap in these two years is negative with values, respectively, of 9 percent and 10 percent below potential output (see Table 5). This is in contrast with the 1996–2001 period, where the annual average output gap is a positive 2 percent above the trend.

Regarding the volatility of fiscal outcomes and output gap, during the period 1996–2001, the discretionary component of the fiscal stance is as volatile as the cyclical component. In particular, the volatility of non-oil primary expenditures is four times as volatile than non-oil revenues.

VII. Concluding Remarks

The paper has analyzed the effects of business cycles on fiscal policy and the fiscal policy performance in Venezuela during the period 1991–2003, by using several statistical approaches to analyze trends and cycles of economic output and fiscal outcomes.

On the characteristics of the business cycle, a strong dominance of short-term cyclical components—each cycle having an average duration of about 2–3 years—is observed for both the oil economy and the non-oil economy. However, the volatility of the business cycle (i.e., the amplitude of the cycle) of the non-oil sector GDP is more than two times as large as the correspondent volatility of the oil sector GDP. This evidence seems to indicate that business cycle volatility in Venezuela could also be exacerbated by volatility related to factors other than those related to the oil sector economy. However, the paper provides evidence that the trend of the oil GDP is more volatile than its cycle, indicating that the primary source of fluctuations in oil GDP seems to originate from shocks to the trend rather than from the business cycle.

The paper has provided cross-section evidence among developing countries that there is a significantly positive correlation between public revenue and expenditure volatility. In particular, oil-exporting countries and countries with main export commodities—such as Brazil, Costa Rica, Nigeria, and Venezuela—do tend to exhibit the highest volatility in both revenues and expenditures. Within this sample of countries, Venezuela has high public sector revenue and expenditure volatility, with an annual average standard deviation of around 4 percent of GDP during the period 1990–2002.

On the revenue side, however, non-oil revenues exhibit far less erratic behavior than oil revenues, which are mostly affected by the short-term volatility of the oil price. As a result, to gauge the underlying fiscal stance of Venezuela, we based our analysis of fiscal policy on the primary balance of the non-oil public sector, thus abstracting from the impact of the oil sector. When decomposing the volatility of the fiscal stance in Venezuela in both discretionary and cyclical components, the volatility induced by the discretionary component is as high as the volatility induced by the business cycle, while non-oil primary expenditures are much more volatile than non-oil revenues.

These results indicate that the fiscal stance has been procyclical, with strong non-oil primary expenditure growth in a period of positive economic growth (1995–2000) followed by expenditure restraint during the recessionary period of 2001–03. From 1995 to 1998, on a cumulative basis, the discretionary component of non-oil primary expenditure has grown by 29 percent in real terms. However, the growth rate of non-oil revenues was, on a cumulative basis, only 8 percent in real terms. These trends were however reversed during the recessionary period of 2001–03, when the output gap was up to 10 percent below its potential level. During this period, non-oil revenue fell by about 15 percent in real terms, or three times more than non-oil primary expenditures on a cumulative basis.

DETRENDING METHODS

Hodrick and Prescott Filter

The HP filter is a moving average filter that is widely used among macroeconomists to obtain a smooth estimate of the long-term trend component of a series. It removes a smooth trend τ_t from some given data y_t by solving:

$$\min_{\tau_t} \sum_{t=1}^{T} \{(y_t - \tau_t)^2 + \lambda[(\tau_{t+1} - \tau_t) - (\tau - \tau_{t-1})]^2\} \tag{4}$$

The *business cycle component* will then be measured as the deviation from the trend $y_t - \tau_t$. The parameter λ in equation (4) controls for the smoothness of the trend series by penalizing the acceleration in the trend relative to the business cycle component. The method was first used by Hodrick and Prescott (1997) to analyze postwar U.S. business cycles.

ARIMA–based filter

Following Kaiser and Maravall (2000), the starting point of this approach is the identification of an ARIMA model for the observed series. Denote by B the backward operator, such that

$$B^j x_t = x_{t-j} \quad (j = 0,1,2,...) \tag{5}$$

and let x_t denote a quarterly observed series. Then the following operators are defined:

- Regular difference: $\nabla = 1 - B$
- Seasonal difference: $\nabla_4 = 1 - B^4$;
- Annual aggregation: $S = 1 + B + B^2 + B^3$;

Where these three operators satisfy the identities: $\nabla_4 = \nabla S$ and $\nabla\nabla_4 = \nabla^2 S$;

Then an ARIMA model is given by the following expression.[45]

$$\nabla\nabla_4 x_t = \theta(B) a_t, \quad a_t \text{ is } niid(0, V_a) \tag{6}$$

where θ (B) is a polynomial in the lag operator B. If the model in equation (6) is invertible, then the series contains a nonstationary trend and seasonal components, and it can be decomposed into the following expression:

$$x_t = p_t + s_t + u_t \tag{7}$$

[45] See Kaiser and Maravall (2000) for details.

where p_t, s_t, and u_t denote the trend, seasonal and irregular component, with u_t a stationary process. The AMB approach ensures that under certain conditions this structural model can be identified. The solution to this identification problem is referred to as the *canonical* decomposition which maximizes the stability of the trend and seasonal components compatible with the equation (5) for the observed series, x_t.

The AMB estimators for the trend, seasonal and irregular component are Mean Minimum Square Errors (MMSE) or *optimal* estimators based on the observed series.

Frequency-Domain Filter

The aim of the frequency domain analysis is to determine how important cycles of different frequencies are in explaining the behavior of a series Y_t, which can be represented as a weighted sum of periodic functions of the form $\cos(\omega t)$ and $\sin(\omega t)$, where ω denotes a particular frequency. The spectral representation of Y_t is motivated by the Spectral Representation Theorem, which states that if Y_t is a covariance stationary stochastic process, with covariances $R_k = \operatorname{cov}(x_t, x_{t-k})$, then it can be represented as:

$$Y_t = \int_0^{\pi} \cos(\omega t)\, d\alpha(\omega) + \int_0^{\pi} \sin(\omega t)\, d\delta(\omega) \tag{8}$$

where $d(\alpha\omega)$ and $d(\delta\omega)$ are zero mean random variables that are mutually uncorrelated, uncorrelated across frequency, but having variances that depend on frequency. This representation decomposes Y into a set of strictly periodic components, uncorrelated with each other, and with it's own variance, σ^2_t. This process has three interesting characteristics: (i) it is periodic: Y_t repeats itself with a period of $2\pi/\omega$; (ii) the random components α and δ give Y a random amplitude (value at its peak) and a random phase (value at t=0); (iii) the process is covariance stationary. Thus, the variance of these strictly periodic components of Y is frequency specific and is represented by the function

$$S(\omega) = \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} R_k e^{-ik_\omega} \pi \leq \omega \leq \pi \tag{9}$$

which is called the power spectrum (or the spectral density) of the series Y_t.
The spectrum has four important properties: (ii) it can be interpreted as the variance of the cyclical component (of period $T = 2\pi/\omega$) of the time series corresponding to the frequency ω;[46] (ii) it is a variance function, so it is always nonnegative; (iii) it is symmetric, so plots of the spectrum can be presented for frequencies ω in the range 0–π (where π = 3.14...); (iv) the area underlying the spectrum is equal to the total variance of the series.

[46] For example, the frequency ω corresponding to four quarters (i.e., T = 4), is equal to π/2 or approximately 1.57. With quarterly data, this frequency will correspond to four quarters or one year.

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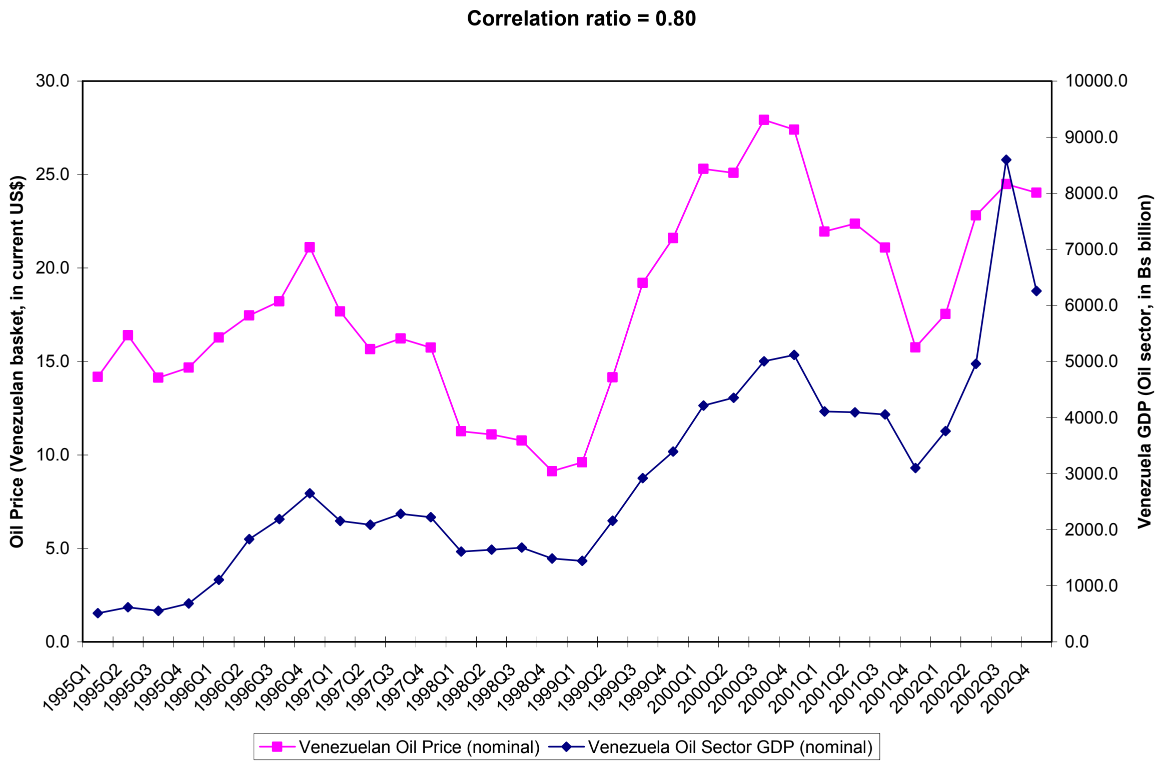
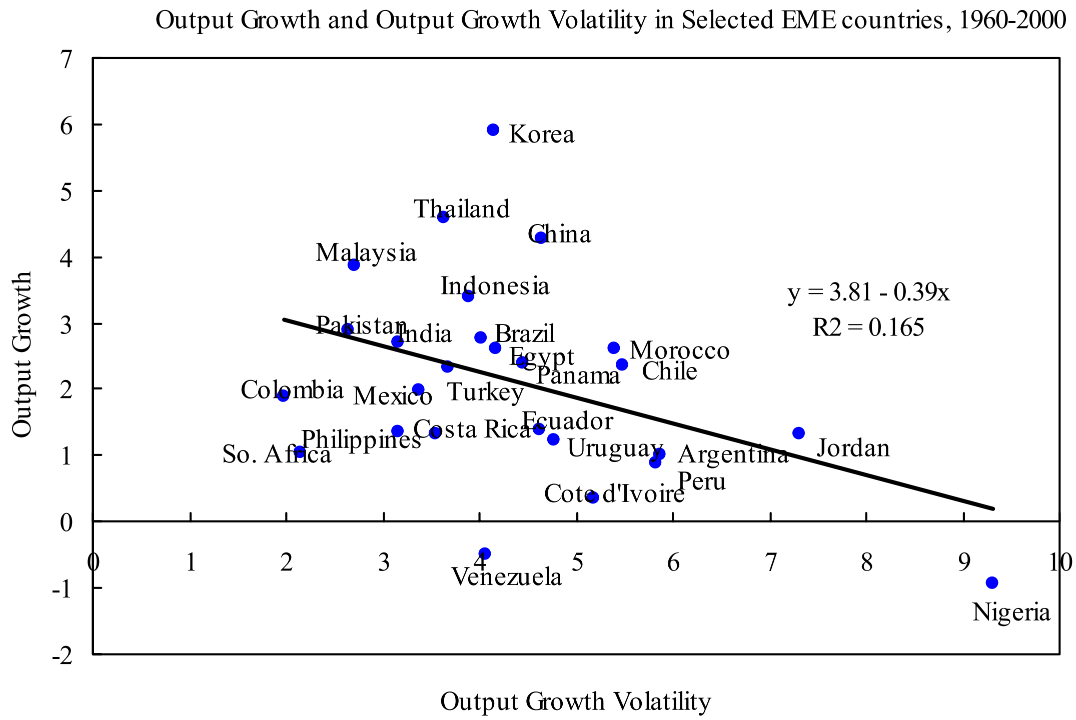
Figure 1. Venezuela Oil Price and Oil Sector GDP Fluctuations, 1991–2002



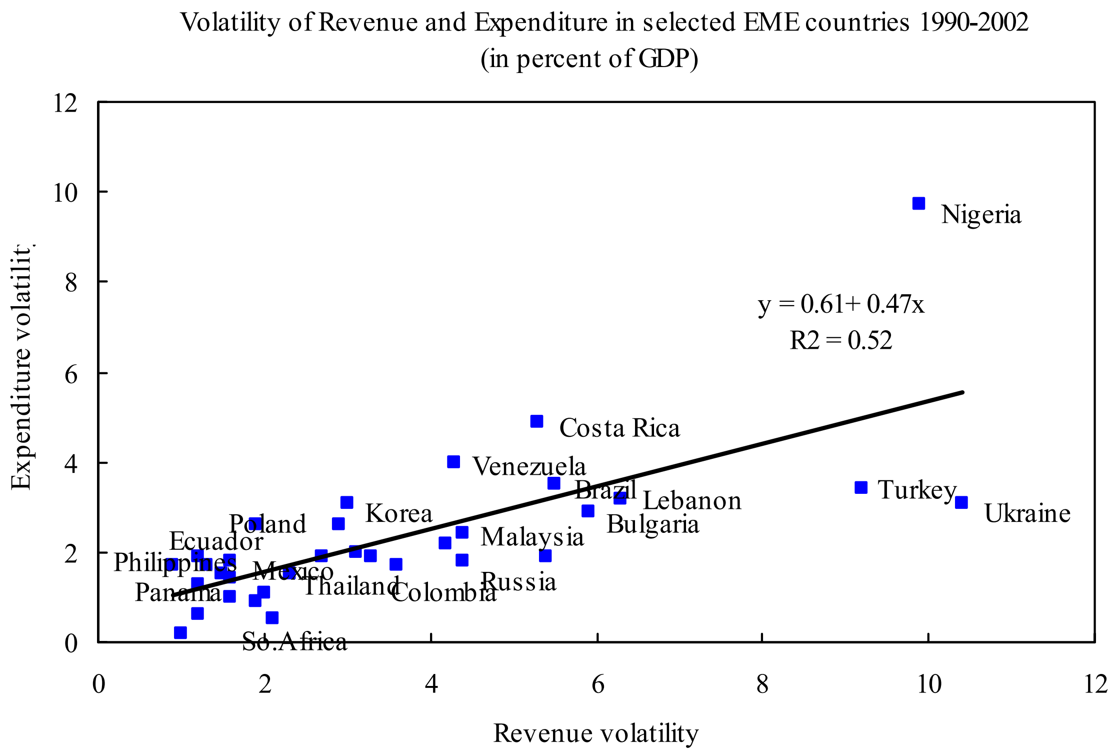
Source: Banco Central de Venezuela (BCV), Venezuelan Ministry of Finance (MOF), and IMF' staff calculations.

Figure 2. Output Growth and Output Volatility in Selected Emerging Market Countries, 1960–2000 (In percent of GDP) 1/



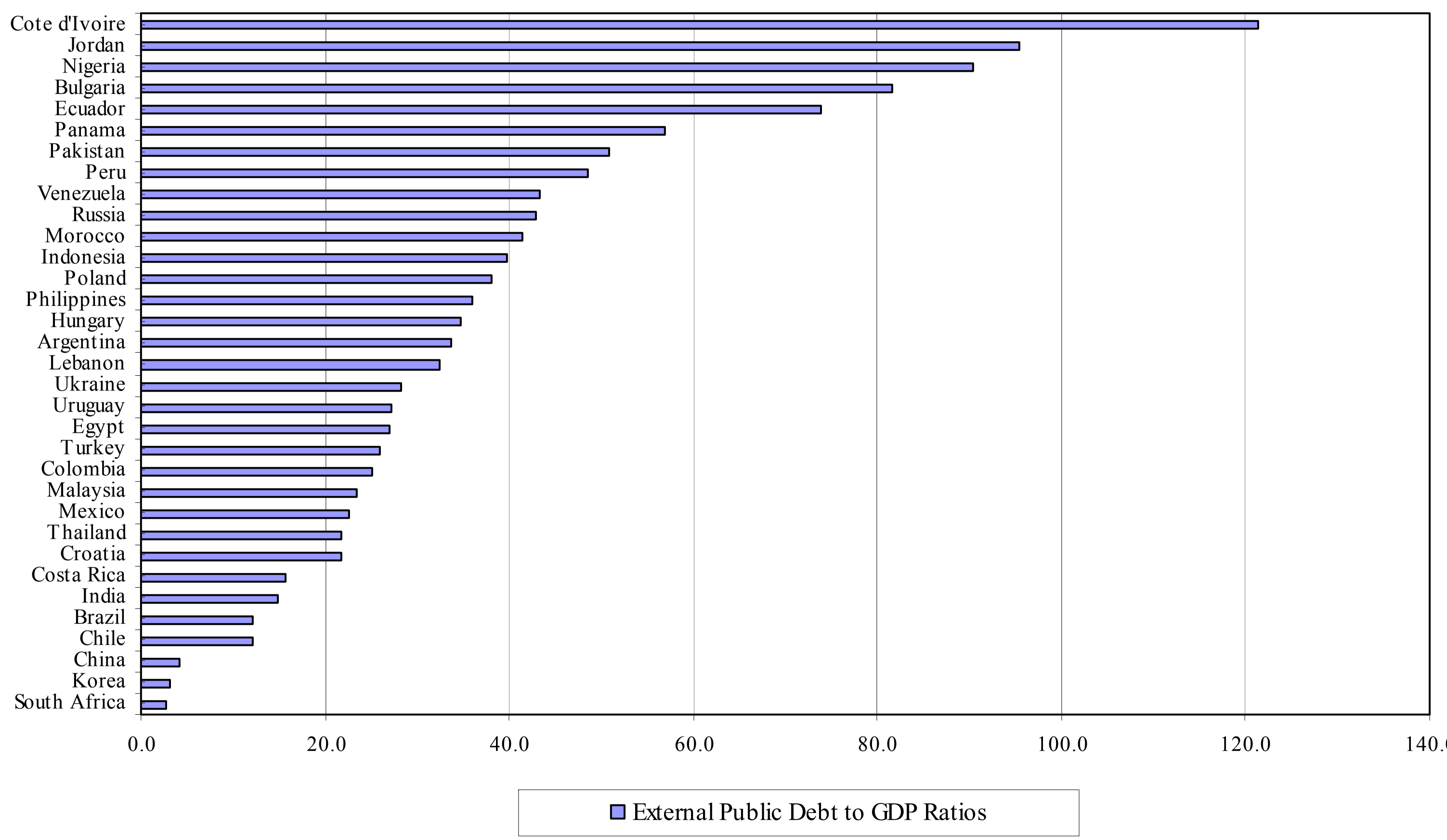
1/ Volatility is measured by standard deviation.
Source: Kose, Prasad, and Terrones (2004), and author's estimation.

Figure 3 .Volatility of Public Revenue and Expenditure in Selected Emerging Market Countries, 1990–2002 (In percent of GDP)



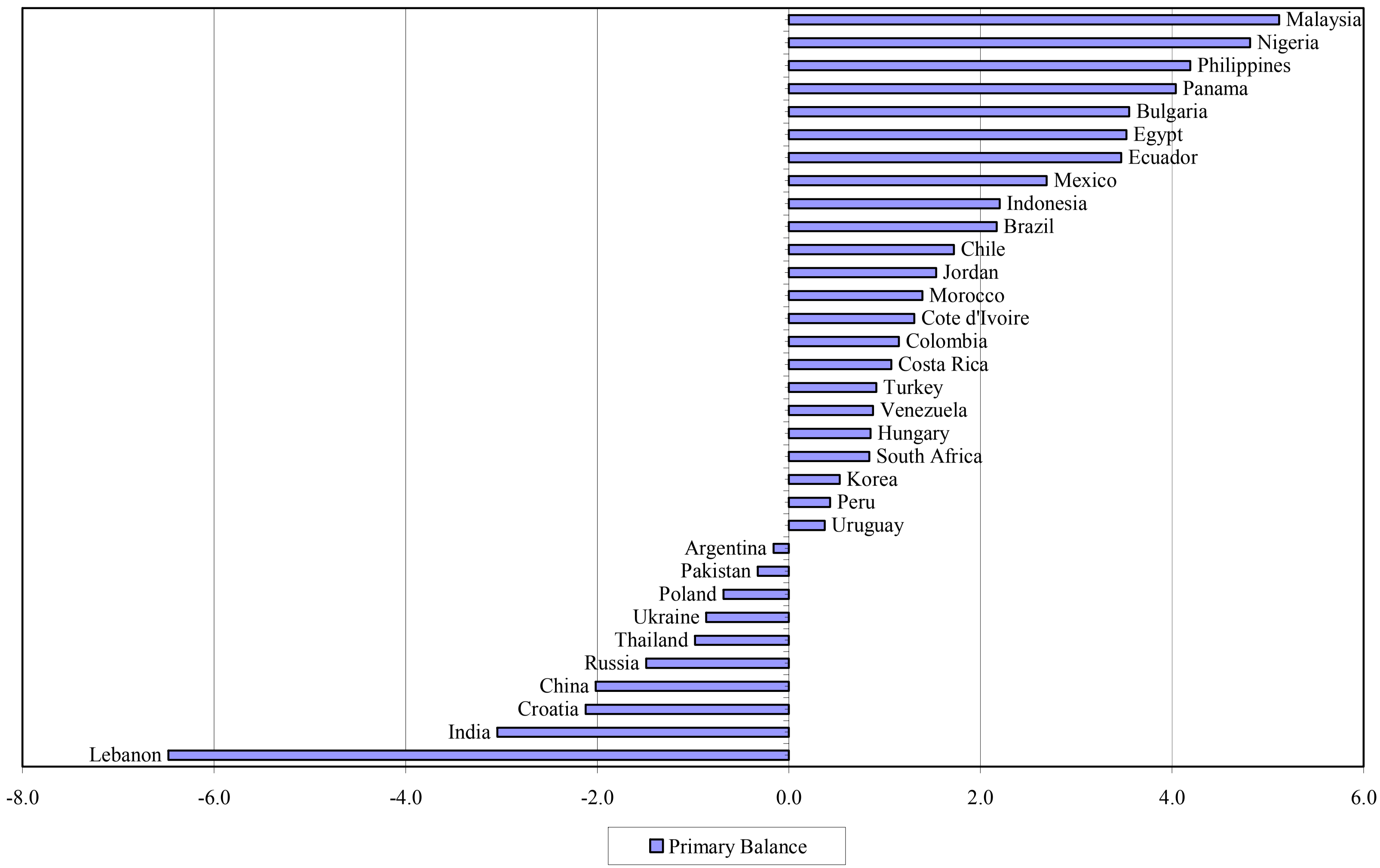
1/ Volatility is measured by standard deviation.
Source: IMF(2003), and author's estimation.

Figure 4. External Public Debt in Selected Emerging Market Countries,1990–2002
(In percent of GDP)



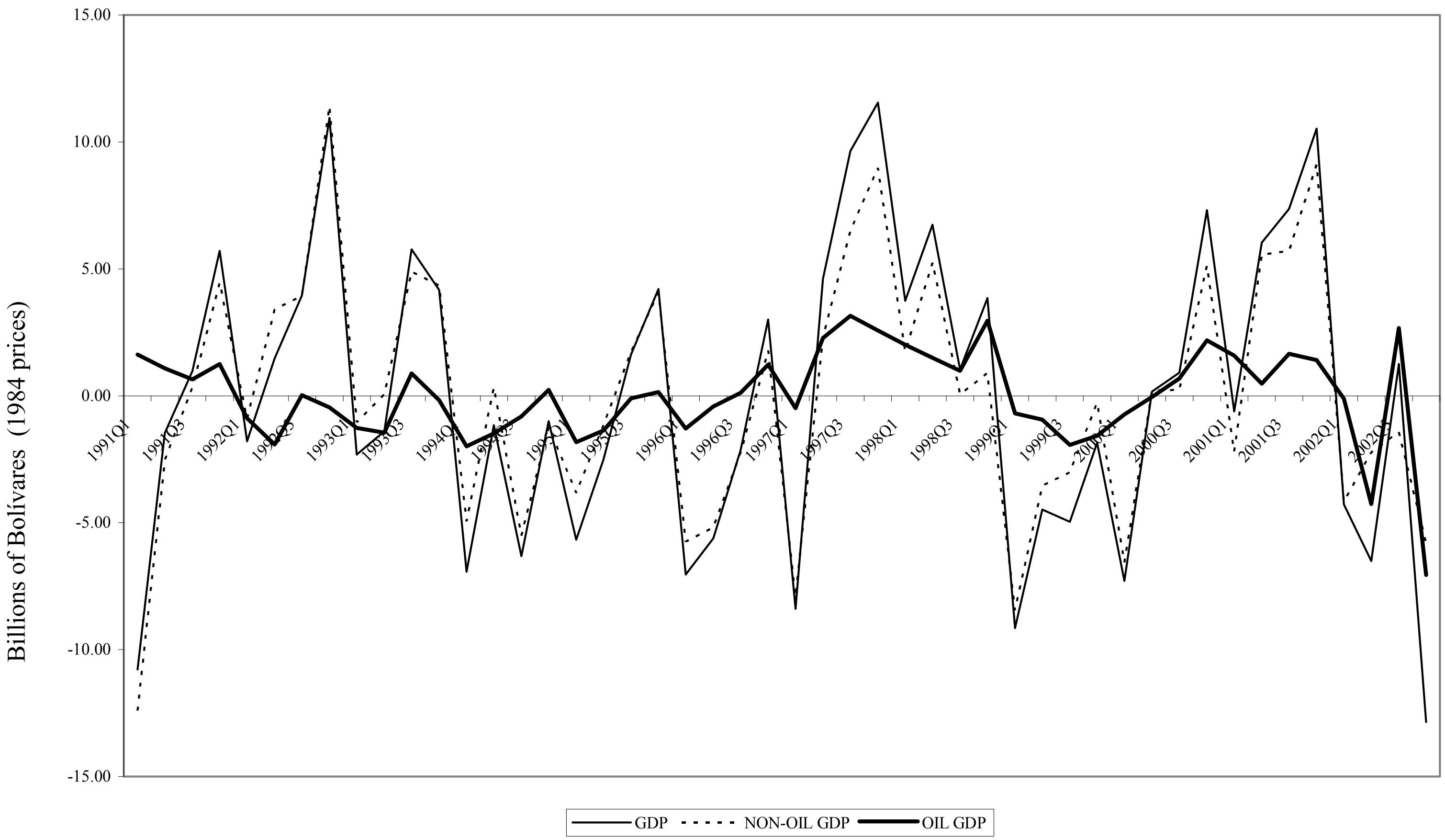
Source: IMF (2003).

Figure 5. Primary Balance in Selected Emerging Market Countries,1990–2002
(In percent of GDP)



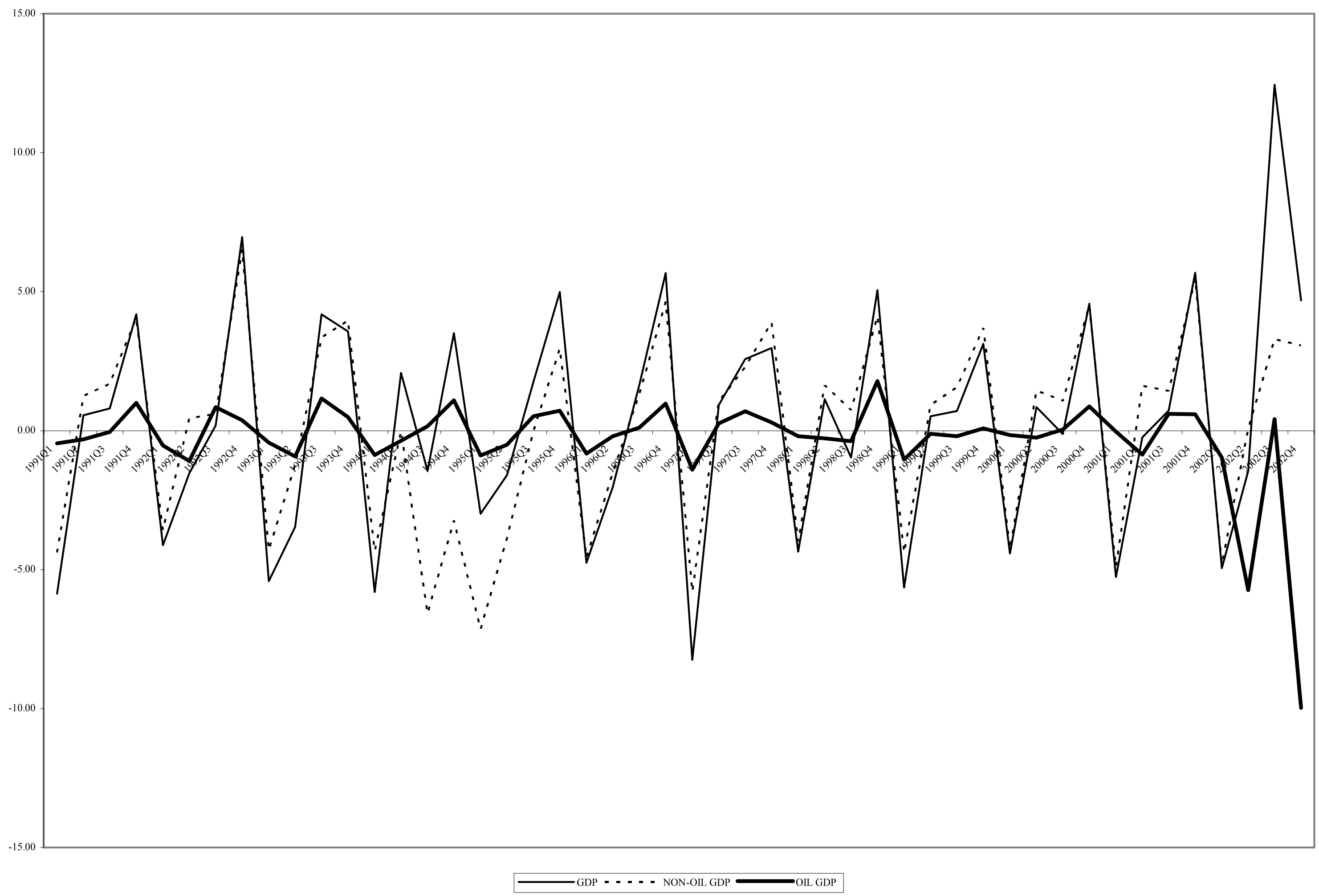
Source: IMF (2003)

Figure 6. Venezuela: Business Cycles with HP Filtering Procedure, GDP, Non-Oil GDP, and Oil GDP, 1991–2002 (In billions of Bolívares, at 1984 prices)



Source: BCV, MOF, IMF (2003), and author's estimations.

Figure 7. Venezuela: Business Cycles with ARIMA-Model Filtering Procedure,GDP, Non-Oil GDP, and Oil GDP, 1991–2002
(In billions of Bolívares, at 1984 prices)



Source: BCV, MOF, IMF (2003), and author's estimations.

Figure 8a. Venezuela: Real Non-Oil GDP—Squared Gain of Trend-Cycle Filter

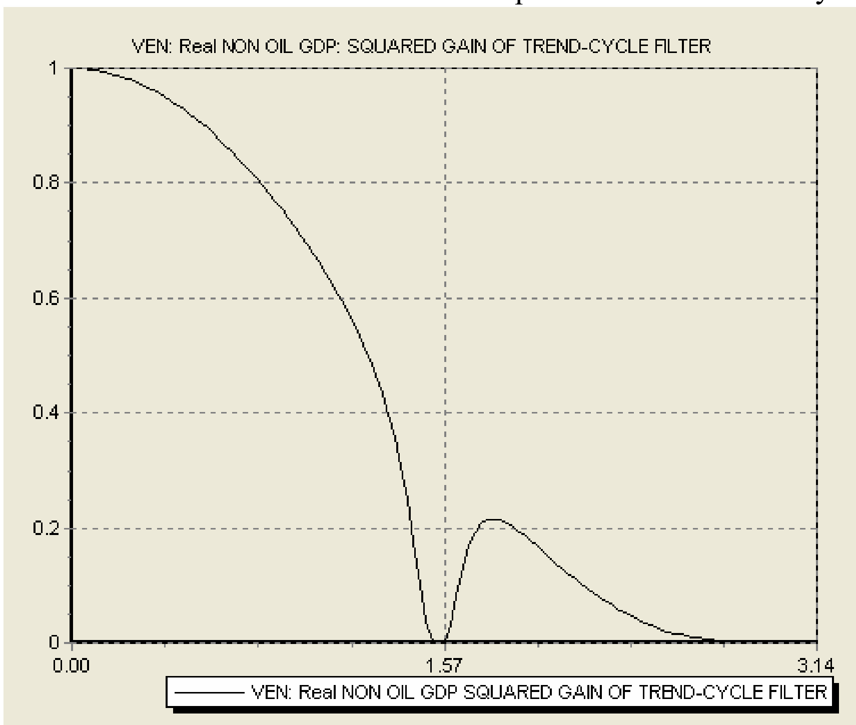
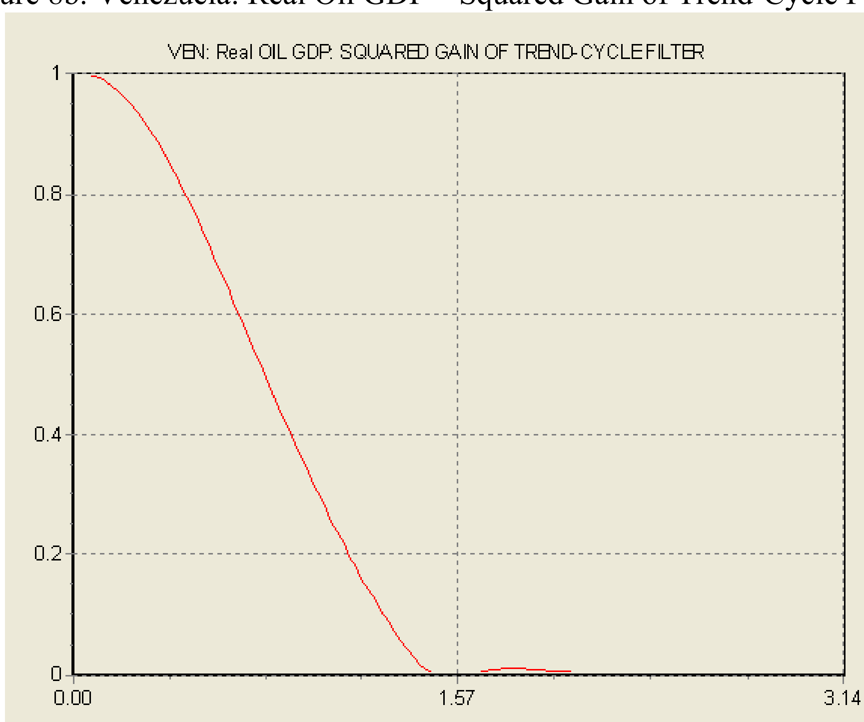
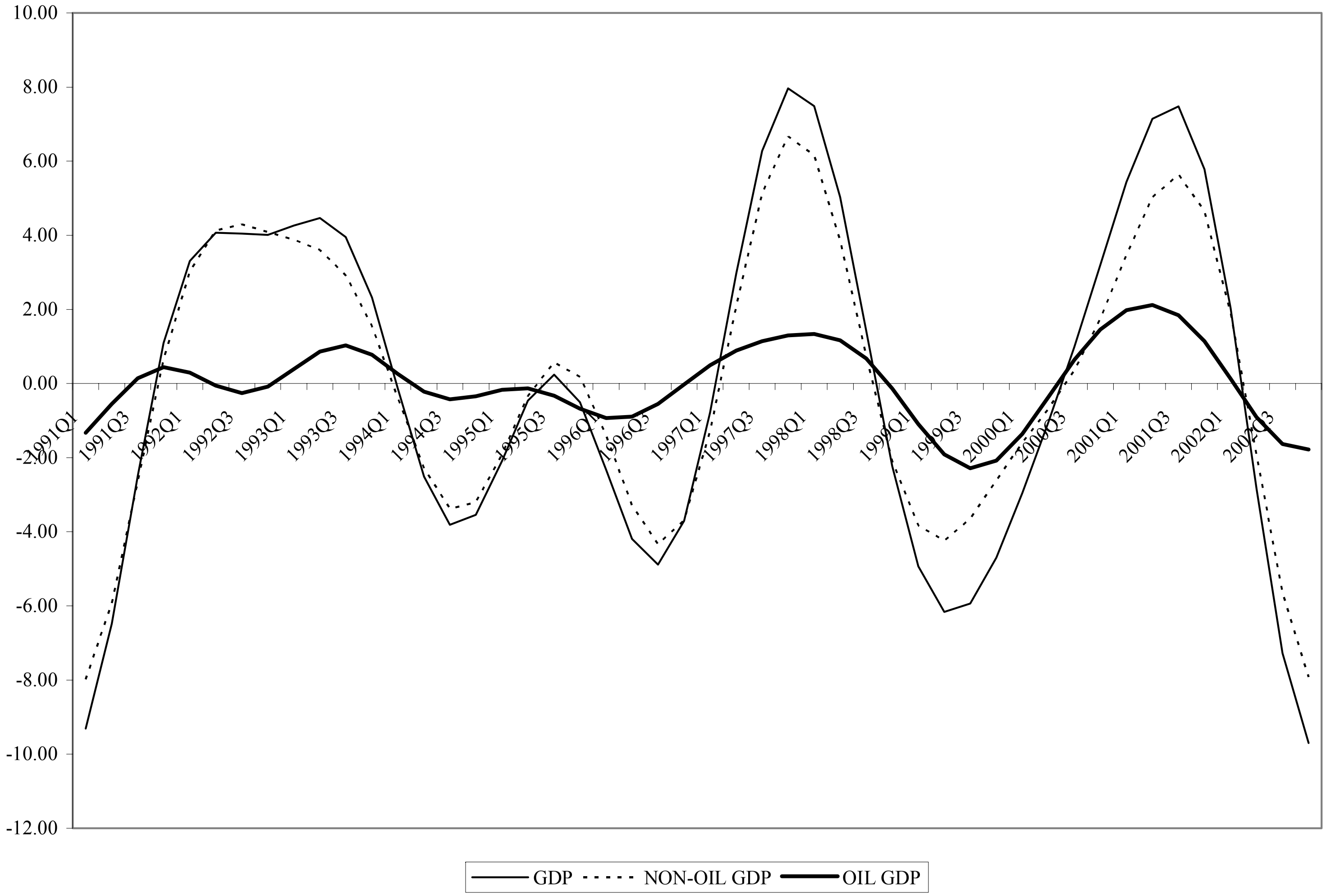


Figure 8b. Venezuela: Real Oil GDP—Squared Gain of Trend-Cycle Filter



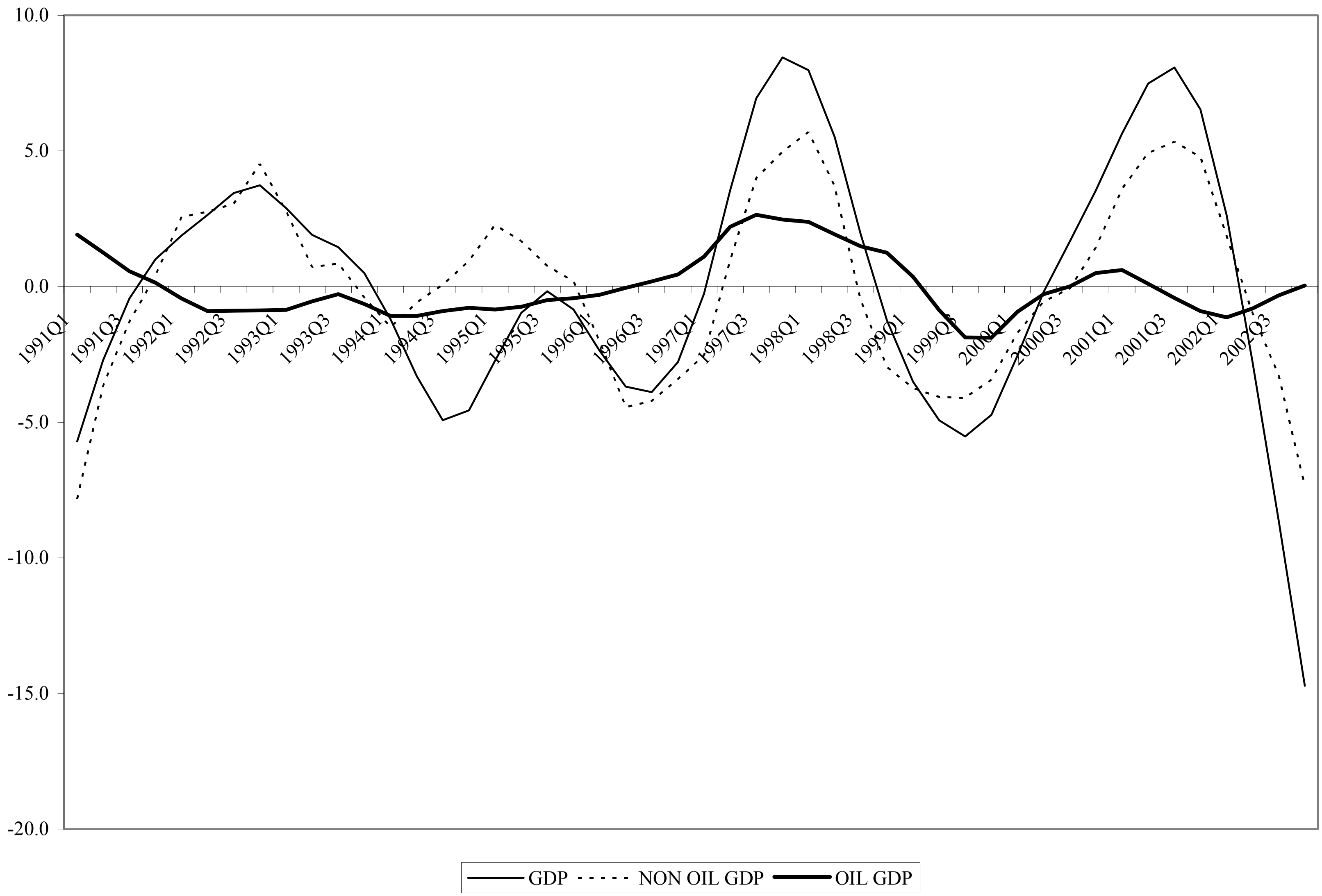
Source: BCV, MOF, IMF (2004), and author's estimations

Figure 9. Venezuela: Business Cycles with Band-Pass Filtering Procedure, GDP, Non-Oil GDP, and Oil GDP, 1991–2002
(In billions of Bolívares, at 1984 prices)



Source: BCV, MOF, IMF (2003), and author's estimations.

Figure 10. Venezuela: Business Cycles with Modified Hodrick-Prescott Filtering Procedure, GDP, Non-Oil GDP,and Oil GDP, 1991–2002 (in billions of Bolivares, at 1984 prices)



Source: BCV, MOF, IMF (2004), and author’s estimations.

Table 1. Effects of Filtering on Moments: Volatility, 1991–2002 (In billions of Bolívares, at 1984 prices)

A. Standard deviations (proxy for volatility)

			Trends			Cycles 1/ 4/		
Variable	Period	Unadjusted series	Hodrick-Prescott Trend (HP-X11 SA)	Modified Hodrick-Prescott Trend	ARIMA Trend-cycle (TSW)	HP-X11SA Cyclical component 4/	Modified HP Cyclical component	ARIMA(TSW) short-term cyclical component
Macroeconomic variables								
real GDP (Bn BS)	1991:1–2002:4	7.7	4.5	7.2	6.9	5.3	4.7	4.2
real oil GDP	1991:1–2002:4	4.7	4.0	4.2	4.5	2.3	1.2	1.8
real non-oil GDP	1991:1–2002:4	5.1	0.7	1.3	3.8	3.7	3.3	3.6
EMBI								
Seigniorage (in percent of money base)	1996:4–003:3	3.6%	1.5%	0.4%	1.1%	1.2%	0.8%	0.2%
Oil Price								
WEO quarterly data (1984:1–2003:3)		5.2	3.7	3.8	5.2	3.4	3.4	0.6
VEN quarterly data (1994:1–2003:4)		5.2	3.8	3.7	5.7	3.5	3.5	0.7
Real fiscal variables (nonfinancial public sector)	1995:1–2003:4 2/							
Expenditure		7.7	0.4	0.8	0.7	7.1	0.1	1.9
Revenues		6.7	2.6	2.4	5.3	5.7	4.8	1.8
Non-oil revenues		2.6	2.6	1.1	1.6	1.9	0.8	1.5
Oil revenues 3/		6.9	1.8	MA(2)	MA(2)	6.3	MA(2)	MA(2)
Non-oil expenditures		6.3	2.2	1.2	1.8	3.6	1.5	3.3
Non-oil primary expenditures		6.5	2.6	2.5	3.9	3.8	2.7	4.8
Non-oil primary balance		7.1	3.7	3.2	3.9	3.9	2.1	2.7

Source: BCV, MOF, IMF (2003), and author's calculations.
1/ Computed as the difference between the series and its respective trend.
2/2003 :4 is staff projection.
3/ Since oil revenue time series were estimated as an MA(2) process, no decomposition is performed for the Modified HP and TSW filters.
4/ The frequency-domain filter estimates were omitted as they are similar to the Modified HP filter.

Table 2. Effects of Filtering on Moments: Persistence, 1991–2002 (In billions of Bolívares, at 1984 prices)

B. First-Order Correlation (proxy for persistence)

			Trends			Cycles 1/ 4/		
Variable	Period	Unadjusted series	Hodrick-Prescott Trend (HP-X11 SA)	Modified Hodrick-Prescott Trend	ARIMA Trend-cycle (TSW)	HP-X11SA Cyclical component	Modified Hodrick-Prescott Cyclical component	ARIMA(TSW) short-term cyclical component
Macroeconomic variables	1991:1–2002:4							
real GDP (Bn BS)		0.47	0.94	0.87	0.80	0.49	0.92	-0.24
real oil GDP		0.84	0.95	0.95	0.97	0.19	0.88	-0.06
real non-oil GDP		0.23	0.84	0.89	0.71	0.71	0.73	-0.38
GDP deflator								
Inflation								
EMBI								
Seigniorage (in percent of money base)	1996:4–2003:3	-0.30%	0.87%	0.86%	0.76%	0.03%	0.70%	-0.64%
Oil Price								
WEO quarterly data (1984:1–2003:4) 2/		0.80	0.93	0.95	0.89	0.76	0.83	-0.13
VEN quarterly data (1994:1–2003:4)		0.87	0.94	0.94	0.89	0.81	0.83	-0.14
Real fiscal variables (nonfinancial public sector)	1995:1–2003:4 2/							
Expenditure		-0.08	0.85	0.92	0.91	0.55	0.93	-0.44
Revenues		0.66	0.91	0.92	0.85	0.68	0.80	-0.23
Non-oil revenues		0.69	0.90	0.91	0.92	0.46	0.92	0.20
Oil revenues 3/		0.73	0.91	MA(2)	MA(2)	0.74	MA(2)	MA(2)
Non-oil expenditures		0.09	0.92	0.89	0.95	0.46	0.66	0.36
Non-oil primary expenditures		0.30	0.92	0.92	0.92	0.58	0.88	-0.21
Non-oil primary balance		0.29	0.92	0.93	0.95	0.48	0.90	0.10

Source: BCV, MOF, IMF (2003), and author's calculations.
1/ Computed as the difference between the series and its respective trend.
2/ 2003:4 is staff projection.
3/ Since oil revenue time series were estimated as an MA(2) process, no decomposition is performed for the Modified HP and TSW filters.
4/ The frequency-domain filter estimates were omitted as they are similar to the Modified HP filter.

Table 3. Effects of Filtering on Moments: Cyclicality,1991–2002 (In billions of Bolívares, at1984 prices)

C. Contemporaneous Correlations with GDP (proxy for cyclicality)

			Trends			Cycles 1/ 4/		
Variable	Period	Unadjusted series	Hodrick-Prescott Trend (HP-X11 SA)	Modified Hodrick-Prescott Trend	ARIMA Trend-cycle (TSW)	HP-X11SA Cyclical component	Modified Hodrick-Prescott Cyclical component	ARIMA(TSW) short-term cyclical component
Macroeconomic variables	1991:1–2002:4							
real GDP (Bn BS)		1.00	1.00	1.00	1.00	1.00	1.00	1.00
real oil GDP		0.77	0.99	0.58	0.63	0.85	0.33	0.44
real non-oil GDP		0.81	0.71	0.23	0.57	0.93	0.56	0.55
Seigniorage (in percent of money base)	1996:4–2003:3	0.27%	-0.15%	-0.05%	-0.32%	0.26%	-0.41%	-0.05%
Oil Price								
WEO quarterly data (1984:1–2003:4)		0.13	0.26	-0.10	0.13	-0.05	-0.11	-0.30
VEN quarterly data (1994:1–2003:4)		-0.17	-0.10	-0.10	-0.18	-0.22	-0.16	-0.30
Real fiscal variables (non financial public sector)	1995:1–2003:4 2/							
Expenditure		0.61	0.13	0.03	0.05	0.44	0.21	0.25
Revenues		0.09	0.11	0.11	0.0	0.09	0.03	-0.18
Non-oil revenues		0.45	0.33	0.33	0.49	0.45	0.48	0.38
Oil revenues 3/		-0.07	-0.06	MA(2)	MA(2)	-0.18	MA(2)	MA(2)
Non-oil expenditures		0.41	-0.55	-0.31	-0.04	0.33	0.47	0.11
Non-oil primary expenditures		0.49	-0.1	-0.1	0.32	0.46	0.52	0.41
Non-oil primary balance (minus implies procyclicality)		-0.43	0.33	0.31	-0.18	-0.37	-0.39	-0.14

Sources: BCV, MOF, IMF (2003), and author's calculations.
1/ Computed as the difference between the series and its respective trend.
2/ 2003:4 is staff projection.
3/ Since oil revenue time series were estimated as an MA(2) process, no decomposition is performed for the Modified HP and TSW filters.
4/ The frequency-domain filter estimates were omitted as they are similar to the Modified HP filter.

Table 4. Performance of Fiscal Policy in Venezuela, 1995–2003

(quarterly data, Billions of Bolívares at 1984 prices)

	Volatility 1/		Correlation with Oil Revenues 2/	
	Unadjusted	Discretionary 3/	Unadjusted	Discretionary 3/
Oil-revenues	6.89	...	1.00	...
Non-oil revenues	2.65	...	-0.24	...
Non-oil primary expenditures	6.43	2.54	-0.04	-0.27
Non-oil primary balance	6.91	3.04	-0.06	0.24

Source:
1/ Measured by the standard deviation.
2/ Correlation with unadjusted oil revenue series.
3/ Discretionary component computed as the extracted Modified HP trend after applying the ARIMA based model (AMB) estimation (Kaiser and Maravall, 2004).

Table 5. Venezuela Fiscal Stance, 1995–2003

(In billions of Bolívares, at 1984 prices)

Nonfinancial Public Sector	1995	1996	1997	1998	1999	2000	2001	2002	2003	1996–2001		2002–03	
										average	st. dev.	average	st. dev.
Fiscal stance 1/													
Non-oil primary balance													
Unadjusted series	-12.6	-9.6	-35.3	-19.7	-30.2	-40.4	-65.4	-45.6	-41.2	-30.5	17.8	-43.4	2.2
Adjusted series (ARIMA estimation) 2/	-15.4	-11.1	-31.4	-27.5	-15.3	-40.1	-60.2	-46.1	-40.7	-28.7	16.0	-43.4	2.7
Discretionary component) 3/	-13.3	-17.8	-22.5	-27.1	-32.2	-38.0	-43.0	-46.1	-48.0	-27.7	10.0	-47.0	0.9
Cyclical component 4/	-2.1	6.7	-8.9	-0.4	16.9	-2.2	-17.2	0.0	7.2	-1.0	10.0	3.6	3.6
Non-oil revenue													
Unadjusted series	72.7	72.4	81.8	93.3	80.9	74.2	73.4	70.3	61.7	78.4	7.1	66.0	4.3
Adjusted series (ARIMA estimation) 2/	71.0	73.2	81.1	85.7	80.7	74.8	72.8	69.3	64.3	77.0	5.0	66.8	2.5
Discretionary component) 3/	73.6	76.4	78.8	79.8	79.0	76.7	73.4	69.6	65.6	76.8	2.4	67.6	2.0
Cyclical component 4/	-2.61	-3.21	2.35	5.89	1.73	-1.87	-0.61	-0.33	-1.34	0.2	3.0	-0.8	0.5
Non-oil primary expenditure													
Unadjusted series	85.4	81.9	117.1	113.0	111.2	114.6	138.8	116.0	102.8	108.9	18.1	109.4	6.6
Adjusted series (ARIMA estimation) 2/	86.4	84.3	112.5	113.2	96.0	114.9	133.0	115.4	105.0	105.8	16.3	110.2	5.2
Discretionary component) 3/	86.9	94.2	101.2	106.9	111.2	114.6	116.4	115.8	113.6	104.5	10.2	114.7	1.1
Cyclical component 4/	-0.5	-9.9	11.3	6.3	-15.1	0.3	16.6	-0.4	-8.6	1.3	10.4	-4.5	4.1
Fiscal impulse 5/		4.5	4.7	4.7	5.1	5.8	5.0	3.1	1.8	5.0	0.4	2.5	0.6
of which: non-oil revenues (discretionary component)		-2.8	-2.3	-1.0	0.8	2.3	3.2	3.8	4.0	0.0	2.3	3.9	0.1
of which: non-oil primary expenditures (discretionary component)		7.3	7.0	5.7	4.3	3.5	1.8	-0.7	-2.2	4.9	2.0	-1.4	0.8
Output gaps (in percent of trend) 6/		-1.8	7.2	-6.6	-1.7	8.0	6.9	-8.5	-9.7	2.0	5.6	-9.1	0.6
Structural balance (b_str = b - e*output gap)7/		-8.9	-38.1	-17.1	-29.6	-43.5	-68.1	-42.3	-37.4	-34.2	19.2	-39.8	2.5
Non-oil primary expenditures, real growth (discretionary component)		8.43	7.46	5.60	4.00	3.11	1.55	-0.56	-1.87	5.0	2.4	-1.2	0.7
Non-oil revenues, real growth (discretionary component)		3.86	3.03	1.27	-0.99	-2.91	-4.23	-5.15	-5.76	0.0	3.0	-5.5	0.3

Source: BCV, MOF, IMF (2003), and author's calculations.
1/ In oil-producing economies, non-oil primary balance is a better indicator to analyze the fiscal stance and sustainability.
2/ Adjusted by applying the ARIMA based model (AMB) estimation (Kaiser and Maravall, 2004)
3/ This is a measure of discretionary fiscal policy, as it removes the cyclical or 'automatic' components of the budget
4/ First-difference of discretionary component of non-oil primary balance.
5/ Discretionary change in non-oil primary balance. A positive sign implies either a revenue impulse (i.e., revenue reduction) or an expenditure impulse (i.e., spending increase).
6/ Defined as the cycle-to-trend output ratio. Real GDP trend or "potential" output is estimated using ARIMA univariate detrending methods and then applying the Kaiser-Maravall methodology (see text for details).
7/ Defined as the non-oil primary balance adjusted by the cyclical component. The estimated elasticity of the fiscal balance is set at 0.39.