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MSc Economics

Business Cycle Volatility and its Relation with Natural Resources and Country Size

A Master's Thesis submitted for the degree of
"Master of Science"

supervised by

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Affidavit

I, Zahra Ebrahimi

hereby declare

that I am the sole author of the present Master's Thesis,

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27 pages, bound, and that I have not used any source or tool other than those referenced or any other illicit aid or tool, and that I have not prior to this date submitted this Master's Thesis as an examination paper in any form in Austria or abroad.

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Abstract:

Considering output volatility as an indicator for economic performance has been considered by many researchers. It has also been suggested by several studies namely Barlevy (2004) and Ramey and Ramey (1995) that volatility has negative effect on welfare and growth rate. Thus, the search for factors affecting business cycle volatility seems to be a worthwhile task. Sachs and Warner (1995) found a negative relation between natural resource endowment and growth, and Furceri and Karras (2008) have shown a negative effect of country size on business cycle volatility. This paper tries to investigate the effect of both factors on business cycle volatility. Using a panel of 101 countries from 1969-1970, it is shown that natural resource endowment has a positive effect on volatility and that smaller countries experience more business cycle volatility than larger countries. The results are robust to the choice of using HP or BP filter for detrending, different sample periods and estimation methods.

1. Introduction

The objective of this paper is to investigate the empirical relationship between business cycle volatility, natural resource endowments and country size. The reason for our interest in business cycle volatility is that recent contributions use this variable as an indicator of economic performance along other measures, such as economic growth and income per capita.

While in his famous monograph “Models of Business Cycles” Robert Lucas (1987) argued that the costs associated with business cycles are virtually nonexistent, more recent research has challenged Lucas’s conclusions. For example, Mendoza (2000), Jones (1999), Matheron and Maury (2000), Epaulard and Pommeret (2003) showed that business cycle volatility reduces welfare, not least because of its negative effect on growth. Krusell and Smith (1999), and Storesletten et al. (2001) showed that in a model with heterogeneous agents the benefits from eliminating business cycle fluctuations are sizeable. Barlevy (2004) argues that economic fluctuations remarkably decrease welfare by affecting the growth rate of consumption. At the same time, a growing empirical literature starting with Ramey and Ramey (1995) has established that cyclical volatility negatively affects growth and investment. Fatas (2002) by using an updated sample confirmed their result. We conclude that business-cycle volatility matters. So, variables those have a significant effect on volatility matter, too, and need to be investigated.

Sachs and Warner (1995) showed that countries with big natural resources grow slower. Considering the negative link between volatility and growth, it is worth investigating the relation between natural resource and volatility.

I argue that a high natural resource endowment creates more volatility and one candidate to explain this, is the volatility of commodity prices which influences the source of revenues of the country. Singer (1950, 1998) argued that prices of primary commodities are more volatile than of manufactured commodities. Since the two price variables are positively correlated, it might be the case that the negative volatility effect on growth is actually a result of the natural resource endowment.

These commodities could include not only petroleum but also minerals and agricultural raw materials which reflect the climate and other natural assets of a country.

What commodity prices lack in trend, they make up for in volatility (Deaton, 1999). A recent detailed examination by Blattman et al. (2007) of the growth performance of 35 countries during the historical period 1870-1939 suggests the following conclusions. Countries that specialize in commodities with substantial price volatility have more volatility in their terms of trade, enjoy less foreign direct investment and experience lower growth rates than countries that specialize in commodities with more stable prices or countries that are industrial leaders.

In another study, Sachs and Warner (1997), using a sample of 95 countries, showed that economies with a high ratio of natural resource exports to GDP in 1970 (the base year) tended to grow slowly during the subsequent 20-year period 1970-1990. This negative relationship holds true even after controlling for many variables.

Another variable of interest is country size which could be one of the possible reasons that some countries have more volatile economy than the others. In recent years there has been a growing economic literature concentrating on the effects of scale and country size on various economic outcomes. From a theoretical point of view, the sign of such a scale effect is ambiguous: larger countries should outperform smaller countries only if the benefits of size dominate the costs.

In particular, the main benefits of scale (in terms of population size) have been thought to originate in economies of scale in the production of public goods and redistributive policies, market scale and specialization, market size and competitiveness, market size and human capital accumulation, scale economies and increasing returns on trade, scale effects and growth. (Furceri and Karras, 2008)

Therefore, whether size affects the economic performance, is really an empirical question. Rose (2006) used several economic indicators and found that "country size really doesn't matter" for economic success. Even though he provided robust evidence in support of this conclusion, Furceri and Karras (2006 and 2008) by investigating the empirical relationship between business cycle volatility and country size, suggested a very strong relationship between country size and business cycle volatility which is negative and statistically significant. This implies that smaller countries are subject to more volatile business cycles than larger countries. Moreover, the results are robust to different sample periods and several detrending methods. It follows that country size really matters, at least in terms of cyclical fluctuations. Therefore I have chosen country size as another explanatory variable of volatility behavior.

2. Data

I use annual data for real GDP (in billions of 2005 dollars) from the World Bank World development indicators, which has available data for 1969–2008 for 167 countries. As suggested by many including Karras (2008), the quarterly frequency seems to be more appropriate for BC questions. Unfortunately, data at a quarterly frequency is just available for OECD countries (used by Furceri and Karras (2008)) which does not seem to be sufficient to estimate the effect of natural resource variable since most of the countries in this category are not resource rich and do not have a natural resource based economy.

Based on the availability of data, I have chosen 101 countries with different economies, to estimate the model.

Using the same approach as Furceri and Karras (2008) and Rose (2006), the logarithm of population has been used as a measure of country size, and the logarithm of country's total area has been used as an instrumental variable for population. Data has been taken from IMF and CIA-The World Fact book respectively.

For natural resource variable, the main issue is finding an indicator which reflects the amount of natural resources owed by a country. Heckscher-Ohlin's resource based trade theorem would indicate that countries would export the good that intensively uses the factor that the country is abundant in. Thus the logical measure for a country's relative endowment would be the primary goods export share in aggregate output, as in Sachs and Warner (1995). However, if a large part of the exports are re-exported primary commodities then this measure would overstate the natural resource endowment so using net primary export to GDP could be a solution. In addition, net primary export to total export of goods and services and as share of mineral production in GDP, has been considered by some researchers.

Ozer and Norrbin (2005) have studied the effect of using these three export based measure on their result which reveals that it does not affect the sign and significance of relationship.

However some authors including Ding and Field (2005) and Ploeg and Poelhekke (2008) criticized this approach. They distinguish between natural resource dependence and natural resource abundance (endowment) and argued that these proxies mostly measure dependence of economy on natural resources. Natural resource dependence measured by this approach has a negative effect on growth rate, while natural resource endowment measured by the capital stock approach has a positive effect.

I used the ratio of primary goods (defined as agricultural goods, minerals and fuels) export to GDP (EXG) which is available on UNCATD online database for 1995–2008 as my natural resource endowment variable. In addition, considering Ding and Field approach, I used natural capital estimation data from a World Bank report (1997) as an instrumental variable for EXG. In this report, they tried to estimate natural, human and produced capital figures for different countries. Natural resource assets in the World Bank data set are built up from estimates of agricultural land, pasture land, forests, protected areas, metals and materials, and coal, oil, and natural gas. Unfortunately this effort does not cover all countries. Especially it does not include most of the OPEC member countries. So I used the data to estimate the model for 63 countries.

3. Business cycles

The main variable of interest, volatility, has been defined as fluctuations of business cycles. So it is needed to consider the definition and review the literature related to business cycles. From classical point of view business cycles have been defined as:

"a type of fluctuations in the aggregate economic activity of nations that organize their work mainly in business enterprise: a cycle consists of expansions occurring at about the same time in many economic activities followed by similarly general recessions, contractions, and revivals which emerge into the expansion phase of the next cycle; this sequence of change is recurrent but not periodic". (Burns and Mitchell (1946, p.1))

Another definition suggested by Lucas (1987) is the recurrent fluctuations of output about trend and the co-movements among other aggregate time series. Prescott (1986) suggested, as opposed to Lucas, that the term business cycle is too narrow a term. This is due to the fact that any time series, regardless of oscillating components included, exhibits business cycle characteristics and that the conventional dichotomy between growth and cyclical fluctuations is too restrictive. Consequently, Prescott suggests that the term business cycle should be changed to business cycle phenomena. He follows Lucas definition and defines fluctuations as deviations from some slowly varying path which he calls "trend".

So in order to find business cycles it is needed to extract the trend and define cycles as deviations from the trend. Several methods has been suggested and studied for detrending and there exist huge literature about this issue. However, it seems detrending is a controversial issue as it is clear by looking at discussions in many empirical papers about business cycles. It seems there is no "best method" to be used to estimate the trend. As Canova (1998) mentions, there are two main problems in this regard. The first one is the fundamental disagreement on the properties of the trend and its relationship with cyclical component of series. And the other problem arises from standard measurement without theory concern. He thinks that economic-based decompositions try to approximate unknown features of a series and therefore subject to specification errors.

In economics, traditionally time series are decomposed into different components. If y_t represents an economic time series, generally it can be expressed as:

$$y_t = T_t + C_t + S_t + \epsilon_t$$

Where

T_t is global trend,

C_t is cycle,

S_t is the seasonal variation,

ϵ_t is an irregular component

There are basically two ways of extracting trends from time series. One way is to fit some functions which are capable of adapting themselves to any form that trend may have. A linear or quadratic function may be appropriate if the trend in question is increasing or decreasing. Otherwise polynomials of higher degrees might be fitted:

$$\phi(t) = \phi_0 + \phi_1 t + \cdots + \phi_p t^p$$

The alternative way is to apply a variety of filters which eliminates all other components which are not regarded as trends. A filter is a carefully crafted moving average which spans a number of data points and which attributes a weight to each of them. The weight should some to unity to ensure that the filter does systematically inflate or deflate the values of the series. So filters are designed to smooth away the irregularities of the data.

Among all filters has been designed to extract trends and cycles, Hodrick-prescott (HP) and Baxter-king (BP) filters are most frequent used in economics literature. I have also used this two method to extract business cycles from my real GDP data.

3.1 . HP-Filter

The Hodrick-Prescott (1980) filter is one of the methods of extracting stochastic trends as opposed to deterministic trends. The usual statistical model of such a trend is second-order or integrated random walk which may be subject to drift (Pollock, 2008). The HP filter may be derived in reference to the equation:

$$y_t = \mu_t + \varepsilon_t$$

Which represents the observed time-series variable, y_t, as sum of trend component μ_t which follows a second order random walk and a residual component ε_t .

In this framework, the trend is independent of the cyclical (residual) component and moves smoothly over time. By assuming that components have normal distribution, the maximum likelihood estimate of μ_t is found by solving following minimization problem:

$$\underset{\{\mu_t\}_{t=1}^{T}}{Min} \; [\sum_{t=1}^{T} (y_t - \mu_t)^2 + \lambda \sum_{t=2}^{T} ((y_{t+1} - y_t) - (y_t - y_{t-1}))^2]$$

Here, T is the sample size, and λ is a parameter that penalizes the variability of trend. It determines the smoothness of the trend. If it is equal to zero then $y_t = \mu_t$ and if $\lambda = \infty$ then the trend is linear.

Taking F.O.C with respect to μ_t yields:

$$-2(y_t - \mu_t) + 2\lambda [(\mu_t - \mu_{t-1}) - (\mu_{t-1} - \mu_{t-2})] - 4\lambda [(\mu_{t+1} - \mu_t) - (\mu_t - \mu_{t-1})] +$$
$$2\lambda [(\mu_{t+2} - \mu_{t+1}) - (\mu_{t+1} - \mu_t)] = 0$$

This implies that:

$$
\begin{aligned}
c_t = y_t - \mu_t &= \lambda(\mu_t - 2\mu_{t+1} + \mu_{t+2}), && t = 1 \\
&= \lambda(-2\mu_t - 5\mu_t - 4\mu_{t+1} + \mu_{t+2}), && t = 2 \\
&= \lambda(\mu_{t-2} - 4\mu_{t-1} + 6\mu_t - 4\mu_{t+1} + \mu_{t+2}), && t = 3,\ldots,T-2 \\
&= \lambda(-\mu_{t-3} - 4\mu_{t-1} + 5\mu_{t-1} + -2\mu_t), && t = T-1 \\
&= \lambda(\mu_{t-2} - 2\mu_{t-1} + \mu_t), && t = T
\end{aligned}
$$

This can be written compactly as:

$$c_t = \lambda M \mu_t$$

Where M is

$$
M = \begin{bmatrix}
1 & -2 & 1\ldots & & & & 0 \\
-2 & 5 & -4 & 1 & 0\ldots & & 0 \\
0 & 1 & -4 & 6 & -4 & 1 & 0\ldots0 \\
. & & & & & & \\
. & & & & & & \\
0 & 0 & 0 & & 1 & -2 & 1
\end{bmatrix}
$$

So we would have:

$$\mu_t = (\lambda M + I)^{-1} y_t$$

With I denoting the identity matrix. When the trend has been obtained, the cyclical component can be computed as deviations from the trend.

In order to select the smoothing parameter λ, Hodrick and Prescott (1980) assumed that the cyclical component and the second differences of the growth components are identically and independently distributed with mean zero and variances σ_1^2 and σ_2^2, the conditional expectation of the μ_t's given the observations, would be the solution to program when $\sqrt{\lambda} = \frac{\sigma_1}{\sigma_2}$

So, the value of λ is imposed rather than estimated. HP users select it a priori to isolate those cyclical fluctuations which belong to the specific frequency band that they want to investigate. They have chosen in this way that "our prior view is that a 5% cyclical component is moderately large, as is a 1/8 % change in growth rate in a quarter" so this let them to chose λ such that:

$$\sqrt{\lambda} = \frac{5}{1/8} = 40 \text{ So } \lambda = 1600$$

This leaves in the data cycles of average duration of 4-6 years. This value will be smaller for yearly data (λ is about 100) and much bigger for monthly data (λ is about 14,000).

Since the appropriate λ relies on an estimate of variance of the underlying stochastic components, it is likely to be different across series and data frequencies.

There are a number of studies attempting to find the right smoothing parameter for the annual frequency. Ravn and Uhlig (2002) addressed the issue of the relationship between the smoothing parameter and the data frequency. They suggest a smaller value of 6.25 for annual data on the basis of the band-pass filter properties outlined by Baxter and King (1999). Figure 1 shows the trend and cyclical component of logarithm of real GDP data for US which has been extracted using HP filter.

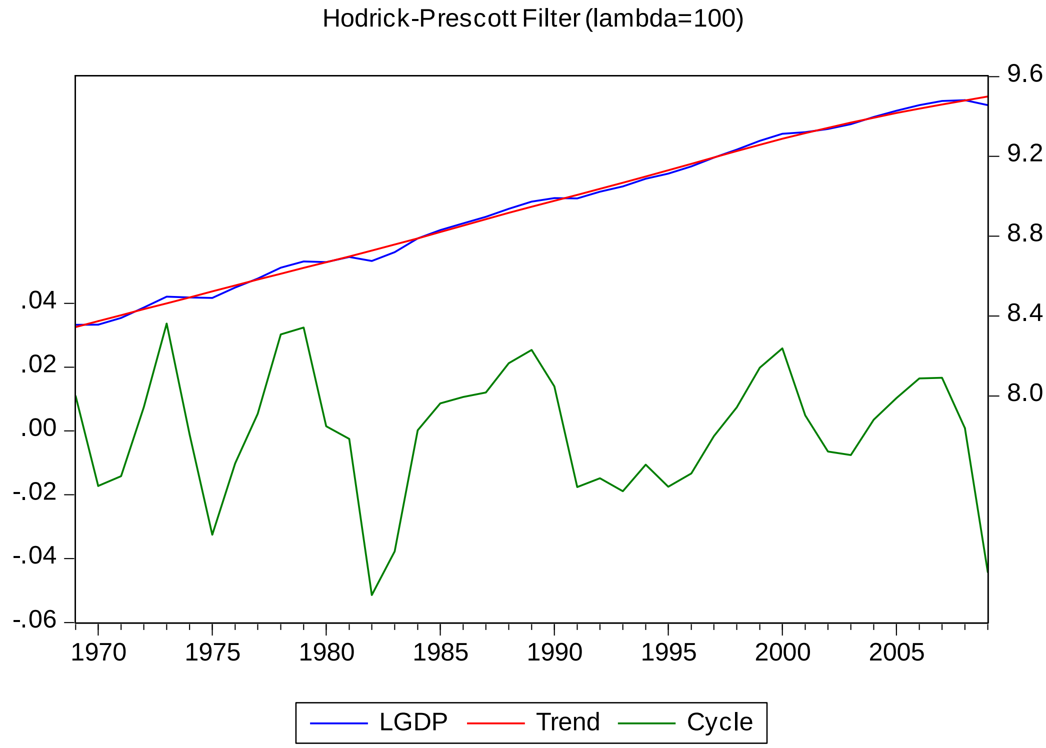


Figure 1: Logarithm of real GDP data, Trend and Cycles (1969-2008), World Bank,HP Filter

3.2. Band-Pass Filter (BP)

Baxter and King (1999) used Mitchell and Burns' concept of business cycles to construct a filter as a moving average (MA) of lags and leads for K periods. Their goal was to derive an ideal band-pass linear filter that extracts the frequencies $\omega \in [\omega_1, \omega_2]$.

Mitchell and Burns (1946) defined business cycles as components of not less than 6 quarters and not more than 32 quarters in duration and a desired filter is a filter which passes through components of the time series with this much frequency while removing the others at higher or lower frequencies. The ideal BP filter then would be a moving average of infinite order, so an approximation of this optimal filter would be needed for empirical applications.

Baxter and King (1999) define six objectives that a desirable filter is supposed to meet. First, the filter should extract a specified range of periodicities and otherwise leave the properties of this extracted component unaffected. Second, the ideal band-pass filter should not introduce phase shift, i.e., it should not change the timing relationships between series at any frequency. These two properties define an ideal moving average of the data with symmetric weights on leads and lags. Third, the filter is an optimal approximation to the ideal band-pass filter. They specify a particular quadratic loss function for discrepancies between the exact and approximate filter.

Fourth, the application of an approximate band-pass must provide a stationary time series. By assuming the presence of stochastic trends in economic time series based on the suggestion of many empirical works, they design their filter such that it makes the filtered time series stationary if the underlying time series is integrated of order one or two. This requirement also means that BP filter will eliminate quadratic deterministic trends from a time series. Fifth, the filter yields business-cycle components that are unrelated to the length of the sample period. Technically, this means that the moving averages be time invariant, in that the coefficients do not depend on the point in the sample. And finally, the method must be operational. In the general filter-approximation problem, there is an important tradeoff. The ideal BP filter can be better approximated with the longer moving averages, but adding more leads and lags also means that observations must be dropped at the beginning and end of the sample, thus leaving fewer for analysis.

Applying a moving average to a time series y_t, produces a time seriesy_t^*, with

$$y_t^* = \sum_{k=-K}^{K} a_k \, y_{t-k}$$

Or using lag operator (L)

$$a(L) = \sum_{k=-K}^{K} a_k \, L^k$$

One of the applications of moving averages is to eliminate the trend in economic series. It can be shown that if a symmetric moving average has weights that sum to zero, it can be written in the following form:

$$\alpha(L) = (1 - L)(1 - L^{-1})\psi(L)$$

Where $\psi(L)$ is a symmetric moving average with *K-1* leads and lags. So symmetric MA with weights that sum to zero will provide a stationary process that contains quadratic deterministic trends.

From frequency point of view, if $y_t$is zero-mean stationary, it can be written as:

$$y_t = \int_{-\pi}^{\pi} \xi\,(\omega) d\omega$$

Where $\xi(\omega)$ ‘s are random periodic components that are mutually orthogonal.

Filtered time series could also be represented as:

$$y_t^* = \int_{-\pi}^{\pi} \alpha(\omega)\xi\,(\omega) d\omega$$

Where $\alpha(\omega) = \sum_{-k=K}^{K} a_k\, e^{i\omega k}$ is frequency response function of the linear filter.

It is important to note that the frequency response function takes the value of zero at zero frequency iff sum of the filter weights is zero since constructing filter subject to this constraint, provides stationary time series when applied to nonstationary data.

3.2.1. Filter design

An ideal band-pass filter that transmits all elements within the required frequency range and blocks all others has the following frequency response:

$$\alpha(\omega) = \begin{cases} 1, if\,|\omega| \in [\omega_1, \omega_2] \\ \\ 0, otherwise \end{cases}$$

The coefficients of the corresponding time-domain filter are obtained by applying an inverse Fourier transform to this response to give:

$$\alpha(\omega) = \int_{\omega_1}^{\omega_2} e^{ik\omega} d\omega = \frac{1}{\pi k}\{\sin(\omega_2 k) - \sin(\omega_1 k)\}$$

$$= \frac{2}{\pi k}\cos\{(\omega_1 + \omega_2)k/2\}\sin\{(\omega_2 - \omega_1)k/2\}$$

$$= \frac{2}{\pi k}\cos(\gamma k)Sin(\delta k)$$

For $k = 1 \ldots K$

and for $k = 0$, $\alpha(\omega) = \frac{\omega_2 - \omega_1}{\pi}$

There is no "best" value of K (truncation point), increasing K leads to a better approximation to the ideal filter, but results in more lost observations. Thus, the researcher will have to balance these two opposing factors: The best choice of K will depend on the length of the data period and the importance attached to obtaining an accurate approximation to the ideal filter.

Baxter and King (1999) examined the effect of variation in K on computed moments for several macroeconomic data. They have shown that the standard deviation (volatility) is sensitive to the choice of K. such that small values of K provide low variances while good approximations are obtained by $K \geq 12$. Serial correlation (persistence) is lower for smaller values of K, compared to large ones.

Based on empirical analysis of various quantities of *K*, they recommend using moving averages based on three years of past and future data, both for quarterly and annually observed series. Figure 2, represents the trend and cyclical components derived using BP filter for logarithm of US Real GDP data. This figure also shows the

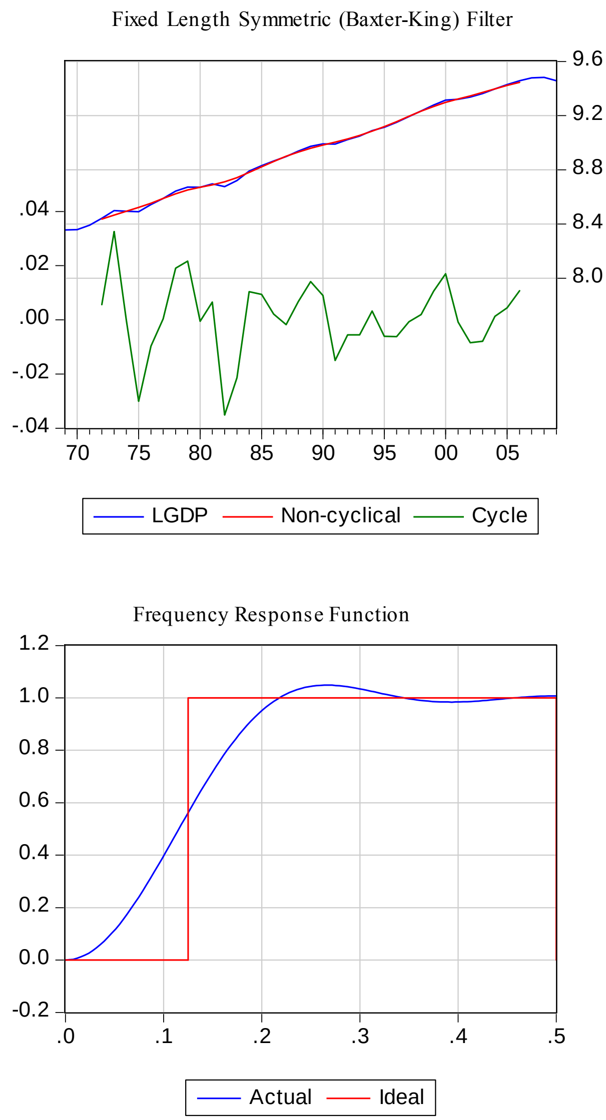


Figure 2: Logarithm of US Real GDP data, Trend, Cycle (1969-2008),BP Filter and Frequency Response Function

frequency response function that represents the response of the filtered series to the original series at frequency ω. At a given frequency, $\alpha(\omega)^2$ shows the extent to which a moving average raises or lowers the variance of the filtered series relative to that of the original series.

3.2.2. Comparing HP and BP

Baxter and King (1999), based on the six criteria for an optimal filter mentioned earlier, compared the HP and the BP filter.

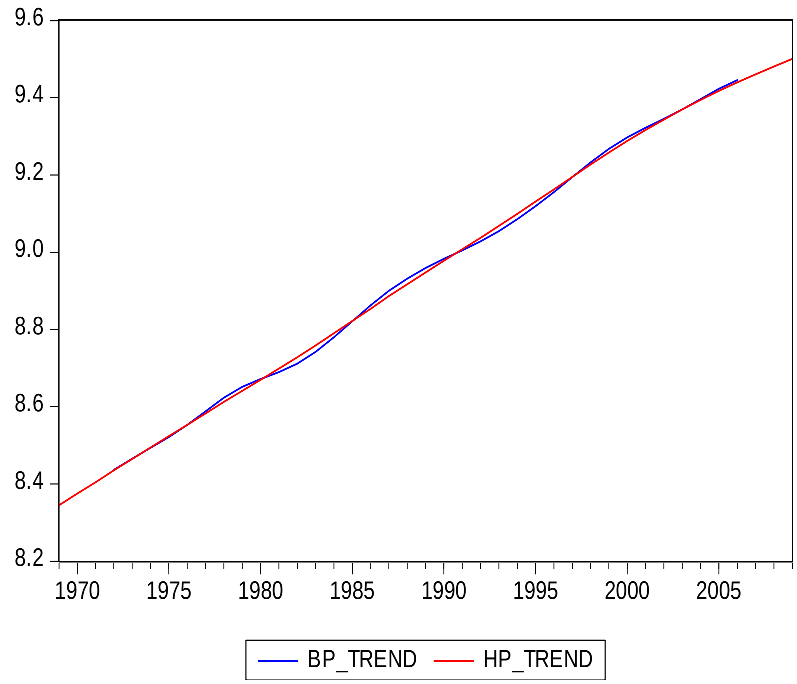
By computing the cyclic component of a time series y_t using the infinite-sample of HP filter as:

$$y_t^c = \left(\frac{\lambda(1-L)^2(1-L^{-1})^2}{1+\lambda(1-L)^2(1-L^{-1})^2}\right)y_t$$

It is clear that HP filter removes unit root components from data (non stationary components that are integrated of order four or less). By showing the time-domain representation of growth component they made it clear that the filter is symmetric so there is no phase shift. In terms of moments, by computing moments for both filters, they showed that HP filters produces volatility statistics that exceeds those of the BP filter , but not by a large amount in most cases.

HP filters are shown to be a rough approximation to a high-pass filter, which means that they retain some high-frequency volatility that is removed by the band-pass filter. Based on these empirical and theoretical analyzing of both filters, they conclude that BP filter is preferable over HP, because first, it has a clear definition of the periodicity of the cycles to be extracted. Second, it does not depend on macro variables or data frequencies.

Figure 3 depicts the trends and cycles extracted for US logarithmic GDP by both methods. While trends are almost identical, cyclical components filtered by BP method are smoother than those provided by HP method.



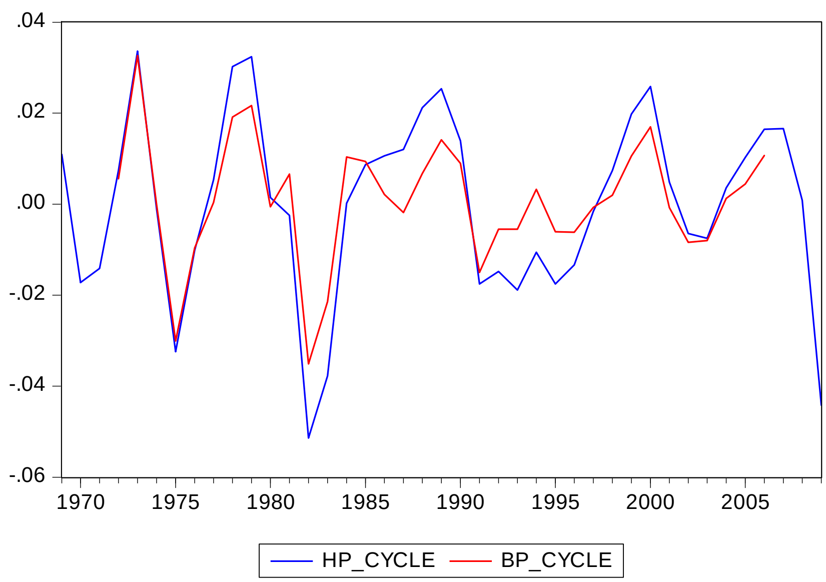


Figure 3 : Comparing Trends and Cycles extracted by HP and BP Filtering for US Log Real GDP data(1969-2008)

4. Model

In the outlined framework, the effect of natural resource endowment and country size on business cycle volatility will be estimated using the following regression model:

$$\sigma_{it} = \alpha + \beta_1 \ln(Pop_{it}) + \beta_2 EXG_{it} + \varepsilon_{it} \qquad (1)$$

Where:

- σ_{it} measures business cycle volatility for country *i* at time *t*,
- Pop_{it} denotes population,
- EXG is Natural Resource endowment measured as ratio of primary good's export to GDP,
- ε_{it} is a well-behaved error term,

The general form of equation (1) has been derived from Karras (2008), to which natural resource dependence (EXG) has been added as a further explanatory variable.

In order to compute volatility of business cycles, computed using HP and BP filters, cyclical components of real GDP data has been estimated and then standard deviation of this component has been used as a measure of volatility. Using standard deviation as a method of volatility is a standard and widespread measure for volatility and has been used in economics literature e.g. Karras and Furceri (2008).

Using panel data of 101 countries for period of 1969-2008 for GDP, I have calculated standard deviation of cycles extracted for logarithm of Real GDP data over three different periods. Once, for period 1995-2008 as a moving backward function. For instance, to calculate the volatility for 1995, I used the observations for 1969-1995, and for the 1996 value I used data for 1970-1996.

I have also divided the data to 3 groups each containing four periods from 1995-1998, 1999-2002 and 2003-2006 and calculated the standard deviation over each period. And finally one time for the entire period 1995-2008 which I used to estimate the cross section regression.

Using panel of 101 countries, equation (1) has been estimated using simple OLS method and once using LSDV as fixed effect model.

Using cross section data for 63 countries, I have also estimated the regression once using OLS method and also by 2SLS method using instrument varibales (total area for population and natural capital stock for EXG).

5. Results

Figures 5 and 6 each provide two scatter plots of volatility against natural resource endowment and country size for entire period 1995-2008. The left panels use the whole sample, for the right panels some outliers were eliminated. Figure 4 exhibits the positive and statistically significant relation between volatility and natural resource endowment.

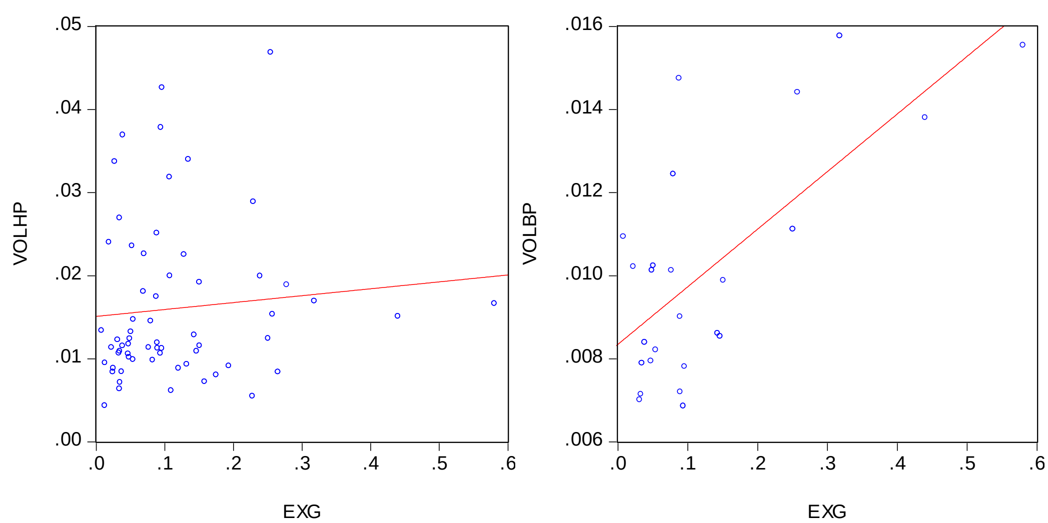


Figure 4: volatility vs. natural resource endowment (1995-2008) (Left plot whole sample of 63 countries, right plot without outliers)

Regression for simple bivariate model:

$$\sigma_i = 0.015 - 0.0083EXG_i \qquad R^2 = 0{,}08$$

(8.44) (0.72)

And by eliminating outliers, the positive relation is confirmed:

$$\sigma_i = 0.011 - 0.0086EXG_i \quad R^2 = 0{,}338$$

(24.57) (3.42)

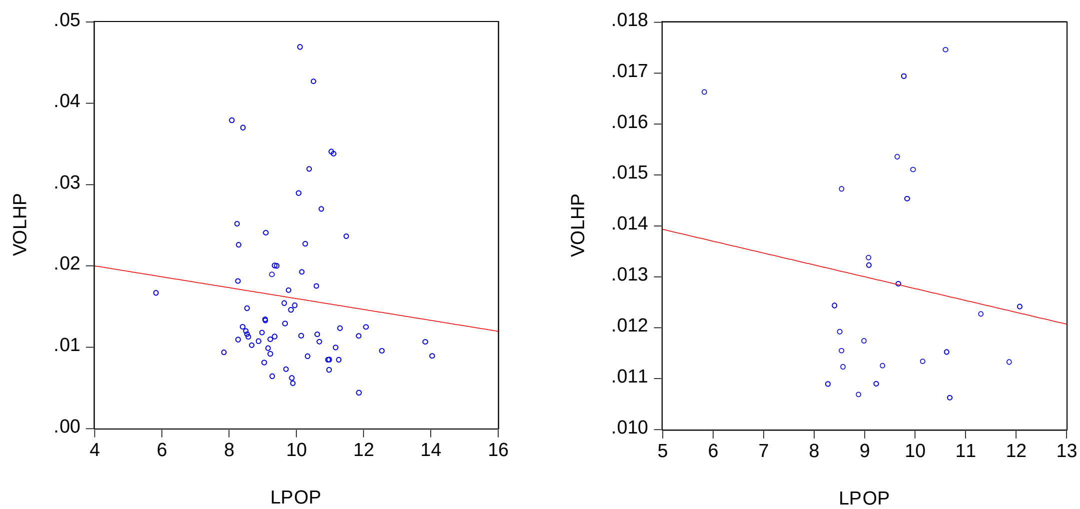


Figure 5: volatility vs. country size (1995-2008) (Whole Sample of 63 countries, Without Outliers)

$$\sigma_i = 0.015 - 0.00235L(pop)_i \qquad R^2 = 0.07$$

(-0.7) (4.8)

Figure 5 exhibits the negative relation of country size (measured by logarithm of population) and volatility for the entire period. The main impression does not seem to be affected by outliers.

Proceeding with more statistical evidence, Table 1 represents the estimated slope coefficient of country size and natural resource endowment measure (EXG), along with the associated t-statistics in parentheses for several specification of equation (1). The two sections of the table refer to two different methods of filtration: HP with smoothing parameter of 6.25 and BP filter. Each section reports three specification variants: the results for the entire period calculating volatility as moving function; calculating volatility for four-year intervals, which leads to three observations for each country; and a pure cross-section estimation for 63 countries. I also tried to use the natural resource capital data as an instrumental variable for EXG and logarithm of total area of the country for logarithm of population which has been represented in last column

The first row reveals that the relation between country size and business cycle volatility is negative. The larger the size of the country, the less volatile is its cycle. Natural resource endowment has positive effect on cycle volatility. This result holds for all estimation models.

Table 1: Business cycle volatility, country size and natural resource endowment

HP Filter (6.25)					
	Whole period(1995-2008)		period divided in to 3 group		Cross Section
	LS(bivariate)	FE	LS(bivariate)	FE	
LPOP	-0.0027 (-9.363)	-0.0079 (-3.791)	-0.00093 (-1.564)	-0.0237 (-1.6891)	-0.005 (-0.544)
EXG	0.0253 (8.128)	-0.01553 (-9.989)	0.01643 (2.476)	-0.0324 (-1.389)	0.0054 (0.462)

BP Filter					
	Whole period(1995-2008)		period divided in to 3 group		Cross Section
	LS(bivariate)	FE	LS(bivariate)	FE	
LPOP	0.0036 (-11.22)	0.0052 (-3.198)	-0.00085 (-1.497	-0.02609 (-1.867)	-0.00622 (-0.722)
EXG	0.0397 (11.076)	-0.0054 (-2.69)	0.0161 (2.558)	-0.0238 (-1.0405)	0.01305 (1.143)

6. Conclusion

Many studies have considered the effect of volatility on economic performance. Ramey and Ramey (1995) suggested that the relationship between growth and volatility is negative. Mendoza (2000), Jones (1999), Matheron and Maury (2000), Epaulard and Pommeret (2003) showed that business cycle volatility reduces welfare. Barlevy (2004) suggested that economic fluctuations remarkably decrease welfare. So variables that influence output volatility, seem to be attractive to be investigated. Sachs and Warner (1995) have shown that natural resource endowment has a negative effect on growth. Rose (2006) and Karras (2006, 2008) have considered the effect of country size on economic performance and volatility and came to two opposite conclusions.

In this paper, the effect of natural resource endowment and country size on output volatility has been investigated. The results suggest that countries which are highly dependent on primary commodities, experience more volatility and small countries have more volatile cycles than large countries. So it follows that country size and natural resource endowment are to explanatory variable which can justify the behavior of cycles in an Economy.

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