FONDATION POUR LES ÉTUDES ET RECHERCHES SUR LE DÉVELOPPEMENT INTERNATIONAL

Measuring macroeconomic volatility

Applications to export revenue data, 1970-2005

Joël Cariolle

Joël Cariolle is a PhD student at Cerdi.
Joël Cariolle is a research assistant at the FERDI.
Contact cariolle.joel@gmail.com

The literature on macroeconomic volatility covers an extremely wide field, reflected in the very broad spectrum of indicators used to grasp this phenomenon. The choice of indicator is generally little discussed, on the grounds that the different methods give rise to volatility scores that are strongly correlated. However, while these indicators do seem to converge when used to measure the average magnitude of volatility, they diverge significantly when one studies its asymmetry (predominance of positive or negative shocks) or the occurrence of extreme deviations. The volatility of an economic variable refers to the notion of disequilibrium, measured by the deviation between the values taken by this variable and a reference value or a trend.

…/…

policy brief
47
March
2012
note brève

• • • / • • • The first stage is therefore to identify and isolate the trend or permanent component of the change in an economic variable. Traditionally, volatility indicators measure the mean deviation range of the variable relative to the reference value, generally on the basis of standard deviation. But such an approach masks other important dimensions of volatility, such as the asymmetry of the deviations (predominance of positive or negative shocks) and the occurrence of extreme deviations. Economic agents may behave or react quite differently depending on whether the volatility is dominated by positive or negative shocks, but also on whether the shocks are frequent and weak or infrequent and strong. We illustrate our analysis based on the annual changes in the export revenues of 134 developed and developing countries over the period 1970-2005 from the World Development Indicators.

Calculation of trend components or reference values

The first stage is to identify the trend component of an economic variable in order to measure the deviations between the values taken by that variable and that trend or reference. Since this first stage may influence the volatility indicators, we put forward here several methods for calculating the reference. The first two methods are based on a parametric approach in which the trend, which takes a mixed (deterministic and random) form, is estimated econometrically:

$$y_t = \alpha + \delta y_{t-1} + \varepsilon_t$$

The trend or reference value is then
$\hat{y}_t = \alpha + \hat{\beta} y + \hat{\delta} y_{t-1}$ and the deviation is
$\hat{\varepsilon}_t = y_t - \hat{y}_t$.
The first alternative is to estimate the trend over the whole period (the so-called "global" trend); the second is to estimate the trend on a rolling basis for each year based on the data for each year and that of the twelve previous years (the "rolling" trend).

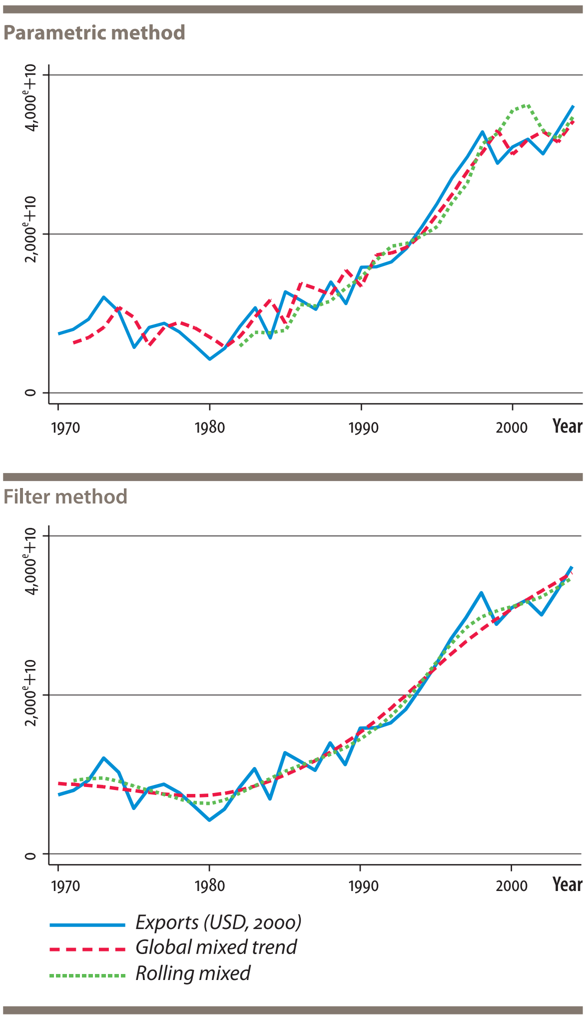
The other two methods of trend computation are based on the Hodrick-Prescott filter. The HP trend is derived from the algorithm:

$$min_{\{HP_t^*\}_{t=1}^{T}} \left[\sum_{t=1}^{T} (y_t - HP_t)^2 + \lambda \sum_{t=2}^{t=1} (\Delta^2 HP_t)^2 \right]$$

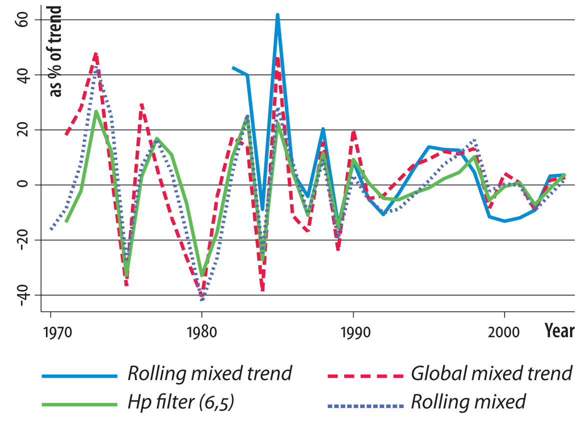
and the deviation is $\hat{\varepsilon}_t = y_t - HP_t^*$

The two alternatives are obtained by selecting a smoothing parameter (λ) of 6.5 or 100, generating respectively a fluctuating or a stable trend. The four reference values and the deviations they generate are illustrated in Figure 1 below, for the case of Argentina.

Figure 1. Reference values applied to the case of Argentina



Deviations compared (as % of trend)



Magnitude of volatility

The most commonly used method is to compute the standard deviation (StdDev) of the variable around its reference value. Here we normalize the deviations by the reference value so as to make them comparable between countries. The formula is the following:

$$StdDev = 100 \text{ x} \sqrt{\frac{1}{T}\sum_{t}\left(\frac{y_t - ref_t}{ref_t}\right)^2}$$

$$with\ T = [1982;2004\text{-}05]$$

where ref_t is one of the four reference values previously presented ($\hat{y}_t$ over the whole period, or rolling, or HP_t of HP filter 6.5 or HP filter 100). Table 1 shows that the indicators of magnitude derived from the different reference values are very strongly correlated.

Table 1. Correlations among volatility magnitude indicators

	(1) Global mixed trend	**(2)** Rolling mixed trend	**(3)** HP 6.5	**(4)** HP 100
Volatilities calculated over period 1982-2004/05				
(1)	1.00			
(2)	0.92*	1.00		
(3)	0.96*	0.95*	1.00	
(4)	0.87*	0.80*	0.87*	1.00

* Significant at 5%. Sample = 134 countries.

Asymmetry of volatility

Indicators of magnitude do not make it possible to identify a possible asymmetry of shocks. The coefficient of asymmetry (CA), or dissymmetry, identifies the profile of the volatility by revealing whether it is dominated by negative or positive shocks. This coefficient is calculated as follows:

$$CA = 100 \text{ x} \frac{\frac{1}{T}\sum_{t}\left(\frac{y_t - ref_t}{ref_t}\right)^3}{\left(\frac{1}{T}\sum_{t}\left(\frac{y_t - ref_t}{ref_t}\right)^2\right)^{2/3}}$$

$$with\ T = 1,\ldots,t$$

A symmetrical distribution of deviations gives a coefficient equal to zero, while a distribution dominated by positive (negative) deviations gives a positive (negative) CA. The greater the positive or negative shocks, the higher the CA. Erreur ! Source du renvoi introuvable. 2 shows that the correlations among the CA derived from the different reference values are weak, suggesting that the choice of reference values is primordial when one is interested in the asymmetry of shocks.

Table 2. Correlations among coefficients of asymmetry (CA) calculated over the period 1982-2005.

	(1) CA (Global mixed trend)	**(2)** CA (Rolling mixed trend)	**(3)** CA (HP(6.5))	**(4)** CA (HP(100))
CA calculated over the period 1982-2005				
(1)	1			
(2)	0.23*	1		
(3)	0.08*	0.14*	1	
(4)	0.29*	0.02	0.65*	1

* Significant at 10%. Sample = 134 countries.

Figure 2 in the appendix shows a positive but weak correlation between measures of magnitude and measures of asymmetry: two countries may have a similar magnitude of volatility but exhibit a radically different asymmetry. The asymmetry of the deviations from the reference value is thus a distinct dimension of volatility, which cannot be grasped by magnitude indicators alone.

Frequency of extreme deviations

A final dimension of the volatility of a macroeconomic variable concerns the occurrence of extreme deviations. This dimension is measured by the fourth aspect of the distribution of observations around their reference value, kurtosis (or coefficient of peakedness). The kurtosis of normalized deviations is calculated by means of the following formula:

$$Kurtosis = 100 \times \frac{\frac{1}{T}\sum_t \left(\frac{y_t - ref_t}{ref_t}\right)^4}{\left(\frac{1}{T}\sum_t \left(\frac{y_t - ref_t}{ref_t}\right)^2\right)^2}$$

$$with\ T = 1, \ldots, t$$

Kurtosis indicates the extent to which observations close to the mean are numerous relative to observations distant from it. In the case of a normal distribution kurtosis is equal to 3 (or 300% when expressed as a percentage of the trend). A higher kurtosis value represents a staggered distribution with thick distribution tails, whereas a lower value represents a distribution concentrated around its mean with thin distribution tails. Combined with the coefficient of asymmetry, the kurtosis can provide information on a country's propensity to undergo extreme negative or positive shocks.
Table 3 sets out the correlations among the kurtoses derived from four trends or reference values. These correlations are stronger than those of the asymmetries but weaker than those of the volatility magnitude indicators, showing that the choice of reference values influences the diagnosis on the occurrence of extreme shocks.

Table 3. Correlations among kurtoses calculated over the period 1982-2004/05.
* Significant at 5%. Sample = 134 countries.

	(1) Kurt. (Global mixed trend)	(2) Kurt. (Rolling mixed trend)	(3) Kurt. (HP(6.5))	(4) Kurt. (HP(100))
(1)	1			
(2)	0.39*	1		
(3)	0.38*	0.28*	1	
(4)	0.49*	0.22*	0.62*	1

Figure 3 in the appendix shows that the correlation between the measures of magnitude and the measures of kurtosis is relatively weak, indicating that the two dimensions are relatively independent. Figure 4 shows the correlation between the asymmetry scores and the kurtosis scores. A U-shaped relationship can be observed between these two measures: at negative and weakly positive levels of asymmetry, the two dimensions are relatively independent, whereas high kurtosis is associated with strong positive asymmetry, for the export data used here.
Overall, the three measures of magnitude, asymmetry and kurtosis appear relatively independent, at least for the data used here, which leads us to consider that these three dimensions generate different information on volatility. It is therefore important to use several types of indicators in relation to the subject studied, or if one wants to establish a complete diagnosis on volatility.

The method is set out in detail in:

- **Cariolle J.** (2012), Mesurer l'instabilité macroéconomique: applications aux données de recettes d'exportation, 1970-2005, FERDI *Working Paper* No.I.14.

If you use these data, please cite this reference, adding: "Data available at: http://www.ferdi.fr/en/Innovative-indicators.html".

► Annexe

Figure 2. Correlation between measures of magnitude and of asymmetry of volatility, by reference value.

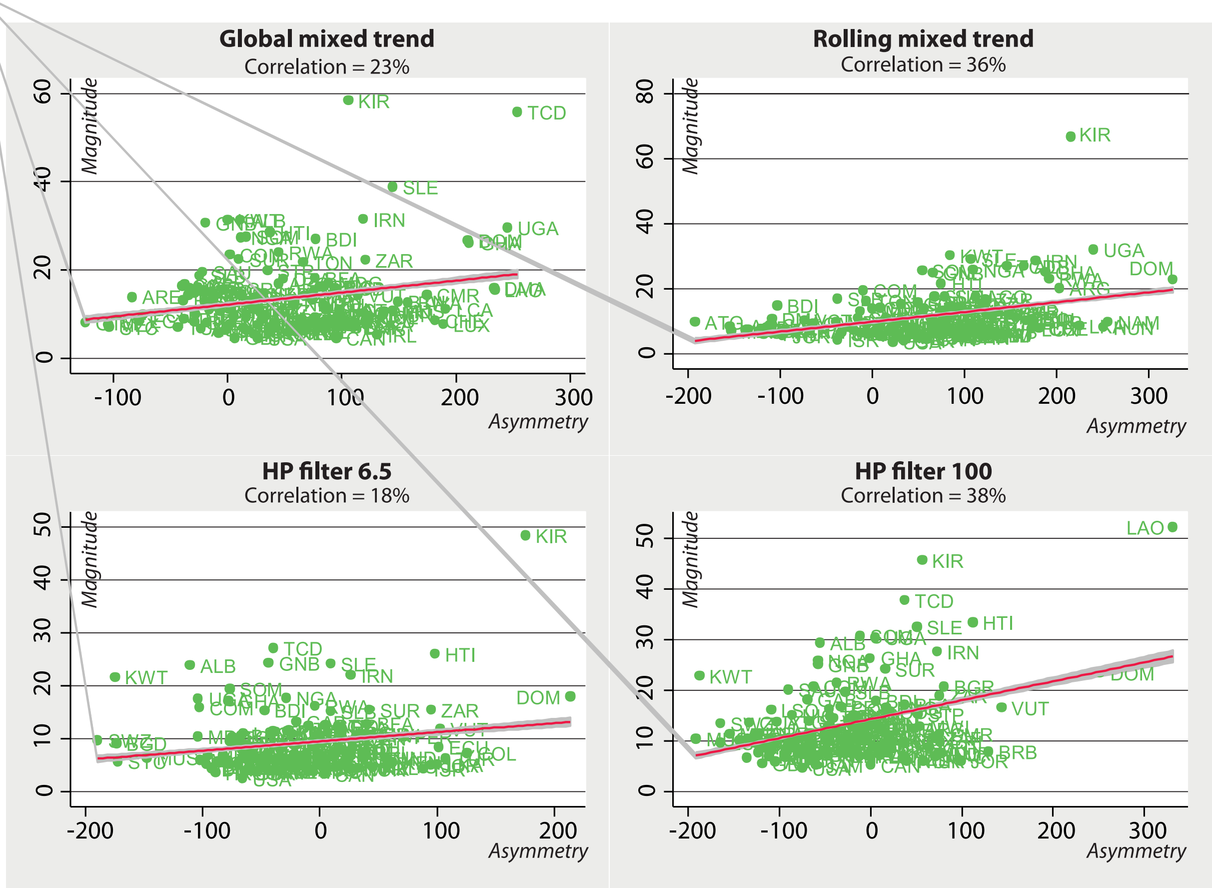


Figure 3. Correlation between measures of magnitude and of peakedness of volatility, by reference value.

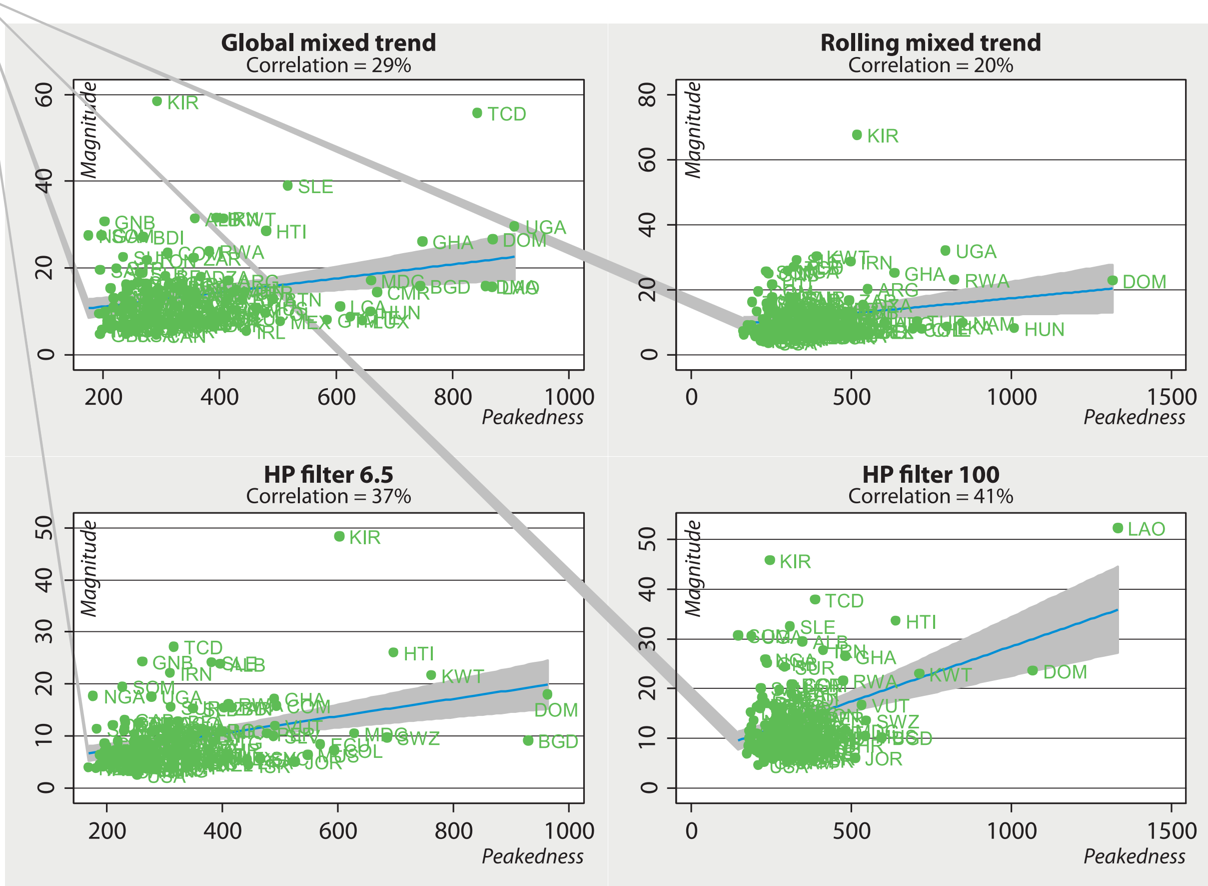
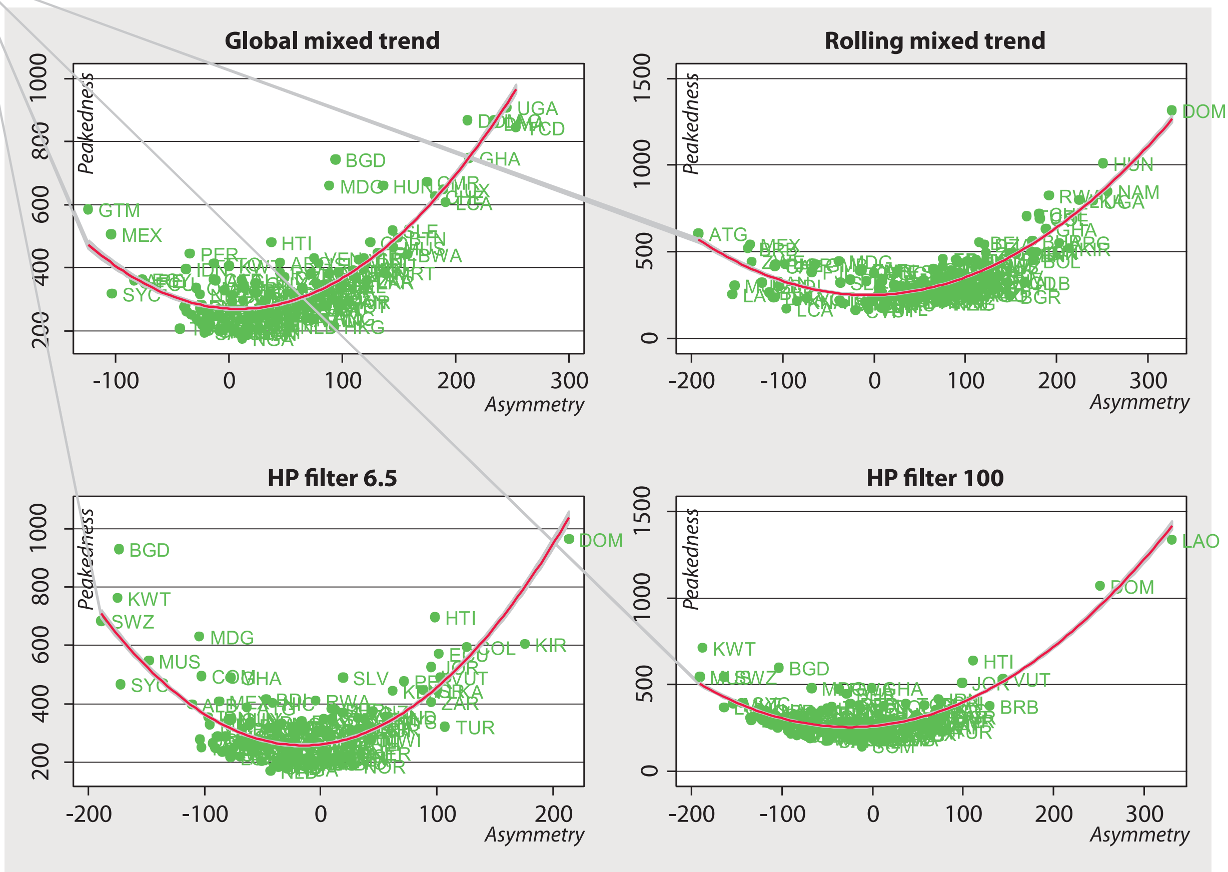


Figure 4. Correlation between measures of asymmetry and of kurtosis, by reference value.



Créée en 2003, la **Fondation pour les études et recherches sur le développement international** vise à favoriser la compréhension du développement économique international et des politiques qui l'influencent.

Contact
www.ferdi.fr
contact@ferdi.fr
+33 (0)4 73 17 75 30

policy brief
47
March
2012
note brève