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Argentine terms of trade volatility. Handling structural breaks and expectations errors.

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Abstract

We perform empirical estimations of volatility on two perspectives, a *statistical* approach and a *expectations based* approach. The TOT volatility and GDP volatility for Argentina along two centuries from 1810 to 2012 under both approaches provide alternative temporal profiles. Further, using the Bai-Perron method and the Bayesian Information Criterion BIC three TOT structural breaks in 1839, 1917 and 1951, and four GDP breaks in 1882, 1913, 1945 and 1975 are found. A rolling window procedure reveals –in line with the literature-, that volatility is not constant throughout. In-sample forecasting allows us to proxy uncertainty as errors of prediction. Main stylized facts found for Argentina are high and changing TOT and GDP volatility, the presence of breaks defining different regimes, an overall pattern with relative high volatility but decreasing in the last decades, and diverse patterns of fluctuations. The impact of TOT volatility on GDP growth is estimated with a VAR.

Keywords: Terms of trade. Structural break. Cycles. Volatility. Land abundance. Argentina.

JEL Classification: C22, F10, F11, F14, F44.

1. Introduction

Central features of the present paper are first the proposal of a method to estimate volatility that is both theoretically sound as a *proxy* for uncertainty in terms of trade (TOT) time series, and operational. Second, estimations for Argentina (a case study representative of a commodity exporter) are performed. Third, causality from TOT volatility to economic activity is explored.

Many countries suffer the high volatility of their TOT, a circumstance which is attracting remarkable attention for the potentially deleterious effect on growth. The

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agreement in this general perception is accompanied by a variety of methods and quantitative estimations which obscure the interpretation of estimated volatility, an ambiguity that needs to be solved to portray the stylized facts and in the study of the effects of volatility.

The empirical relevance of TOT volatility due to the possible associated costs cannot, indeed, be overemphasized. It sends noisy signals for resource allocation in the open economy and matters for macroeconomic fluctuations, external balance, and solvency in indebted economies. Ongoing active research deals with the concept, measurement, identification of volatility, finding causality and extracting policy recommendations regarding volatility. The study of TOT evolution, its trends and cycles, which have been for decades a controversial issue, is nowadays focused on the stylized fact that developing economies terms of trade are highly fluctuating *vis a vis* the group of high income countries. Academic research can contribute to policy makers task by helping understand the process, building accurate information useful for decisions and devising control rules. On the one hand, theoretical research provides hypothesis about causal relationships. On the other hand, empirical research provides hypothesis testing and, more generally, estimations of the phenomenon.

Aizenman and Pinto (2005) point out that economic volatility has “large output and economic growth costs, especially in poor countries” because managing volatility is more problematic in the institutional conditions of developing countries. Understanding the nature of volatility, anticipating its consequences and devising effective interventions should be of considerable interest to policy makers, such that volatility is “now beginning to occupy a central position in development economics”. Loayza and Raddatz (2007) find that fluctuations in the TOT are important sources of external shocks, and across countries 10 percent variation in growth and 25 percent of the variation in growth volatility are explained by differences in the volatility of TOT.

A strand of the literature deals with the interactions between external fluctuations and domestic conditions, such as the exchange rate regime (Broda, 2001), the financial sector (Caballero, 2000, 2002), the endowments and international specialization (Díaz Cafferata and Mattheus, 2010; Sachs and Warner, 2001), institutional quality (Mansfield and Reinhardt 2008).

In similar vein Koren and Tenreyro (2007) write that understanding the sources of volatility is a first order issue for less developed countries[1] and Reinhart and Wickham (1994) note that the potential gains from policy are larger in an uncertain environment. In policy perspective, the need to manage the volatility of exchange prices (assumed exogenous for small developing countries) has stimulated research to characterize the stylized facts, to determine the causes of these fluctuations, and to the identification of channels for the (perceived deleterious) influence on growth, income distribution and poverty, and the social welfare implications.

What is volatility? Definitions and empirical measures under statistical and expectations based approaches.

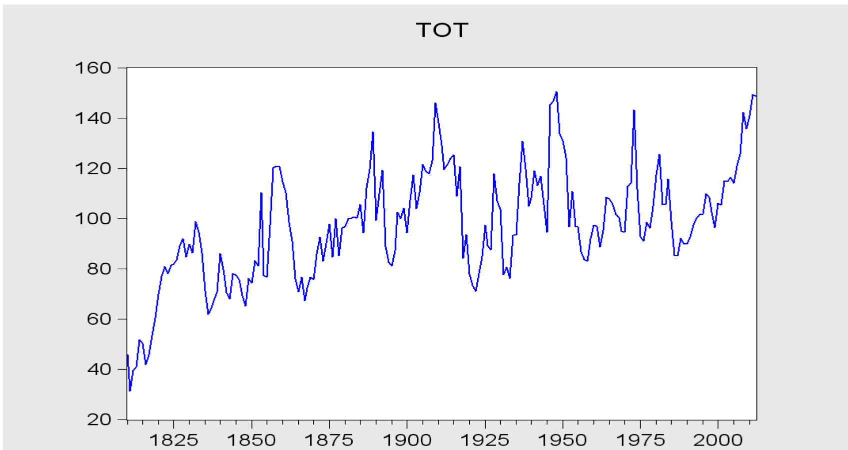
To introduce empirical content in the discussion, Figure 1.1 shows the Argentine TOT index (1993=100) along 203 years between 1810 and 2012. A first eye-view of the phenomenon calls the attention to the large up and down movements, around a long

[1] Cfr. P.243.

term mean equal to 97. TOT fluctuate sharply between peaks as high as 150 and valleys about 80, with frequent swings in its evolution which in common parlance would be referred to as “high volatility”.

Figure 1.1

Terms of Trade Index Argentina 1810 – 2012; 1993=100

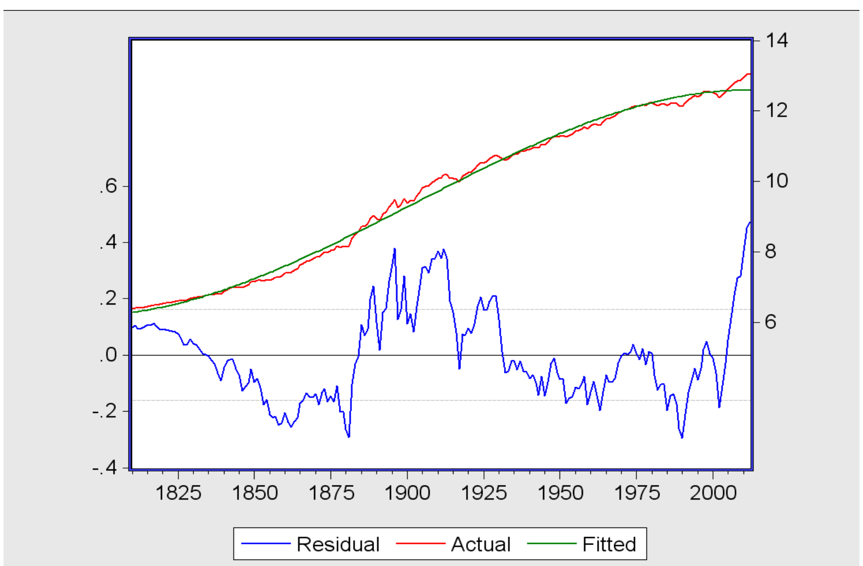


Source: See text for data sources.

Figure 1.2

Argentina, 1810-2012. Log GDP.

Cubic trend (without breaks) and residuals.



Source: See text for data sources.

Figure 1.2 portrays the residuals from a third degree polynomial detrending of the logGDP in the same time span.

Table 1.1

Argentina, 1810 – 2012.

Summary statistics of the terms of trade index 1993=100.

Parameter estimates	
Mean	97.0536
Median	96.8276
Maximum	150.44 (year 1948)
Minimum	31.22 (year 1811)
Standard Deviation (SD)	**22.46**
Coefficient of variation (CV)	**0.23**
Skewness	- 0.0778
Kurtosis	0.2753

Source: own estimations.

TOT Quartiles: Q1: 82.90, Q2 (median) 96.83; Q3: 111.87; Q4 (maximum) 150.44

Q3-Q1=28. Interquartile range [82.90, 111.87]. Range: 150.44 - 31.22= 119.22

A first crude indicator of TOT volatility is the standard deviation (SD) of 22.46 with a coefficient of variation CV=0.23. Note this is a unique measure of dispersion for the whole sample period, in our case 203 years. This estimation of volatility arise further questions for analysis.

Table 1.1 provides summary statistics of the terms of trade. Last; Table 1.2 highlights a few stylized facts of TOT in four sub-periods[2]. The SD is included as a measure of fluctuations. What do the SD informs and how this indicator compare with alternative calculations of volatility? Is volatility constant in the long run or, on the contrary, there are sub-periods of high and low volatility? What statistical properties of volatility are useful for the formulation of stylized facts and for estimation of effects on activity and distribution? Further, are there cycles in the TOT? How should volatility estimations be performed if such cyclical processes exist? Is the statistical data generating process valid throughout the sample or are there different regimes defined by breakpoints?

We shall provide answers to these questions.

In particular, note that when we break down the sample as in Table 1.2, a significant degree of heterogeneity across subperiods is easily noticed. The mean is clearly different in the four regimes, and rising, with a highest value in subperiod IV (1952-2012); also fluctuations measured by the SD are different, high throughout, and with a minimum again in subperiod IV.

Hence, the most recent subperiod with the highest mean and the lowest standard deviation, looks like an environment with a rather favourable combination for the economy.

[2] Details of the estimations are found in the next sections.

Table 1.2

Argentina, 1810 – 2012.
Summary statistics of TOT index 1993=100.
Values in between break-points regimes.

Parameter estimates	Sub-periods between break-points				Whole sample
	(I)1810-1838 29 years	**(II)1839-1916** 78 years	**(III)1917-1950** 34 years	**(IV)1951-2012** 62 years	**1810-2012** **203 years**
Mean	68.93	97.22	104.08	**106.14**	**97.05**
Median	71.20	97.49	104.26	102.11	**96.83**
Maximum	98.80	146.08	**150.45**	149.30	**150.45**
Minimum	**31.22**	65.04	71.04	82.87	**31.22**
Standard Deviation	19.37	19.49	**22.35**	**16.15**	**22.46**
Skewness	-0.33	0.28	0.40	1.03	**-0.08**

Source: own calculations. Breakpoint estimation is explained in detail in sections 3 and 4.

It is worthwhile pointing out that despite the general recognition of the high statistical "volatility" of developing countries´ TOT, and the intuition about the type of economic phenomenon and its importance, there is ambiguity about the precise concept and empirical measure of volatility, making it necessary to understand and compare the information content of alternative measures. Next, we provide a systematization of the empirical methods found in the literature which distinguishes two main approaches to estimate volatility, "statistical" and "expectation based".

Classification of types of volatility

We distinguish two main types of volatility approaches, "statistical" and "expectation based" among empirical measures found in the literature:

> **Type (a)**: A <u>statistical approach</u>, consists of descriptive measures of dispersion.
>
> **Type (b)**: An <u>expectation based approach</u> is related with the signals received by the economic agents, associating higher levels of uncertainty with higher volatility.

In the latter, the question emerges as to how to build empirical measures of unobservable volatility from observed data with an approach that embodies the concept of uncertainty. We make this idea operational in two ways: b1) the decomposition and modeling by a two-step detrending and decycling, associating volatility to the residuals; b2) the other one relies on out of sample forecasting and standard error of prediction.

In this paper we estimate Argentine GDP and TOT volatility with the alternative approaches, and compare the temporal profile of volatility they portray.

There is a difference in the method we use to estimate volatility of the TOT and of GDP. While TOT volatility is estimated with each of the two Type b) methods, GDP volatility will be estimated with only the Type a) statistical approach. The reason for the different procedure is that we associate TOT volatility with uncertainty and empirical volatility is a *proxy* for an unobserved property of the data associated with the degree of ignorance. In contrast, the volatility of GDP is empirically measured by its actual fluctuations.

To deal with the question of which is the appropriate characterization of the phenomenon of high TOT fluctuations, let´s discuss briefly the interpretation of the two approaches that will be elaborated further in Section 4. A key feature of our chosen representation is the assumption regarding the economic agents´ information set. With this principle we elaborate a methodological suggestion with two methods b1 and b2 based on the association of volatility with uncertainty, which is the key feature of our chosen methodology.

Agents are assumed to form expectations through a learning process, which we approximate by extracting information on perceived regularities in the data, based on the distinction between mere “variability” (as a descriptive measure of fluctuation) and the concept of economic “volatility”. The latter is associated not with perceived regularities but rather with the unexpected movements of the time series.

What do agents know and what do they ignore? If there are regularities in the historical evolution of prices, the actual observed fluctuations may be decomposed into un-observable modeled components and un-modeled residuals. Agents are portrayed implicitly as both recognizing regularities in the evolution of TOT and being “surprised” by unexpected events related with uncertainty.

If volatility is associated with the unpredicted component of the time series, the statistical approach that measures the observed fluctuations overestimates volatility[3]. Volatility estimated from the residuals is, naturally, smaller than the one from estimated fluctuations of the raw data. A key issue is in which cases the evolution of prices creates uncertainty. A policy implication of overestimation of volatility is that it may distort the potential costs and benefits of controlling volatility.

We are not spelling out in full detail the precise mechanisms by which uncertainty influences behavior, the channel remaining a black box. But it is useful to discuss the empirical implications of some properties of uncertainty under the two methods of the *expectations* approach.

b1*) First uncertainty approach: detrending and decycling*

The first uncertainty approach is a two step detrending and decycling algorithm (which includes testing for structural breaks), by drawing on the distinction between “variability” (usually represented by the variance or the standard deviation of the variable in a period), and “volatility” (which we meant is related to behavior).

Note that in a purely statistical approach variability and volatility are equivalent indication of *ex post* fluctuations. In contrast they are distinguished when agent´s knowledge (and ignorance) is brought into the picture. The distinction between variability and volatility is discussed in Dehn (2000), and applied in Arrufat *et al*. (2011, 2012). A criterion and an empirical procedure, is needed to determine when one or the other principle is appropriate. The “expectations approach” to volatility is relevant when the decision process is the object of analysis. Three main principles are present when studying TOT volatility under this approach. The first one is that volatility reflects uncertainty. The second one is the recognition of multiple

[3] Which in turn may lead to underestimate the effects of volatility.

dimensions of the evolution of TOT along time (such as the symmetry properties or non-linearities) which cannot be accounted for by a unique statistics. The third is the attention to changes in the data generating process (DGP) along time (with the identification of breakpoints).

A representative individual makes decisions on the basis of perceived information and forward looking inferences about the future in a decision process we try to proxy empirically in the estimations.

In synthesis the state of the art concerning estimation of volatility under method a) and b1) is, in very succinct terms, the use of a statistical measure of fluctuations either on the times series data or based on residuals. We shall now show that both are subject to a critique regarding the time profile.

b2*) Second expectations approach: the time horizon anachronism, out of sample forecasting and "the best one can do".*

Our second measure of volatility is a proposal involving agent´s forecasting procedure to proxy uncertainty by forecasting errors.

To develop this approach we follow Cavallo (1977) and B. Friedman (1979) in noting an anachronism implicit in the detrending and decycling procedure described in paragraphs b1. The modeling of the series (which is meant to represent the *ex ante* perceptions of agents, leaving the residuals as a measure of "surprises" or "volatility") processes all the 203 data points of TOT in the sample 1810-2012 to identify the data generating process.

The usual representation of uncertainty relies on the information the agent can get from the data generating process (DGP). We proceed to recursive estimation, which incorporates sequential learning by drawing a temporal window, to account for the fact that individuals cannot at a point in time observe the whole sample. Rather, their data set contains information from some limited period (assumed fix in our case) in the past. But the parameters of this process are generally calculated using at any point in time the whole sample, even when the future is unobservable. It can be seen the impossibility that at each point in time (except the last year) an agent be using information about a future that is beyond his actual historical experience. A more satisfactory perspective we provide, reflects the fact that people learn from the observed data but certainly not of future events.

In synthesis. One implication of the usual analysis is that people are implicitly portrayed as perceiving at any given point in time the data generating process (DGP) which is itself estimated using the whole sample. It can be said that they know all the past and have the gift of prescience. This in our knowledge has not been a major concern in the literature, which may be so because these studies are concerned with much shorter historical periods.

We can at this point describe the estimations made for Argentina, starting with the statistical measure of volatility calculated as the SD or as the SD of detrended residuals. Then, variability and volatility are distinguished, and estimated, the latter by detrending and decycling, as a proxy for TOT uncertainty following Arrufat *et al*. (2012). Further, since the estimation of a unique statistic of dispersion for the whole sample may be informative, but less so if the behavior changes along time, we use a rolling window which provides the evolution of volatility along time, and is useful to identify sub-periods of high and low volatility. Use of the SD of a five-year rolling sample provides the temporal evolution of uncertainty. Three alternative algorithms are used to estimate "volatility" by the two step procedure. The whole sample is used and we proceed to the estimations with the prior identification of breaks.

Beyond the choice of approach it is necessary to control if the presence of sudden large jumps is followed by changes in regime. For the detrending, we can *a priori* presume that breaks in the data generating process of Argentine TOT may exist due to phenomena such as the closing of the XIXth Century growth of the New Settlement countries, the two World Wars, the modern international segmentation of production, and technical change, among others, which may have changed the process of international price formation, altering the TOT data generating process (DGP). The identification of statistical structural breaks provides useful indication of posible changes in the data generating process (DGP) working of the economic system. In particular we study the characteristics of cycles and the evolution of volatility across sub-periods, and compare these values with the estimations without breaks.

One is usually advised to take possible breaks into account to avoid erroneous characterizations of the nature of the series. The most obvious example is that of mistakenly arriving at the conclusion that a series is stationary in differences when it is, in fact, trend stationary with a segmented trend. Additionally, and very important for one objective in this paper, severe pitfalls may arise when trying to isolate cycles. An important outlying observation may lead the researcher to identify a bogus cycle the period of which is excessively lengthy.

Despite substantial structural changes in Argentina, a stable feature of its international trade, namely, the bulk of exports are natural-resource-based, and its external TOT are driven by exogenous price movements. This rather rigid export composition becomes a long-term structural restriction, influential and difficult to change. For example, it is difficult to follow usual recommendations pointing to the generation of dynamic advantages via industrial and commercial policies. These structural characteristics create external vulnerability and a policy problem regarding the strategy of integration in the world economy, and the trade-offs between specialization and diversification. Policy implications of the empirical findings shall be interpreted in the context of a rigidity caused by the extreme land-abundant endowment, which diminishes the incentives for export diversification. Export diversification has been limited, because it is costly.

Contribution. Useful knowledge attained with the multiple characteristics approach to volatility.

In our chosen approach volatility is associated with uncertainty, i.e. measures of unobservable volatility from observed fluctuations. We perform empirical estimations with alternative methods, elaborate measurement procedures, and explore causality in Argentina. Useful gain in knowledge is obtained from the added complexity in characterization of volatility, and precision in the estimations, showing the new information provided by refined statistics versus a simple measure of volatility. A general observation at this point is that more detailed and precise information helps improving the quality and sophistication of the analysis, and also more precise identification of specific policy objectives and instruments.

The contribution involves a characterization of different measures of volatility and an evaluation of the different measures, and providing estimates of volatility under alternative empirical methods with application to Argentina. In short, all the alternative measures of volatility show differences in level and a general pattern: volatility rises along the XIXth Century, with a peak around 1975. Falls until the first decade of the 20th Century follows a U movement until 1950 and falls from about 0.15 to 0.10 along the last half Century.

A second particular issue we deal with is the fact that the TOT of developing countries suffer large sudden jumps (either outliers or structural breaks). This phenomenon a priori shall be taken into account by testing the presence of structural breaks in the time series, and this gives origin to a new question regarding how to identify volatility in the presence of breaks. One intended contribution is to deal carefully with the presence of structural breaks, a task performed in Section 3.

We provide stylized long-run features of TOT and GDP for Argentina, and by estimating Granger causality and a VAR model we test the hypothesis of TOT and GDP volatility association. As regards the effects of volatility the question is whether the phenomenon of high GDP volatility and high TOT volatility are associated, and if there is causality from the latter to fluctuations of economic activity.

The rest of the paper develops the discussion and estimations as follows. Section 2 provides a concise literature review stressing the identification of the long-run TOT either as a continuous trend or as stationary with sharp breaks, a fact that seems to be a central feature of the evolution of the TOT for developing economies, explaining the shift of attention from TOT trends towards structural breaks and volatility. Section 3 offers the estimation of stylized facts of TOT and GDP Argentine time series with the identification of structural breaks both in the original data and in TOT and GDP volatility, performing the estimations with a rolling window. The evidence is interpreted in a framework of sub periods in the historical evolution in Argentina. Section 4 discusses methodological issues in the empirical estimation of volatility, provides a classification of three methods, characterizes each and discusses our suggestion to *proxy* the learning process via the estimation of recursive errors between 1810 and 2010. Section 5 deals with the econometric estimations. Section 6 examines the evidence of association between the behavior of the TOT and GDP. Section 7 concludes with a synthesis and policy implications.

2. A perspective of the literature, shocks and volatility

Given our attention to volatility and breaks let´s highlight the relevance they have today in the literature. We shall not address the controversy about the secular terms of trade deterioration hypothesis but focus instead on the increased research attention to these concepts related with dynamics of TOT and activity. We can mention as a historical reference the active debate, is still alive after half a century, about the allegedly long-run deterioration of the TOT of developing countries (the “periphery” in the centre-periphery scheme of Raúl Prebisch) the so-called Prebisch-Singer hypothesis after the seminal Prebisch (1950) and Singer (1950) contributions. Spraos (1980) addresses the statistical debate, and provides an analysis of the hypothesis. Harvey, Kellard, Madsen and Wohar (2010) examine historical data from the seventeenth until the twenty-first century for 25 primary commodity prices, finding that several of them present a significant and downward trend over all or some fraction of the sample period, and conclude that in the very long run a secular deteriorating trend is a relevant phenomenon for a significant proportion of primary commodities.

Moving to volatility and breaks, Koren and Tenreyro (2007) study the sources of volatility, finding that poor countries GDP is more volatile because first they specialize in few more volatile sectors; second, because they experience more frequent and severe aggregate shocks; and third because macroeconomic fluctuations are more highly correlated with the sectors in which they are specialized.

Sapsford and Balasubramayam (1999) argue that trend and volatility in the TOT are "twin pillars" of the problem of dependence on primary commodities as a source of export revenue. They estimate both deterioration and a marked increase in volatility of TOT for the developing countries. Furth (2010) finds that differences in TOT volatility account for 25% of the cross-country differences in growth in the years 1980-2007. In synthesis, TOT volatility in developing countries is high and perceived as detrimental to growth.

Grilli and Yang (1988) find for the 1900-86 period and a group of selected commodities a downward trend consistent with the hypothesis; and a downward break in level is found in 1921.

A recent publication by Scandizzo, Savastano and Vezzani (2010) contains a comparison of papers with specification of the type of model used in each of them, the main results, and the time span, including the finding of breaks in the econometric evaluation. Cashin and McDermott (2002) synthesizes in its title "small trends and big variability" their finding: volatility of commodities price (rather than the TOT) increased after the time of the Great Depression with a declining trend in real terms of 1.3% between 1862 and 1999. They argue that in any case the greatest problem is a high variability with large and sudden changes. The policy relevance of the decline is relatively minor compared with the "rapid, unexpected and often large movements in commodity prices".

Blattman, Hwang and Williamson (2007) study countries with specialization on commodities of different degree of volatility, and conclude that volatility was much more important for growth than was secular change, and that volatility contributes both to the under-performance of the periphery and the divergence in incomes within the periphery. One channel of influence seems to be the negative effect on foreign investment.

Structural breaks

We also point out as a relevant feature the importance to identify the presence of structural breaks. Cuddington, Ludema and Jayasuriya (2002) in *Prebisch-Singer Redux* present a summary of the main issues in the Prebisch-Singer debate and contend that "rather than a downward trend, real primary prices over the last century have experienced one or more abrupt shifts, or "structural breaks," downwards"; in particular, they find a single break in 1921, with no trend, positive or negative, before or since. Also Cuddington and Urzúa (1989) find for the real primary commodity price index a break in 1921. There is no evidence of an ongoing secular deterioration but "only a permanent one-time drop in prices after 1920" (p438). Hence, it is "inappropriate to describe the movement of real primary commodity prices since the turn of the century as one of ´secular deterioration´." (p441). Similar results are found in Cuddington (2002).

Bleaney and Greenaway (2001) point out that there is evidence that specialization in the production of primary products may be harmful to growth. Working in a panel of annual data of 14 sub-Saharan African countries from 1980 to 1995, they find that volatility of the real exchange rate and volatility in the terms of trade have negative impact on growth. In Bleaney and Greenaway (1993) also the presence of structural break is noticed.

Scandizzo, Savastano and Vezzani (2010) argue that, together with the question of the decline of TOT, the distribution of the possible declines appears as a relevant feature of the data because, once the distribution is considered, the evidence appears to be against the existence of a secular trend, and point out instead the presence of two significant structural breaks before 1921 and after 1973 (the end of World War I and the first oil crisis together with the end of the fixed Bretton Woods agreements dollar-gold parity).

Ocampo and Parra-Lancourt (2010a, b) show that barter TOT for commodities versus manufactures improved since the mid-19th Century until the early 20th century and then declined, but the decline has been unevenly distributed and was not continuous, with a stepwise deterioration in 1920 and 1979. Similar phenomenon is detected in Ocampo and Parra (2003) who find in the evolution of the TOT between commodities and manufactures in the 20th Century two negative jumps in 1920 and 1980.

Perry (2009) argues that high volatility does not seem to be going away in developing countries as globalization advances, and proceeds to evaluate how much of the volatility is related to external factors and how much to domestic factors. With this purpose he decomposes total volatility into six influences: of fiscal volatility, TOT volatility, money growth volatility, capital flow volatility, oil price volatility and financial development. For 1970-2005, 44% of "excess" volatility in developing countries compared with industrial countries was associated with exposure to external shocks.

The effects of TOT volatility

A related field is concerned with the consequences on growth, inequality[4] and vulnerability stemming from TOT volatility, and the evidence regarding causality It has been found difficult to draw general conclusions, because the results are frequently dependent on the idiosyncratic features of the economy.

One perspective is the long run effect of price shocks on growth. Hadass and Williamson (2001) provide a review of the literature on the Prebisch-Singer hypothesis and discuss the impact of price shocks on LR economic performance.

Kim (2007) argues that openness can lead to more or less domestic volatility, because trade can concentrate or diversify economic risk. The theoretical presumption is ambiguous because a more specialized production may be more vulnerable to external shocks, but the expansion of the market reduces volatility. Also, openness may cause less or greater volatility depending on whether international market integration concentrates or diversifies economic risk. (p 185-186). Kim argues that openness is the level of exposure to the international economy; external economic risk is related to the instability of conditions, which is captured by the TOT.

Powell (1991; p.1494) concludes that although non-oil exporting developing countries "do not face a stable declining terms of trade, they face the even more serious problem of infrequent booms and sharp negative ´jumps´ in their terms of trade".

In synthesis, research has failed to find an uncontroversial significant declining trend at the level of aggregation in which the Prebisch-Singer hypothesis was formulated, such that the TOT trend is <u>not nowadays a priority concern for policy</u>. There is, on the contrary, fairly general agreement on the external vulnerability of developing countries, in particular commodity exporters, associated with specialization and the consequences in the volatility of their terms of trade. In any case there has been a shift of attention and a more recent generation of studies is concerned with the problems created by volatility and cycles of the TOT, and the sudden and irregular jumps in prices. But this perception is blurred because disparate conclusions are obtained with alternative specifications and a loss has been observed at different sub-periods, and for selected commodities. The issue is not closed for the future, but research on the one hand shifts the attention towards the problem of volatility and, on the other hand, points out the presence of idiosyncratic country effects and structural characteristics.

In the particular case of the evolution of volatility in Argentina we shall examine the possible presence of regime changes, as the presence of structural breaks has become an issue in the analysis of volatility.

[4] We can add that even if there are not aggregate effects on growth, the distributive effects may be significant. This is an issue of interest for further research.

3. Breaks in Argentine Terms of Trade and GDP

This section briefly reviews the statistical methods for identification of structural breaks and the presence of sub-periods in TOT volatility and in GDP in Argentina. Secondly, we propose a refinement in the econometric estimation of volatility recognizing the learning process in expectations formation.

Two approaches for the empirical identification of volatility are based one in the filtering of the component of the time series that are perceived by the economic agents, via detrending and decycling "cum" structural breaks identification. The other one is a recursive method to proxy the learning process.

Historical and econometric grounds and reasons for testing for structural breaks.

In the last two decades, the Argentine TOT went up steadily from an index of 85.14 in 1987 to 148.7 in 2012. This is not the best performance: between 1810 and the beginning of the WWI the TOT went from 45.71 to 123.78. Not only the level but also TOT volatility itself has been fluctuating, creating the presumption of structural breaks in Argentine economic history. We are interested in finding if there are different regimes in TOT series, and when structural breaks happened.

Time series analysis provides identification of the statistical process, including trends, cycles and volatility, and helps to make predictions. On this matter, if the statistical data generating process changes across sub-periods, the information can be extracted with the identification of breaks, providing useful indication of possible changes in the working of the economic system.

For technical reasons, the presence of breaks shall be evaluated. Firstly, in empirical econometrics one is usually advised to take possible breaks into account because failure to do so may result in erroneous characterizations of the nature of the series. The most obvious example is that of mistakenly arriving at the conclusion that a series is stationary in differences when it in fact trend stationary but with a segmented trend. Secondly, and very important for our main objective in this paper, severe pitfalls may arise when trying to isolate cycles. An important outlying observation may lead the researcher to identify a bogus cycle the period of which is excessively lengthy.

In particular we study the characteristics of cycles and the evolution of volatility in the subperiods and compare these values with the estimations without breaks[5].

[5] In a previous paper the present authors warned that the long term historical TOT and GDP statistical series may have been subject to structural breaks. Finding a true measure of TOT volatility needs to assert the stability of the process along time. With this end, we shall examine previous estimations of TOT volatility for Argentina and compare the results with the inclusion of breaks.

Empirical identification of breaks in the Argentine TOT between 1810 and 2012

Argentine TOT modeling relies on the following data: for the period 1810-1985, Ferreres (2005) and for the period 1986-2012 INDEC (www.indec.gov.ar).

Following Zeileis *et a*l. (2003), we use the R-language *strucchange* package to estimate the number and location of the breaks. The package is based on the structural change test presented in Bai and Perron (1998).

When trying to find structural changes most classical tests rest on one of these two very restrictive assumptions: First, there is just one structural break in the data. Second, the dates and types of change are known in advance by the researcher. These two factors are easily handled by the typical Chow breakpoint test.

The advantage of the Bai-Perron approach which we adopt is that it overcomes these restrictions and is able to estimate multiple breaks which take place at unknown dates within the context of a linear regression model (remember that linear in this context refers to the model being linear in parameters) estimated by least squares.

For our empirical purposes, we use a simple polynomial structure made up of an intercept, *t* (time trend), and *t2 (*time squared) with a maximum of *m* breaks. Bear in mind that m breaks define m+1 regimes. We adopt the following convention: the sample to be used runs from T_0 up to T, and the breakpoints (that is the times at which the estimated parameters suddenly change), are labeled T_1, T_2, …, T_m.

The relevant equations we use for the estimation of the first two regimes are the following. Equation (3.1) applies to the first regime, estimated with observations running from T_0 through (T_1 -1).

$$\ln(TOT_t) = \alpha_0 + \beta_0 t + \gamma_0 t^2 + u_t, t = T_0, \ldots, T_1 - 1, \tag{3.1}$$

In our definition, T_1 is the first breakpoint and the therefore the time of the first observation of the second regime. The last observation of the second regime is in consequence (T_2 -1). For the second regime the specification is therefore the following:

$$\ln(TOT_t) = (\alpha_0 + \alpha_1) + (\beta_0 + \beta_1)t + (\gamma_0 + \gamma_1)t^2 + u_t, t = T_1, \ldots, T_2 - 1, \tag{3.2}$$

where t now runs from T_1 to T_2-1

Notice that at T_1 and up to T_2-1, the new intercept is equal to the old one, α_0, plus α_1. In similar vein, the coefficients associated with the linear and quadratic time variables also experience a sharp jump (either upwards or downwards) from their former values β_0 and γ_0, to $\beta_0 + \beta_1$, and $\gamma_0 + \gamma_1$, respectively. For the second regime to exist, at least one of these new parameters (α_1, β_1, or γ_1) has to be significantly different from zero. Going down the list from regime 2 to 3,…, to m + 1, the relevant formula for this latter one is:

$$\ln(TOT_t) = \sum_{i=0}^{m} \alpha_i + \left(\sum_{i=0}^{m} \beta_i\right)t + \left(\sum_{i=0}^{m} \gamma_i\right)t^2 + u_t, t = T_m, \ldots, T. \tag{3.3}$$

which applies to the observations between T_m and T. A maintained hypothesis is that the variance of the errors terms is the same throughout the whole sample. The R implementation we employ allows for the computation of Heteroskedasticity and Autocorrelation Consistent (HAC) estimates of the standard errors of the estimated parameters.

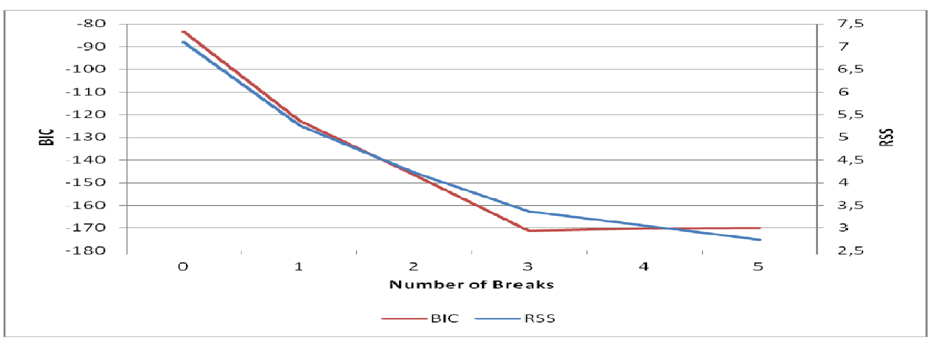
The successive incorporation of these differential coefficients is accomplished by introducing dummy variables which take on a value 1 as from the year at which the break happens and zero otherwise. So, for example, let us assume that a break takes place in 1839. The pertinent dummy variables to account for this fact is labeled D_1839 and takes two values: 0 from T_0 = 1810 up to T_1-1 = 1838, one year before the break, and 1 for the years running from T_1 = 1839 up to T = 2012.

This dummy variable is just sufficient to acommodate the upward or downward jump from α_0 to $\alpha_0 + \alpha_1$, the shift in the intercept. To account for shifts in the linear and quadratic trends, use must be made of additional dummies, like DT_1839 and DT2_1839, which involve the product of D_1839 with t and t squared, respectively.

What is the minimum time distance at which the breakpoints may be located? As the first regime contains only three parameters, a minimum of 4 observations must be employed for least squares estimation. The basic theory underlying least squares estimations establishes that the degrees of freedom for this simple model are given by the (n – 3), n being the number of observations. So, even though 4 observations might be used, it is obviously advisable to use more. How many more? A conflict clearly emerges here: the more observations one uses to estimate the parameters of a specific regime, the fewer potential breakpoints one is able to identify. This trade-off is dealt with by assigning a value to a scalar **h** which sets a lower limit to the fraction of total sample observations to be used in the estimations. This scalar **h**, which applies to the estimation of the first regime is also applied to the **m** remaining regimes. A value typically suggested for h is 0.15, the implication being that at least 15% of the whole sample (T_o – T) observations must be used for the distance between breakpoints. As our sample is made up of 203 observations (T_0 = 1810, T = 2013), this criterion implies that the maximum number of possible alternative regimes to be considered cannot exceed 6.

Figure 3.1

BIC and Residual Sum of Squares - TOT



The Bai-Perron algorithm estimates the optimal partitions for each of the number of possible breaks and then compares one another to estimate the global optimal breakdowns. As stated before a maximum number of 5 breaks (6 regimes) arises on account of the value we have chosen for of **h**, as explained above. Remember that in certain circumstances, such as the availability of a very long time series, a larger value for h may have to be entertained in order to keep computer time within reasonable bounds[6].

[6] The optimal number of breaks found is less than 5 and therefore the restriction implied in the choice of h was not binding.

To compare the optimal partitions for the models with 1 up to 5 structural changes, the Schwarz Bayesian Criterion (SBC), here denoted Bayesian Information Criterion (BIC).

Table 3.1

Regression results

Dependent Variable: LOGTOT
Method: Least Squares
Date: 04/26/13 Time: 17:24
Sample: 1810 2012
Included observations: 203
Newey-West HAC Standard Errors & Covariance (lag truncation=4)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.362066	0.098095	34.27346	0.0000
T	0.108414	0.013460	8.054764	0.0000
T2	-0.002710	0.000428	-6.323660	0.0000
D_1839	0.924637	0.193853	4.769775	0.0000
D_1951	2.896144	0.767735	3.772321	0.0002
DT_1839	-0.107136	0.014487	-7.395544	0.0000
DT_1917	-0.012252	0.004351	-2.816071	0.0054
DT_1951	-0.022708	0.005533	-4.103961	0.0001
DT2_1839	0.002745	0.000430	6.388672	0.0000
DT2_1917	7.39E-05	3.93E-05	1.878739	0.0618

R-squared	0.728881	Mean dependent var	4.545221
Adjusted R-squared	0.716239	S.D. dependent var	0.256449
S.E. of regression	0.136609	Akaike info criterion	-1.095385
Sum squared resid	3.601756	Schwarz criterion	-0.932173
Log likelihood	121.1816	F-statistic	57.65175
Durbin-Watson stat	0.908417	Prob(F-statistic)	0.000000

The results reported in Figure 3.1 show that m = 3 gives the optimal number of breaks, the corresponding years being $T_1 = 1839$, $T_2 = 1917$, and $T_3 = 1951$. Three breakpoints give rise to 4 regimes. In Table 3.2 statistics included refer to only three subperiods to ease comparisons with the expectations approach. A positive level shift is found in 1839 and 1951 while negative linear trend shifts are found in the three periods. Quadratic trend positive shifts are also found for the break-points in 1839 and 1917.

The regression model we obtained is reported in Table 3.1; Figure 3.2 and Figure 3.3 illustrate the results from the regression and in Figure 3.2 we display the outcome of the detrending process.

In turn, Figure 3.3 shows the detrended series and the component accounted for by cycles. The process closes in Figure 3.3 with the time evolution of volatility. Last, in Table 3.2 we provide a summary of the main statistical features of the series: the mean, maximum, minimum and median values of volatility measures across regimes, as well as for the whole sample period. A significant degree of heterogeneity is easily noticed with regard to each of these measures. Take, for instance, the mean: the 1917-1950 period displays a value of 0.1232, significantly bigger than 0.0943 which characterizes de 1840-1916 period. A further examination also reveals the 1917-1950 also features a very high maximum value for TOT volatility.

Amplitude and asymmetry of the transition band in structural breaks

We argue that the breaks in either log GDP or log TOT are not to be interpreted as strict, but rather indicative of a particular point in time in the vicinity of which the break takes place. Support for this contention arises from Zeileis & Kleiber (2005). In the results reported by these authors, the first one of the three breakpoints they estimated by using the Bai-Perron algorithm has a point estimate corresponding to 1996-IV, and a confidence interval spanning the period 1965-II to 1969-III which, as the reader can notice, is not symmetric around the point estimate.

The existence of this type of confidence interval, whether symmetric or not, leads us to argue that the degree of uncertainty surrounding the said breakpoints we have just pointed out, suggests that a not too strict interpretation of the breaks should be exercised when examining the historical background in the vicinity of the years contiguous to the dating of breaks. The preferred specification is the one thas boasts the lowest SBC value, i.e., it happens to be the most parsimonious for a given goodness of fit.

Table 3.2

Argentine TOT breakpoints 1839, 1917, 1951. Volatility estimated with a 30-year rolling window Standard Deviation of residuals.

Statistical estimators	Subperiods			Whole sample
	1840- 1916	**1917 - 1950**	**1951 - 2012**	**1840 – 2012**
Mean	0.0943	0.1232	0.1123	0.1064
Maximum	0.1144	0.1486	0.1363	0.1486
Minimum	0.0743	0.0863	0.0782	0.0743
Median	0.0879	0.1297	0.1173	0.1085
Years	77	34	62	173

Source: Own estimations. Please notice that the original sample spans the 1810-2012 period. The use of the 30-year rolling window SD used for the volatility estimation implies that figures for the shorter1840-2012 are available.

The length of the subperiods is quite dissimilar: 77, 34, and 62 years, respectively. The 1840-2012 period has a length of 173 years whereas the original sample 1810-2012 spans 203 years. Also important but not reported in the table is the evolution of the standard deviation of volatitility across subperiods. Its estimated values are as follows: 0.0134, 0.0179, and 0.0157 for the first, second, and third subperiods, respectively. For 1840-2012 its estimated value amounts to 0.0191.

Figure 3.2

Argentina, log GDP. Quadratic trends cum breaks

Breakpoints: 1882, 1913, 1945, and 1975

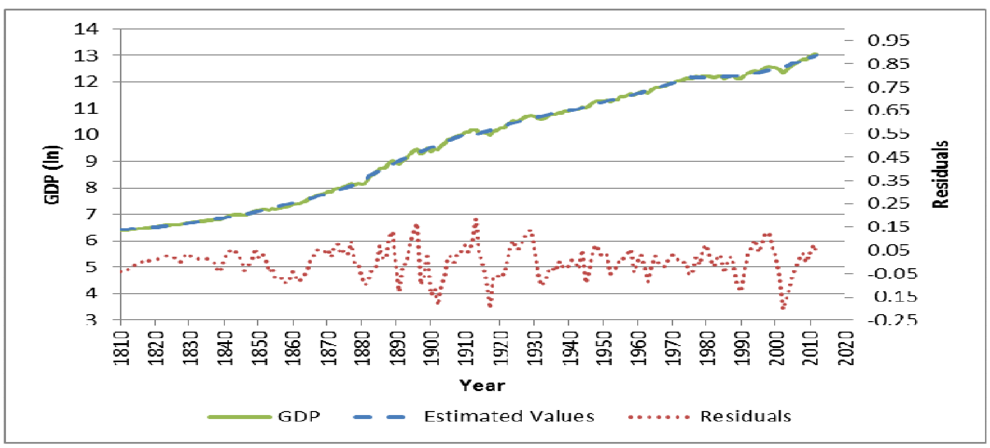
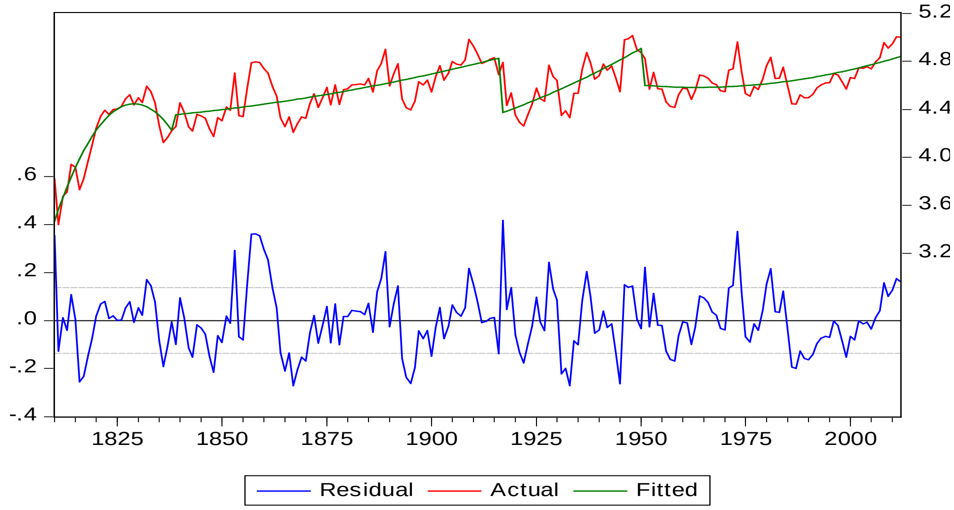


Figure 3.3
Log TOT with a segmented trend.
Breakpoints in 1839, 1917, and 1951



4. Different approaches to measuring volatility

Argentine terms of trade rise and fall, on occasions violently. A very rough measure of these movements is provided by an ordinary standard deviation. Is there a need to make an extra effort to compute more complex indicators? There are certainly a few.

The pattern of observed ups and downs is rarely symmetric, with the speed of their rise in general different to that at which they fall. The TOT may contain unobservable cyclical regularities which themselves may follow a homogeneous pattern along time or be different in sub-periods. It has been found that the frequency and type of unexpected shocks matter. Their nature, whether permanent or transitory, may make a difference. Also the amplitude of their fluctuations has been found to matter. There might be structural breaks which define different regimes in the DGP.

This diversity of perspectives implies that a unique statistic will not be able to capture the whole of the properties of the TOT, a feature that gives in consequence rise to different approaches, and each of the different measures shall be understood as points of view; as different perspectives of the process with different degree of formalization in measuring fluctuations of an economic variable along time.

As an outcome of the application of alternative calculations we get <u>different degrees of “volatility”</u>, as well as different volatility “profiles” along time (i.e. both the level of uncertainty and how uncertainty changes along time). The outcome of different methods and emerging profiles of volatility can be compared to determine the role of different empirical measures. Also, it is necessary to improve the understanding of when one or the other <u>method of estimating volatility is more appropriate</u> to tackle a particular problem.

First generation, statistical approach. Volatility as standard deviation of detrended residuals.

To organize the discussion on the information content and application of "volatility", we shall start with the simple statistical measure of a single value of the standard deviation of the raw variable in a period of time.

To convey a feel of the order of magnitude of fluctuations in GDP consider the standard deviation of the rate of growth using the raw log GDP and decomposing the observed data in the unobserved trend and detrended residuals. The trend is a quadratic equation in time with intercept, including structural breaks. Naturally, the fluctuations of both series are of the same sign, but the detrended series are of smaller magnitude.

Table 4.1

Argentina, 1810 – 2012.

GDP non-detrended, and detrended, rate of growth.

"Volatility" measured by a unique standard deviation for the whole sample period.

Parameter estimates	GDP not detrended. Rate of growth.	GDP detrended. Rate of growth.
Mean	0.0331	0.0004
Median	0.0352	0.0067
Maximum	0.2305 (1882)	0.1281
Minimum	-0.2093 (1897)	-0.2345
Standard Deviation	**0.0560**	**0.0539**
Skewness	-0.2987	-1.0100
Kurtosis	5.1475	6.2140

Source: own estimations. The mean 0.0331 is the average of the log difference. Note since one year is lost when computing the rate of growth, the estimations are based on 202 data points (1811- 2012). The contemporaneous estimated correlation coefficient is 0.9177.

For the interested reader, the long- run rate of growth of real GDP between the endpoints of our sample 1810-2012, computed in the usual way as:

$$R = (Y_{2012}/Y_{1810})^{(1/(T-1))} - 1 = (468301/586.4651)^{(1/202)} - 1 = 0.03363626$$

Note that a single value of the SD may be little informative if volatility itself is fluctuating, as is the case for Argentina. A first comment about the growth is that the average rate of growth has been far from regular. On the contrary, there is a large difference between a peak of annual growth of 0.2305 in the year 1882 (and about that time growth decelerates, with a crisis in 1890, the so called "Baring Brothers crisis") and a trough with a large fall in year 1897. The ratio of the SD over the mean (i.e. the coefficient of variation) is a high 1.692.

It is a common practice even in this type of estimation to calculate volatility as the SD of the detrended residuals.

One example, Perry (2009, p13) measures “volatility” as the standard deviation of cyclical components from the trend, a procedure that provides a unique measure of volatility for the whole period.

CEPAL (2008) presents a glossary which is indicative of the lack of a unique definition. The two operational definitions are: a) The standard deviation of per capital GDP growth rate; b) the second one relies on long-run detrending (which they note is usually a controversial topic). In any event they argue in empirical studies the particular choice of detrending methods adopted has not a bearing on the results.

Frenkel *et al* (2002; 225-231) measure volatility as the standard deviation of the (first difference) Hodrick-Prescott with lambda equal to 100 detrended variable. From a sample of 58 countries in the period 1967 to 1990, the terms of trade volatility of the seven largest developed countries (USA, UK, France, Germany, Italy, Canada, Japan) is in the range between 3.64 for Canada and 7.11 for the USA. Japan, an oil importer, has a much higher SD equal to 14.77. The correlations between TOT and GDP for these seven countries are positive, but are for the UK and Canada. In comparison the TOT volatility of less developing countries is much higher, between 5.94 for Israel and more than 35 for Algeria, Nigeria and Venezuela. The Latin American countries double the volatility thus measured of the largest developed countries: Argentina 10.64; Brazil 14.17; Chile 13.62; Mexico 14.20, Peru 10.77.

Aizenman and Pinto (2005) note that “realized volatility” is “most commonly measured by a standard deviation based on the history of an economic variable”.

Heterogeneity across subperiods and the application of a rolling sample

Hnatkovska and Loayza (2005, Cap 2; 65) use also the Standard Deviation of *per capita* GDP growth around a constant mean as one of two measures of volatility.

They also make 10-year calculations to allow for possible heterogeneity. They also undertake significant refinements to this basic approach. One is the incorporation of the Baxter-King filter. Second, they break volatility down into normal and crisis to account for possible asymmetric effects, finding that it is crisis volatility that impairs long-run growth. For Argentina 1960-2000 they compute a 5.41 SD of *per capita* GDP growth, somewhat higher than a world volatility of 4.13. To the mean world growth of 0.95 they add and subtract the world SD of 4.13 to provide a symmetric band (u+- 1S) which provides a yardstick as a measure of “normal” fluctuations; the values of Argentine volatility out of the band are named “crisis”. Nine episodes of crisis volatility happen: one at the beginning of the 1960´s; six episodes between the mid-seventies and the beginning of the 1990´s; and other two in the mid and the end of the1990´s.

Some authors, instead of computing a unique value of the standard deviation for the whole sample, resort to decomposing the sample in subperiods, which in some cases are based on a criterion of homogeneity and in others appear as just arbitrary subperiods, such as decades, or the duration of business cycles.

To capture further useful information which can be processed about the way an economic variable moves along time, some refinements are introduced. One of them is the contrast between variability and volatility and a rolling window. We propose some “third generation” refinements, associated with expectations formation to these notions.

One alternative to the computation of the SD in subperiods, is the estimation of the evolution of the TOT volatility as the rolling standard deviation. This calculation uses the data of a subset of the sample chosen with some criterion (for example, five years has been used as the duration of the business cycle) and the estimations moves the window one year at a time preserving the size. This procedure provides a profile of the volatility along time.

Mendoza (1995) computes variability by means of the standard deviation based on residuals obtained from Hodrick-Prescott filtering algorithm with lambda equal to 100. He quotes that TOT variability for G-7 countries amounts to 4.7 percent standard deviation. This figure is 2.5 times smaller than that of developed countries.

Also Furth (2010, p7) reports TOT volatility two measures of TOT volatility both unfiltered (Mean= 0.23, and HP Mean=0.010) measured by the standard deviation of Hodrick-Prescott (lambda 100) detrended TOT[7]. He comments that the researcher shall make "a non trivial choice of how to measure price volatility". He adds that he is "aware of no theoretical reason" for assuming that price ratios are either autoregressive or contain a long-term trend, and follows Mendoza (1995) in estimating a Hodrick-Prescott filter with lambda 100.

Lutz (1994) uses a 3-year window (cited by Furth 2010, p3).

Koren and Tenreyro argue that the understanding of the sources of volatility is of paramount importance for less developed countries. "Understanding the sources of volatility is a first-order issue" for developing countries. Income fluctuations are not only larger and more abrupt but also the weaknesses of their financial structure prevent them from having access to efficient means of hedging against those fluctuations. For empirical purposes they make the definition of volatility operational by computing the standard deviation of GDP growth from 1960 to 1996 against log real GDP *per capita* in 1960. They conclude that the higher GDP growth volatility in poor than in rich countries is explained by their specialization in more volatile sectors: they also experience more frequent and more severe aggregate shocks (p282). Volatility is associated with risk such that greater specialization in high-risk sectors[8] or greater macroeconomic risk raises volatility. They associate volatility in activity with the variance of the innovations in the growth rate of GDP per worker in a given country (p247). Innovations to growth in value-added per worker in country j and sector s are computed as the deviation of the growth rate from the average growth rate of country j and sector s over time p252). They associate "risk" and volatility by country with the variance or the standard deviation (Table VII p 264). Poor countries are more volatile because they have higher global sectoral risk, more idiosyncratic sectoral risk and higher country-specific risk (p271).

[7] Furth 2010, Table 1, p6; estimations for 54 countries in the period 1980-2007.

[8] They define high-risk sectors as those exposed to large and frequent shocks.

The problem of volatility and risk

Bleaney and Greenaway (2001) argue that growth is reduced by specialization in primary products exports. Possible explanations for this are the presence of adverse trends as well as high variance of primary products prices. TOT volatility is measured as the standard error of the regression of the log TOT on a time trend. A very important issue that they raise is the following: important new ideas have been put forward in the literature in the context of investment theory by emphasizing significant features like the combination of irreversibility and uncertainty. This provides a promising avenue to explore. Relevant empirical studies suggest that governments may misread temporary for permanent positive TOT shocks and engage in unsustainable spending commitments which, in less favorable circumstances, are difficult if not impossible to reverse.

Second generation: the distinction between modeled components and residuals

We have discussed elsewhere the suggestion that movements of a variable that can be modeled and are in consequence predictable should be distinguished from unexpected shifts. Dehn (2000) distinguished variability from volatility suggesting leaving aside the regular part to estimate volatility. Moreover, he observes that uncertainty may change across time. Uncertainty is a concept ex ante different from “variability”, which reflects components that are predictable by producers.

Moledina, Roe and Shane (2004) suggest that volatility should be put into a welfare framework. They also, following Dehn (2000), argue that the predictable components should be removed to measure the volatility of prices; producers are rational and able to generate probabilistic assessment of predictable and unpredictable elements in a price process. Hence, the method relies on purging the known priors; the predictable elements are obtained by testing for U-roots, testing for trend and drift, and estimating the equation for a given commodity. The standard error is the measure of volatility.

As Aizenman and Pinto (2004, p4) put it, if components or trends are predictable, volatility based on ex-post total variability may over-estimate risk.

Following Ramey and Ramey (1995), these components may be modeled as a function of explanatory variables, taking the variance of the residuals as the component of “uncertainty”.

Operational procedure to estimate volatility.

Volatility can be interpreted as related with uncertainty and the prediction errors. The previous approaches assume that our typical agent is able to tell regularities that can be modeled such as trends or cycles, and is *surprised* by the unexpected component which is associated with the residuals from filtering out the trend and the most important cycles. In other words, the standard procedure to identify volatility is to estimate the **standard deviation of the unexplained component**.

The approach which relies in a two-step method by first detrending and then decycling, as in Arrufat *et al*. 2012, appears to be a reasonable representation for the empirical measurement of volatility, with a decomposition of the observed values of the variable in modeled trend and cycles and the un-modeled residuals.

The first step is to obtain the un-modeled residuals. Following Arrufat *et al* (2012) the TOT and GDP time series are modeled, representing the knowledge (freely available) an agent has about the DGP. A Fourier regression is run to identify the four most important cycles in terms of their contribution. The number of cycles is a matter of judgment related to the representation of the agent´s information about the cyclical characteristics of the terms of trade or the variable under study.

In this case the Fourier regression identifies eight estimators/parameters: two are the sine and cosine related with each cycle, times four selected cycles. In the period of the example1810-1839 these cycles accumulate 67% of the total sum of squares. Next, a regression is run of the log TOT against the Gj and the eight parameters (19 degrees of freedom) with the thirty years data of the period under examination.

The Fourier decomposition time-domain approach provides breakdowns of a series into sines and cosines which capture the relative importance of cycles of different periodicities or frequencies. Details of the procedure are in an Arrufat *et al* (2012).

We next break down Z_{1t} into its periodic components by running the following Fourier-type regression:

$$Z_{1t} = \sum_{i=0}^{101} \alpha_i \cos\left(2\pi i \, {}^{t}\!/_{T}\right) + \sum_{i=0}^{101} \beta_i \sin\left(2\pi i \, {}^{t}\!/_{T}\right)$$

Third generation, the "best you can do" expectations approach. Anachronism implicit in the formulation.

However when one ponders more carefully on the implicit assumption about the information set available to the economic decision maker, one comes to realize that the estimation of volatility is a statistical function which depends on the data for the whole sample period of two centuries. This procedure introduces an anachronism because the estimated parameters which characterize the data generating process (DGP) associated with the trend and cycles, are based on the whole sample of annual observations for time t=1 to t=T, between 1810 and 2012. Note that the residual at an arbitrary point in time t_0 in the interval (1,T), "in sample" is one measure of uncertainty equal to the difference between the actual and fitted values. But the latter have been calculated using information on the whole series. This is not a completely satisfactory feature since the agent at said time t_0 is not in the position to know the data in the future period time t_0 –T.

We find the discussion in Cavallo (1977) useful. He argued that some of the assumptions about the mechanism of expectations formation usually employed in the literature appear to be rather unrealistic regarding the assumed information dataset available. In particular, for our present purposes in this paper, we single out the basic idea that people will try to use whatever information can be obtained so far as the cost is less than the gains to be had from predictive accuracy.

Cavallo notes that the agent is usually modeled implicitly as using information for the whole sample period. But this involves the use of information that the economic agent could not have used, simply because it belonged to the future[9].

Friedman (1979, p24) draws a distinction between two approaches from Rawls and Muth. The former author´s conception of rationality simply requires using optimally whatever information is available. In contrast, Muth models agents perception as eventually converging to actual outcomes, without an explicit learning procedure.

In our estimations of volatility we assume that agents use the free knowledge contained in the past and update their perception of uncertainty by incorporating a new data point at a time. As they use a fixed-length data base to make forecasts, for each data point they add, the oldest one must be dropped.

Accumulation and memory of past data

Let us illustrate how this works by means of an example. Consider an individual in Argentina at the beginning of the year 1840. If we assume that he can see data on the TOT back in time for the previous 30 years, he will use the annual data from 1810 to the year 1839. Each piece of information is regarded as certain, has equal weight independent of the time distance; and is completely forgotten in the year thirty one[10]. Agents make forecasts at each point in time based on the experience of the last 30 years which make up his data base.

But, on the contrary; how could they have used plausibly in 1840, the full knowledge of the statistical generating process that uses the whole series spanning 1810 to 2012. At a given point in time people may reasonably be assumed to have information about the past, but certainly not about the future beyond this point.

To face this criticism Cavallo argued that an acceptable principle is to adopt “the best you can do” approach to modeling expectations. This idea follows the Benjamin Friedman approach[11]. How is the general idea of the “best you can do” implemented here?

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[9] We quote Cavallo (1977): "Another specification of "rational expectations", which will be referred to as Muth-Friedman "best one can do" expectations, is much more appealing ... Economic agents are assumed to use all relevant information available at the moment they are making the prediction. They are assumed not to know the true value of the parameters in the relevant relationships of the economy, but they rather estimate them using the least squares method. … they use the estimated equation to predict the future value of the desired variable. This prediction, under certain assumptions, is known to be optimal in the minimum quadratic error sense. Benjamin Friedman has recently shown that this kind of expectations is also adaptive in form, but with "coefficients of adaptation" … dependent on the past values of the exogenous variables. This expectations assumption is very interesting because it implies that economic agents are neither irrational nor seer. In addition it allows for computation for each period, not only of a predicted (or expected) value but also of the variance of the prediction error, which is precisely what we need in order to replace the two unobservable variables which remain in our model."

[10] Alternative approaches are sometimes found in the literature usually known under the heading of discounted least squares, where the near past carries more weight than the more distant past by means of a discount factor.

[11] Benjamin Friedman and Martin Feldstein were Cavallo´s thesis advisors in Harvard University.

First, the agent estimates a quadratic trend model for the TOT:

Log $TOT_t = \gamma_1 + \gamma_2 * t + \gamma_3 * t^2 + E_t$

The parameters $\boldsymbol{\gamma_1}$ **,** $\boldsymbol{\gamma_2}$*** ,** $\boldsymbol{\gamma_3}$ in the equation, are estimated by ordinary least squares (OLS). The corresponding estimates are labeled $\boldsymbol{\gamma_1´}$ **,** $\boldsymbol{\gamma_2´}$ **,** $\boldsymbol{\gamma_3´}$, respectively, which are used to obtain the detrended residuals.

Second, the detrended residuals are in turn, decomposed into cycles by means of a Fourier type regression. Only the four most important cycles will be retained for use in the next step.

Third, we run a regression similar to the one in the first step, but now adding the 4 sine and 4 cosine variables associated with the four most important cycles just identified and the standard error of prediction (SEP from now on), for k periods ahead, is computed in the usual way by using the appropriate values for t. The time frame we used for the estimations is 30 years, assumed here to be the length of the relevant information set that people rely on to form expectations. So the first time the estimation is made in the whole 1820-2012 sample, the regression is run using only the data for 1810-1839. The one-period ahead prediction error, therefore, measures uncertainty for year 1840 which is denoted as SEP_1.

Fourth, the agent moves one period forward and considers data for the new 30 year interval, now (1811-1840). So he adds 1840 and drops 1810 data and repeats steps 1 to 3. Having run through steps 1 to 3 as indicated, the agent has to update the algorithm by considering 1812-1841, as already indicated. By moving one period forward at each iteration, the agent reaches the point at which he uses 1981-2010 for his forecasting exercise and computes SEP_1 which applies to year 2011. This marks the end of this step and the agent moves to next step.

Fifth, having completed step 4, when the agent moves one period forwar he uses data for the period 1982-2011 and the one-step ahead prediction errors that he computes refers to 2012. Consequently, all the iterations have been completed and a series made up of 173 standard errors of prediction, spanning the period 1840-2012 are now available as proxies for TOT uncertainty. For example Figure5.3 shows the corresponding behavior of TOT volatility labeled standard error of prediction SEP_1.

When is the use of the expectations approach adequate?

TOT evolution provides signals for the economic agents to make decisions such as how much to produce and how, how to consume, or how to invest. This information provides a definite structure of incentives.

The particular method employed to estimate volatility must be adapted to the type of variable for which the agent must make predictions.

There is, in our view, a clearcut distinction between the TOT and the GDP as regards the treatment of volatility.

In the case of the TOT, the uncertainty approach assumes that the estimated volatility is a proxy to the risk associated with forward-looking decisions which have the price as a determinant. Greater volatility is associated with the unobservable uncertainty for the economic agents. The rationales of our procedure, in this sense, is that we try to build the econometric model incorporating the regularities which are assumed to be in the information set of agents by the process of detrending, decycling and forecasting. The expectations formation have in consequence an stochastic modeled component, and an stochastic residual whose variability is the volatility of the TOT.

In contrast, the volatility of GDP does not have this expectations component. Rather, the variable along time is the observed outcome of forces driving the aggregate activity. The degree and type of fluctuations are an outcome of interest as a policy objective, since high instability as measured by the variance or the standard deviation is likely be welfare reducing. From the statistical point of view the movement along time can be decomposed in trend and cycle, to distinguish growth from short-run fluctuations, or other properties such as the presence of cycles.

Conclusions

In synthesis, far from a unique concept of volatility a noted feature is an ample variety of choices in the literature, a fact that must be acknowledged for comparisons of the different studies. It is also necessary to be specific about what prices are being compared such as commodities vs manufactures, or developing countries exports vs industrial countries exports. Or how countries are aggregated. The use of annual or quarterly, or monthly prices.

5. Empirical identification of GDP and TOT volatility

This section provides the empirical estimates of TOT and GDP volatility. At this point it is worth reminding the reader that the volatility of the TOT is estimated with two alternative approaches. First, structural changes are recognized identyfing specific breakpoints by means of the Bai-Perron approach. Then the logged TOT series is detrended using a function with an intercept, a linear time trend and a quadratic trend. This is followed by decycling of the so obtained series, to pick the regular cyclical components that are assumed to be perceived by the economic agents. This step relies on a Fourier type regression which isolates the contributions of the four more important cycles. Finally, TOT volatility is measured by the fluctuations of the residuals, i.e. the movements along time of the part of observed TOT that go beyond the regularities perceived by people when making decisions. The second procedure consists of recursive estimation.

With regard to GDP the approach we have adopted is simpler, as in our interpretation the evolution of GDP doesn´t carry the implication that its fluctuations are describing signals for decisions in this framework. In consequence no decycling is carried out. Again the trend is a quadratic function and the breakpoints are estimated *à la* Bai-Perron.

Estimations and comparisons of TOT volatility

We calculated the 30-year and 5-year rolling window versions, both based on the same detrending procedure to assess how sensitive the calculations are to the particular time-frame used. Whereas the former series shows clear signs of non-stationarity, the unit-root null hypothesis is rejected for the latter.

Figure 5.1

30-year rolling window Log TOT volatility.
Upper line (blue) Detrended version. Lower line (red) Detrended and decycled

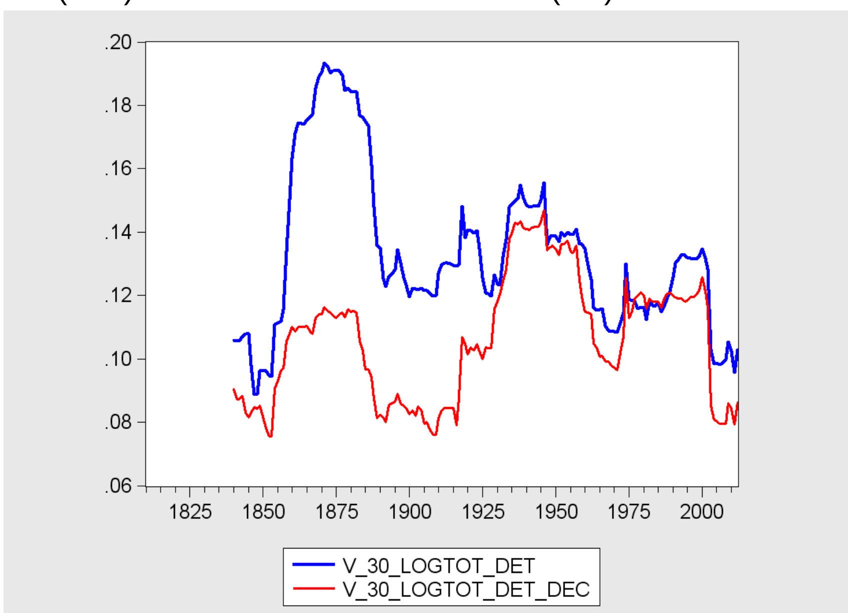
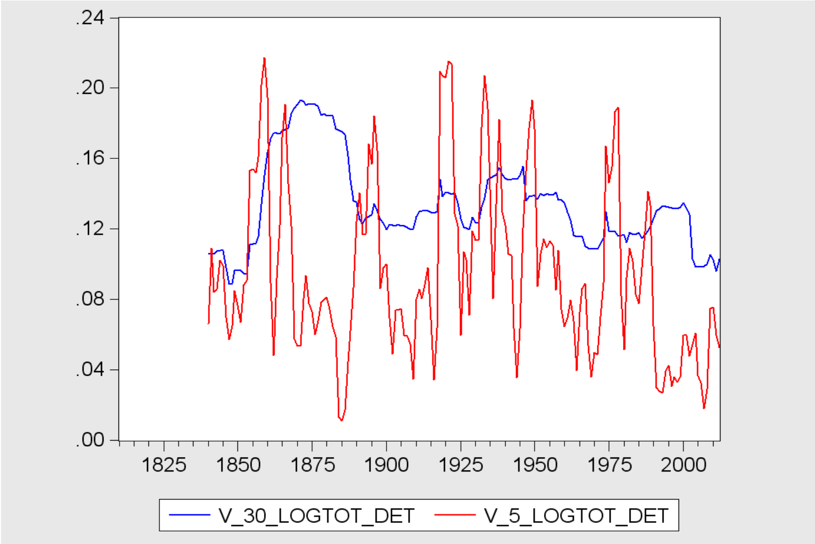


Figure 5.2

5-year rolling window Log TOT volatility (Blue) vs
30-year rolling window Log TOT volatility (Red)



The best you can do approach. Recursive estimation

As shown in Section 3, three TOT breakpoints are found in 1839, 1917 and 1951 giving rise to four regimes (note that the number of regimes is number of breakpoints plus one, and the year of breakpoint is the first year of the new regime). In consequence the historical subperiods are first between 1810 and 1838, second between 1839 and 1916, third between 1917 and 1950, and the current one between 1951 and 2012.

Figure 5.3

30-year rolling window Log TOT volatility (Blue) vs
One-period ahead Standard Error of Prediction (SEP_1) (Red)

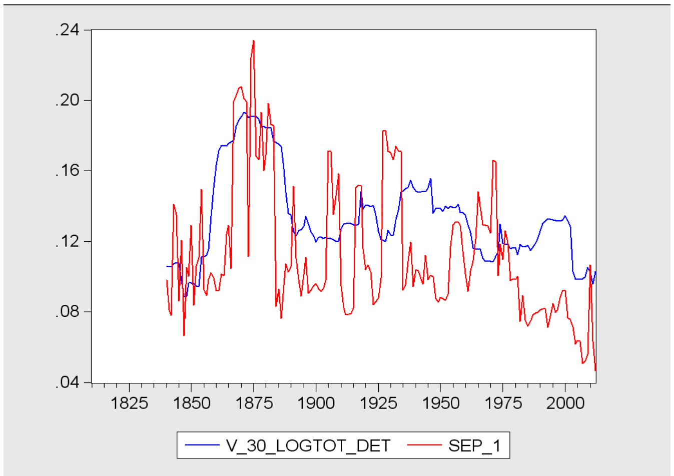


Figure 5.4

5-year rolling window Log TOT volatility (Blue) vs
One-period ahead Standard Error of Prediction (SEP_1) (Red)

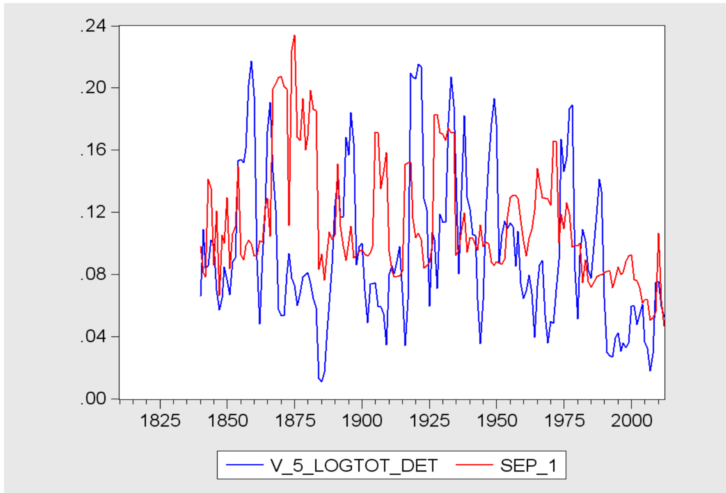


Table 5.1

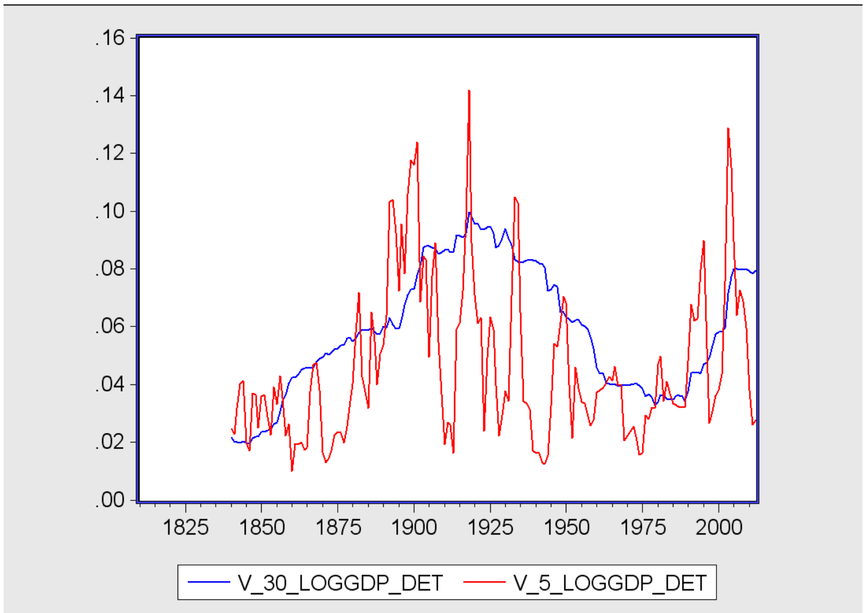
Basic statistics of TOT volatility. Argentina (1840-2012)

	Terms of Trade volatility				
	30-year window		5-year window		1-period ahead Standard Error of Prediction
Parameter estimate	detrended	detrended + decycled	detrended	detrended + decycled	
Mean	0.13	0.11	0.10	0.09	0.11
Median	0.13	0.11	0.08	0.08	0.10
Maximum	0.19	0.15	0.22	0.22	0.23
Minimum	0.09	0.08	0.01	0.01	0.05
Std. Dev.	0.03	0.02	0.05	0.05	0.04
Skewness	0.76	0.17	0.74	0.81	1.02
Kurtosis	2.92	1.99	2.79	3.39	3.39

Estimation of GDP volatility

Figure 5.5

30-year rolling window Log GDP volatility (Blue) vs
5-year Log GDP volatility (Red)



Breakpoints 1882, 1913, 1945, 1975
Five regimes 1810-1881; 1882- 1912; 1913-1944; 1945- 1974; 1975- 2012

Table 5.2

Argentine. 1810-2012 (Annual data)
Dating of breakpoints for logTOT and logGDP and other subperiods

logTOT	1810	1839				1917		1951		
logGDP				1882		1913		1945	1975	
Cortés-Conde growth*				1875						
Díaz C. long-run growth**				1884					1980	
	Accelerating long run growth				Decelerating long run growth					

Source: Line 1, 2, own estimations based on the Bai-Perron algorithm. * Cortés Conde (1994). ** Díaz Cafferata (2005).

The Bai-Perron algorithm was applied by means of the R package “strucchange” which dates the breaks by stating the first year of the new regime.

The table suggests the following reflections, noticing that although this dating has arisen from a purely statistical method, it bears a striking correspondence with characteristic periods in Argentine economic history.

There are four breakpoints for GDP in years 1882, 1913, 1945, and 1975. For historical interpretation we will consider three main stages. In spite of the fact that the number and the precise dates (years) do not coincide, the overall picture suggests the presence of three epochs – based on the log GDP breakpoints- spanning the years leading up to the First World War, from there on to the post WWII years, and finally, from there on to the present day.

Therefore, we should consider 1945 – 1974 and 1975 – 2012.

Stage I: 1810 –1912. The first interval is characterized by accelerating growth as documented in Díaz Cafferata (2005). He estimates a Hodrick-Prescott trend for log GDP, and its derivative with respect to time is named the “long run rate of growth” with an almost coincidental peak of about 10% , not for 1882 but for 1884 instead. After 1884 the rate of long run growth is still high but suffers a declining trend until the onset of WWI, and continues until the mid seventies. Stage II: 1913-1944 and III: 1945-2012.

For the economic interpretation of the breakpoints one should bear in mind two issues. First even though the Bai-Perron algorithm provides a particular point at which the underlying data generating process experiences a break, a confidence interval is also given which measures the degree on uncertainty associated with this dating. Second, the algorithm relies on statistical, as opposed to historical, considerations. Moreover regime changes do not occur overnight but go through a transition phase. Cortés Conde (1994) provides a reflection of the noted economic history academics about the long run characteristic of the Argentine economy. He notes the irregular growth with the repeated decelerations, with four episodes or stages after 1875. The main feature is that the interruptions to growth are not fluctuations about a regular trend, but there are instead sudden discontinuities where each of these periods, each interruption of growth, is followed by a change in trend. The first period, of high growth, runs from 1875 to 1912. Then a second, of low growth, including the WWI years and the recovery closes in 1927; and two more interruptions occur in 1947 and 1975. These timings are roughly coincident.

6. Association between TOT volatility and GDP growth

This section proceeds to explore the possible association between TOT volatility and GDP growth. A first general perspective is provided by the number of years in which an association between low, intermediate and high values of the two variables is found to be present. A second type of information is provided by testing for Granger causality. Finally, a VAR estimation is carried out.

The association between TOT volatility and growth by levels

There are grounds to expect that higher volatility by mechanisms such as increasing uncertainty and transaction costs, impacts on the behavior of the fiscal balance, reduce the efficiency of the financial system, may reduce growth. To pin down the nature of this relationship, and how it may evolve through time, is a difficult task.Extracting association and causality between TOT volatility and growth is difficult because there are domestic and external forces which have been found challenging to disentangle. Another difficult question to answer is how to disentangle the relationship between the fluctuations of TOT along time and the volatility in GDP due to different processes, macro fluctuations or growth.

Loayza and Raddatz (2007) point out that fluctuations in the terms of trade are important sources of external shocks and influence macroeconomic fluctuations. A related point is that the effects of this type of real external is influenced by domestic conditions interacting with the shock, such that structural characteristics in the operation of markets and institutions matter. They go on to argue that the identification assumption that terms of trade changes are strictly exogenous may be tested by means of standard Granger causality, and allows focusing on these shocks, even when these are not the only exogenous sources of fluctuations. Since only other exogenous forces correlated with TOT such as the world cycles, usually other control variables are also included such as the sign of the TOT changes, trade openness, financial openness, financial development, labor market flexibility, and ease of firm entry.

In spite of these difficulties, the contemporaneous relationship of TOT volatility and GDP growth, or the volatility of growth provide facts that help further develp the theoretical relationships.

Table 6.1 provides a first empirical approximation to the relationship between TOT volatility and growth. Each of the rows are one third of the sample in three levels of high, intermediate and low growth[12], whereas the columns show in similar vein three levels of TOT volatility estimated by the variable SEP_1, the one period ahead standard error of prediction (the Friedman-Cavallo approach).

Each cell contains the number of yearly observations for each combination of percentiles. It is the number of years with this specific contemporaneous combination of the degree of volatility and the rate of growth.

If there was a negative monotonic relationship such that a given year of high volatility was contemporaneously associated with low growth, all observations would lie on the diagonal and the remaining ones would be empty. This clearly does not strictly happen. But there are 62 values in the three cells of the diagonal which would be the strongest test of the hypothesis (against 52 and 59 in each of the other two thirds).

If one relaxes the strong presumption and broaden the hypothesis the cases of high volatility and high growth are only 15, probably for the years of high growth at the end of the 19th Century as shown before. The 22 years with the combination of low TOT volatility and low growth makes it clear that the degree of TOT volatility is not the only factor that influences contemporaneous growth. A related warning is that we should be careful in the economic interpretation of our empirical proxies to volatility.

[12] The groups are 33%, 34% and 33%.

Table 6.1

Argentine 1840-2012 (173 annual observations). TOT volatility and GDP growth: years with contemporaneous low, intermediate and high level of the data cases.

GDP growth	High	21	21	15	57
	Intermediate	14	22	23	59
	Low	22	16	19	57
		57	59	57	173
		Low	Intermediate	High	
		TOT Volatility			

Source: own calculations.

Even if the relationship postulated exists, it is influenced by other variables of the economy, but the table provides a first perspective.

Granger causality

The results obtained by preliminary testing of Granger causation between our two alternative measures of TOT volatility and the rate of growth of log gdp detrended are shown in Table 6.2. The null hypothesis of the Granger causality test is that a variable, say X, does not Granger cause another variable Z and viceversa, employing a given number of lags[13]. The empirical equations are the following. In the case of one lag: $X_t = b_1 X_{t-1} + c_1 Z_{t-1} + e_t$

If c_1 is significantly different from zero, knowledge of past values of Z_t helps predict the current value of X which is precisely what Granger causality means. An F test is employed to test for the joint significance of all the lags associated with Z_t. In similar vein: $Z_t = d_1 Z_{t-1} + f_1 X_{t-1} + u_t$

and the F-test is applied *mutatis mutandi*. In the first column of Table 6.2 we report the number of lags employed. Columns (a) and (b) show the results of the testing procedure with definition (1) of TOT volatility whereas columns (c) and (d) use definition (2). Most of the results point to a strong rejection of the relevant null hypothesis at the usual levels of significance. Exceptions are found in column (c) with 13, 20, and 21 lags: there appears to be a weak evidence of Granger (linear) causality running from TOT volatility to GDP rate of growth, with probability values (p-values) in the 0.12 – 0.15 range. Another exception is column (b) with 1 lag, but the direction of causality is contrary to expected.

The values reported are the p-values associated with the relevant F tests. See, for example, EViews Manual. (a) v_logtot_det_dec Granger causes g_loggdp_detrended; (b) g_loggdp_detrended Granger causes v_logtot_det_dec; (c)sep_1 Granger causes g_loggdp _detrended; (d) g_loggdp_detrended Granger causes sep_1

[13] See details in the EViews 5.0 Manual or Enders (1995)

Table 6.2

Argentina 1810-2012, with structural breaks. Granger causality test: TOT volatility and contemporaneous growth (rate of change of detrended GDP).The figures are the probability values of the F-test.

	TOT volatility (definition 1) and contemporaneous GDP growth			TOT volatility (definition 2) and contemporaneous GDP growth	
Lag	(a) TOT volatility causes growth	(b) GDP growth causes TOT volatility		(c) TOT volatility causes growth	(d) GDP growth causes TOT volatility
1	0.85306	0.10217		0.65048	0.24602
2	0.47597	0.19278		0.79082	0.54175
3	0.6898	0.34392		0.90448	0.49621
4	0.57212	0.44244		0.96934	0.43572
5	0.52076	0.24782		0.80062	0.54979
6	0.51726	0.3212		0.88352	0.53274
7	0.581	0.40779		0.88065	0.6411
8	0.37976	0.39828		0.74248	0.65848
9	0.46356	0.43949		0.44314	0.76538
10	0.60308	0.46248		0.37845	0.61208
11	0.6977	0.53163		0.42143	0.6017
12	0.71992	0.58797		0.47477	0.623
13	0.7694	0.60784		0.12792	0.68333
14	0.81243	0.40347		0.17456	0.7504
15	0.85924	0.376		0.24452	0.75473
16	0.86499	0.35755		0.28243	0.82428
17	0.90675	0.49088		0.21023	0.72552
18	0.97825	0.58773		0.17808	0.77924
19	0.9227	0.39414		0.23564	0.71359
20	0.86908	0.34996		0.12634	0.80284
21	0.93255	0.24155		0.15635	0.65725
22	0.95401	0.30191		0.17217	0.64586

Source: Own estimations. Definition 1: V_30_LOGTOT_DET_DEC; Definition 2: SEP_1

VAR estimations

The variables used for the VAR estimation are the following:

i) G_LOGGDP_NOT_DET is the raw (not detrended) GDP rate of growth.

ii) G_LOGGDP_DET is the detrended GDP rate of growth.

iii) SEP_1 stands for Standard Error of Prediction (1-period ahead) according the Friedman-Cavallo measure of volatility.

iv) LogTOT_detdec_30yearvol denotes the 30-year rolling windows TOT volatility based on detrending and decycling.

v) LogTOT_det_30yearvol; the difference with the previous one is that only detrending, but no decycling, has been performed in this measure of TOT volatility.

vi) LogTOT_detdec_5yearvol, is similar to iv) but based on 5-year rolling window.

vii) LogTOT_det_5yearvol, is the 5-year version of v).

We start by testing these variables for stationarity by means of the Augmented Dickey Fuller statistic. The null hypothesis that the series are not stationary was rejected for both GDP growth variables, labelled i) and ii).

The null hypothesis was also rejected for SEP_1, variable iii).

With regard to the 30-year rolling window measures of TOT volatility (variables iv, and v), the null was not rejected. Consequently we will conduct the VAR estimation on the basis of the 5-year rolling window (vi and vii), which turned out to be stationary.

In synthesis, given our two alternative definitions of the GDP growth (variables i) and ii)) and our 5 definitions of TOT volatility (variables iii), iv), v), vi), and vii)) we carried out the estimations for the different specifications by taking only into account those volatility measures which proved to be stationary, i.e. the Friedman-Cavallo (variable iii), and the 5-year rolling window TOT volatilities (vi), and vii)).

Our preferred specification includes an intercept, a trend, the non-detrended version of GDP growth (variable i)), and the 5-year rolling window version of TOT volatility based on detrending (variable vii)).

The selection of the optimal number of lags (with 10 postulated as the maximum number) was based on the Akaike Information Criterion (AIC) and Final Prediction Error (FPE). Both criteria pointed to 8 being the optimal number of lags.

The estimations were carried out using JMulti. A short description follows:

Endogenous variables: LogTOT_det_5yearvol G_LOGGDP_NOT_DET

Deterministic variables: CONST TREND ; Sample range: [1864, 2010], T = 147

endogenous lags: 8 ; sample range : [1862, 2010], T = 149

The modulus of the eigenvalues of the reverse characteristic polynomial:

|z| = (1.2337 1.1430 1.1430 1.3301 1.3301 1.1618 1.1618 1.0926 1.0926 1.6598 1.6598 1.1245 1.1245 1.6791 1.6791 1.7502)

Here the presence of repeated values (14 in pairs) and greater than 1, reveal the existence of complex conjugate eigenvalues which give rise to dampened oscillations in the dynamic response of the endogenous variables to shocks.

Results of all statistical tests on the residuals included by JMulti[14] were satisfactory except for those involving asymmetry.

The Impulse Response Functions (IRF) for the estimated VAR show:

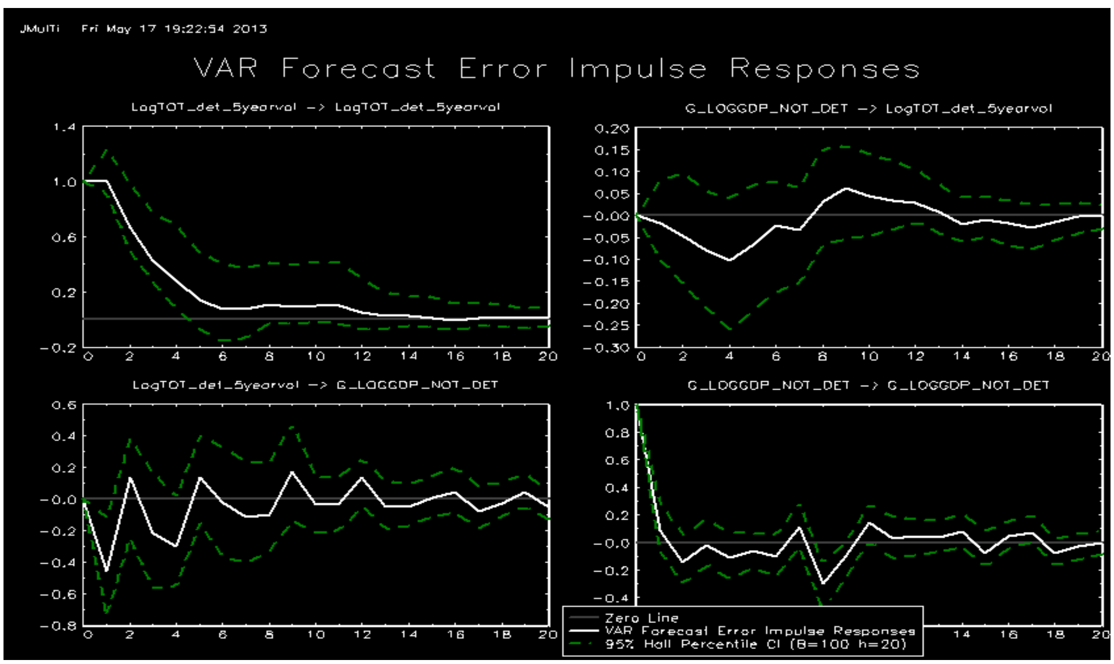
First, a significantly negative one-period effect running from TOT volatitlity to GDP growth, that is, a positive shock to TOT volatility causes a drop in GDP growth in the first period immediately after. Further impacts display an oscillatory convergent pattern around zero which is not significantly different from zero. Hence the effects appear to be confined to the short-run.

Second, there is no significant effect running from GDP growth to TOT volatility which is in accordance with our identifying assumption of TOT exogeneity based on the Small Open Economy (SOE) assumption.

Another result worthy of mention is that an increase in TOT Volatility has a positive, albeit decreasing, effect on the same variable for about 5 periods. This result is in line with historical records.

Figure 6.1

Impulse Response Functions, TOT volatility – GDP growth



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[14] This software may be downloaded freely from the following internet web site; www.JMulti.de.

Figure 6.2

Impulse Response Functions, TOT volatility – GDP growth. 10 years

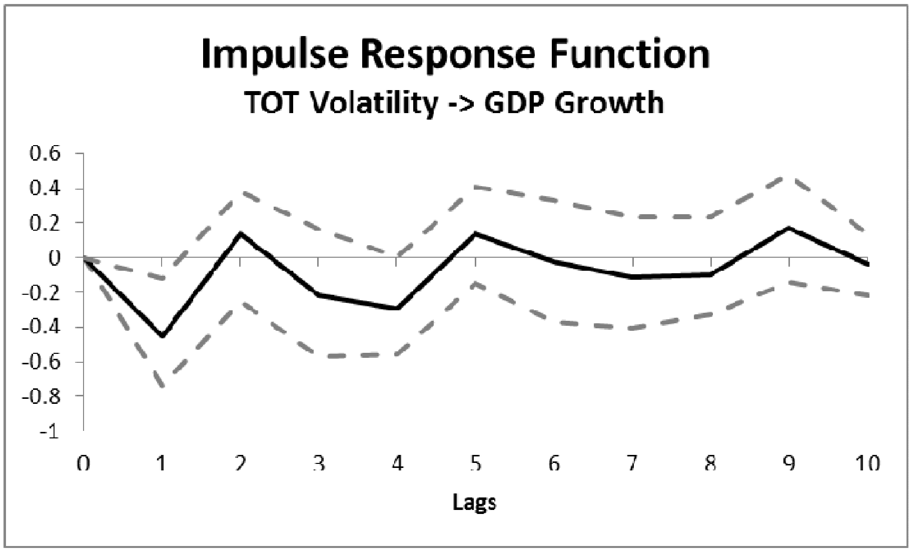
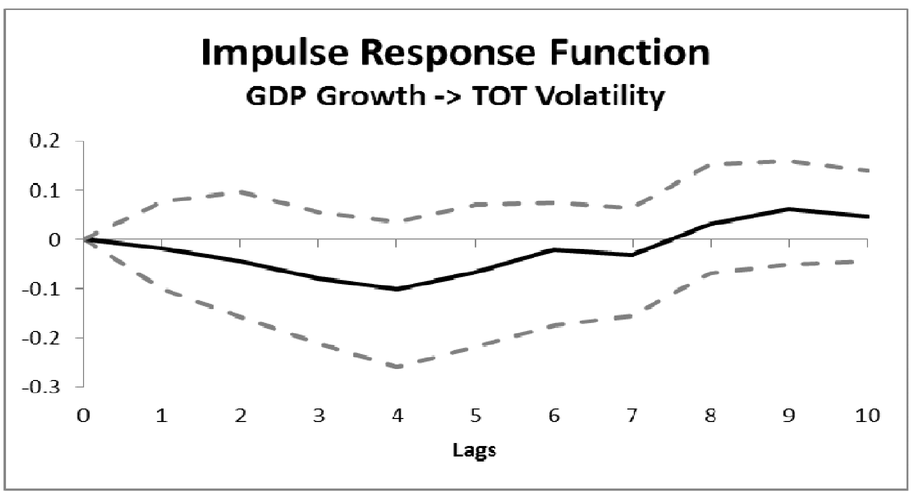


Figure 6.3

Impulse Response Functions, GDP growth – TOT volatility. 10 years



7. Concluding remarks

Our exercises have been based on measures of total TOT volatility, but it would be illuminating a break down for example, into normal and crisis volatility. In this line Dehn, Gilbert, and Varangis (2005; p158) argue for the convenience of testing whether the upward and downward movements of TOT exert different effects on growth. Aizenman and Pinto (2005) stress the importance of concavity, which has disruptive effects in developing countries because they typically lack the capacity to manage countercyclical fiscal policies. Also asymmetry matters, because good times do not offset the negative effects of bad times. Consequently, shocks tend to have a permanent negative effect.

Governments, producers and families take forward looking decisions and would like to know the future of critical variables like the TOT. They cannot. But economic analysis can put restrictions on the pattern of evolution, and help devise responses to innovations in the information set. Future evolution of the terms of trade is a function of two types of forces, international and domestic. As regards the latter, the Argentine economy may be “locked in” in the present type of specialization due to labor abundance and the limited capacity to reallocate its factors of production, a strong structural feature that reduces the ability to diversify, and may be difficult to overturn in the future.

Given the degree of specialization and inherently changing character of volatility, it would be useful to incorporate these features in policy design. Identification of the statistical properties of TOT evolution provides useful information for policymakers about these structural characteristics of the economy. Mistaking the identification of shocks as belonging or not to a change of regime may cause costly errors.

In synthesis, we have defined different empirical measures of TOT volatility which are proxies to the degree of uncertainty faced by economic agents. In this task we used the *detrending cum breaks* plus decycling procedure improving on previous analysis in Arrufat, Díaz Cafferata, Anauati and Gastelú (2012), and introduced in the identification of TOT volatility the Friedman-Cavallo approach which is free of the anachronism implicit in other methods. We analyse the long run experience of Argentine with historical series ranging from 1810 to 2012.

Main stylized facts of the TOT volatility are the following: first, it is high and fluctuating; second, regimes with different behaviour across the sample can be found; third, the results obtained are sensitive to alternative definitions as well as operational measurements of volatility. Despite this heterogeneity, some common patterns emerge. After the structural break in 1951, TOT volatility has experienced a significant reduction from approximately 0.16 to roughly 0.08. This pattern can be found with all the different definitions of volatility used in the paper (in some cases more clearly than in others).

Regarding causality, the Granger approach does not reveal a clear pattern in either direction. The lack of causality running from GDP growth to TOT volatility is in line with the SOE assumption that is used in the identification of the VAR model. Some selected results are reported that show a negative relationship running from TOT volatility to GDP growth implying that more volatility will be reflected in smaller GDP growth in the future. The GDP growth to TOT volatility relationship is not significant, in line with the order in which the variables are included based on the exogeneity of TOT for the SOE.

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