Standard vs. expectation-based indices of TOT volatility in Argentina and other land-abundant countries

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STANDARD VS. EXPECTATION-BASED INDICES OF TOT VOLATILITY IN ARGENTINA AND OTHER LAND-ABUNDANT COUNTRIES.

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Standard vs. expectation-based indices of TOT volatility in Argentina and other land-abundant countries. [1] [2]

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Resumen

Se construyen indicadores de volatilidad con propiedades deseables: reflejan incertidumbre *ex ante;* dependen del tiempo; utilizan el conjunto de datos admisible para los agentes. Se comparan enfoques de la incertidumbre: por una parte, estática comparativa; por otra, series de tiempo. Se estima la volatilidad de TI: a)utilizando procedimientos basados en errores de predicción; b)se explora la robustez de los métodos a cambios en la memoria, los ciclos percibidos, y el horizonte de planeamiento; c)se compara volatilidad entre países abundantes en tierra. Los análisis empíricos demuestran que definiciones alternativas generan patrones de volatilidad no coincidentes, exigiendo racionalizar la elección.

Palabras clave: Términos de intercambio; volatilidad; abundancia de tierra; Argentina; Australia; Canadá; Nueva Zelanda; Uruguay.
Clasificación JEL: F10, F13, F14.

Abstract

We mean to improve upon a standing ambiguity in the meaning of “volatility”, building an indicator that possesses desirable properties: it reflects unobserved *ex ante* uncertainty, makes reference to a time process, and uses the admissible data set for the economic agent. We point out the characteristics of old and new approaches, and estimate TOT volatility evolutions for selected land-abundant countries using our own forward-looking estimation based on forecasting errors. We argue that this estimation is free from methodological weaknesses of other methods. A check on the robustness of methods shows that different definitions provide non-coincident patterns of volatility.

Keywords: Terms of trade; volatility; land abundance; Argentina; Australia; Canada; New Zealand; Uruguay.
JEL Classification: F10, F13, F14.

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[2] The present paper draws on previous work by the authors: Díaz Cafferata and Mattheus (2010); Arrufat, Díaz Cafferata and Viceconte (2011); Arrufat, Díaz Cafferata, Anauati and Gastelú (2012); and Arrufat, Díaz Cafferata and Gastelú (2013). The current paper is a revised version of Arrufat *et al*. (2014).

I. Introduction

What is volatility? How shall it be measured?

The issue is discussed here in the framework of the identification of the effects of terms of trade (TOT) volatility. We argue forcibly that in order to assess the effects of volatility it is of primary importance to work with a time series that exhibits the correct statistical and economic properties for the estimation of the link between volatility and growth. The definition and the use of appropriate indicators of TOT volatility, shall reflect the fact that volatility is unobserved, is an *ex ante* phenomenon, and is related to the behavior of the variables along time.

Economists mostly agree that volatility is detrimental to growth. Aizenman & Pinto (2005, p4) notice the “consistent empirical finding that volatility exerts a negative impact on growth”. Loayza, Rancière, Servén and Ventura (2007) state emphatically that “the empirical connection between macroeconomic volatility and lack of development is undeniable”. Ramey and Ramey (1995) find a negative impact of volatility on growth. And a document of the IADB (1995) concludes that volatility has had a negative effect on development.

Further, volatility may be either of domestic or external origin, and among the latter TOT volatility is in developing countries a typical external source of (macro) fluctuations associated with the export basket. Mendoza (1995) concludes, from simulations, that the TOT account for about one half of the observed variability of GDP. Joaquín Vial (2002) finds that among a set of factors, TOT volatility has the largest negative impact (-0.48%) on growth. Similar conclusions are found in Kose (2002), Loayza and Raddatz (2007), to name a few. Pomery (1984) points out that even when in theory the welfare effect of random TOT are ambiguous, it is generally agreed that the welfare consequences of volatility are negative, usually associated with the possible inefficiency of choice under uncertainty. Mendoza (1997) argues that uncertainty of returns with risk aversion may or may not reduce investment and growth, but in any case its effect on welfare is negative.

Estimating the effects of volatility with constructed regressors.

A particular piece on the task of identification of causality links between external volatility and economic development is the construction of the volatility regressor. The presence and strength of the link between TOT volatility and growth can be modeled in an equation of the type:

$$GDPG_t = f(V_{TOT,t}, \eta_t) \qquad (1)$$

where $GDPG_t$ is the GDP growth rate, $V_{TOT,t}$ is a constructed index of TOT volatility, and η_t represents a set of control variables.

A linear econometric equation may be written:

$$GDPG_t = \alpha + \beta V_{TOT,t} + \gamma\eta_t + \varepsilon_t \qquad (2)$$

where ε_t is an error term.

An alternative is a VAR model such as:

$$x_t = \upsilon + \sum_{j=1}^{p}\Gamma_j x_{t-j} + \sum_{j=1}^{q}\Psi_j \eta_{t-j} + \varepsilon_t \qquad (3)$$

with $x_t = \begin{bmatrix} GDPG_t \\ V_{TOT,t} \end{bmatrix}$

Let us emphasize that in equations (1), (2), or (3), the variable $V_{TOT,t}$,"volatility", rather than observed fluctuations, is *ex ante*. Namely, "volatility" is *unobservable*. It is indeed "constructed" time-variant variable, such that its evolution is influenced by choices of the researcher in the definition and elaboration of the volatility series[3]. In consequence the constructed variable from one or other author may be different. On this issue the reader may review Aizenman and Marion (1999), Larraín and Parro (2008), Ramey and Ramey (1995), and Aizenman and Pinto (2005). We shall not deal here with the econometric estimation with generated variables, but do point out the importance of the proper construction of the generated variable.

Multiple definitions of volatility

Our motivation is that it is of interest the empirical econometric estimation, as in Larraín and Parro (2008), Ramey and Ramey (1995), Mendoza (1997) and Hnatkovska and Loayza (2005). The volatility series are used to estimate causality from volatility to GDP or its growth. The magnitude of the estimated impact on growth, that is to say, the value of the estimated parameters, will depend on the constructed volatility time series.

Mansfield and Reinhardt's (2008) assertion that "there is no universally accepted measure of volatility"[4] summarizes well the state of the art, emerging from the body of literature, both theoretical and empirical, which aims to disentangle the connection with TOT volatility, on the one hand, and a country's rate of growth, on the other. Different authors rely on different definitions of volatility to study such a link, which makes it difficult at times even to summarize the results reported in this vast literature.

For a correct econometric estimation of the influence of volatility on growth, distribution and welfare, the volatility series must embody the theoretical forces they are meant to represent. Further, if there are several alternative "correct" indicators of volatility, it is necessary to examine how robust the empirical findings are to the use of different definitions in applied empirical research, or how the complementary perspectives help the analysis.

Since the constructed variable from one or other author may be different, let us examine and compare alternative definitions and trajectories of volatility against the usual benchmark of the Standard Deviation (SD) or the coefficient of variation (CV). Further, the properties of a "true" measure of volatility should capture the evolution of volatility along time, remove the predictable components, and be free of "anachronism", common to most of the usual indicators of volatility.

A question is posed in the title of this paper as "standard vs. sophisticated" measures of TOT volatility. What is the best approach to measure volatility in the countries of our interest? Are simple standard indicators like the coefficient of variation (CV) informative enough and useful for econometric estimations? Or are there more elaborated indices able to improve the knowledge about the evolution of volatility?

We intend to contribute to the appropriate measurement of volatility of economic variables as follows. In a perspective of approaches in use in the literature, most studies rely on decade-long average measures of variability which are grounded on simple standard deviation over this time-frame. This is not a fruitful approach for us because we need annual measures of TOT which constitutes, in our view an important feature to explain fluctuations in economic growth rates.

[3] For a detailed treatment of some econometric issues which arise in models with constructed regressors see Pagan (1984).
[4] See Mansfield & Reinhardt (2008)

Mendoza (1997) notes that a variable that displays strong variability is likely to be more difficult to predict. There is usually a positive association between variability and the volatility of a variable. The reason to support the choice of a simple indicator such as the standard deviation is that a high variability is associated with a great difficulty to predict, and in consequence reflects the uncertainty of volatility. However it must be noticed that the variability and the unpredictability of a series are not identical.

To this effect we rely on a distinction between mere *variability* and *volatility*[5].The bridge between these two concepts needs some modeling effort that may identify what people should reasonably manage to anticipate, labeling the residuals so obtained as the unanticipated components. While the former is related to raw fluctuations of observed TOT along time, the latter is concerned with the measurement of the unobserved unpredictable fluctuations. In a nutshell, it is these residuals only what should be relied upon to make up a relevant measure of uncertainty and therefore as a true measure of volatility.

As regards the data set, implicit in most studies is the use of the whole available historical data set, which is, in our view incorrect from a logical point of view in estimations of volatility in intermediate years, a problem we call anachronism. By adopting what we refer to as the Friedman-Cavallo approach which relies on expectations formation of the best-one-can do type, we are in a position to obtain time series representation of volatility which do not suffer from anachronism.

Another novelty is a method to measure forecast uncertainty as the “forward-looking volatility”.

We estimate volatility using our index for a group of land-abundant countries: Argentina (AR), Australia (AU), Canada (CA), New Zealand (NZ), Uruguay (UY) on the basis of the presumption that endowments have an influence on productive structure and the direction of trade: the specialization in highly agricultural commodities which have volatile prices, gives rise to aggregate TOT volatility. Such focus on endowments assumes that relative resources still matter as a structural restriction and source of policy problems. Schedvin (1990) states that “the structural characteristics of these countries may be inadequate for the modern conditions of the world economy:” “Australia (with New Zealand and, to some extent Argentina) has been caught in a staple trap”; these economies have suffered adverse movements due to their “inability to move into high value-added production”.

Intended contribution

A contribution of this paper is to contrive a “sophisticated” **empirical indicator of volatility** which is a proper proxy of the theoretical interpretation of uncertainty. The method measures forecast uncertainty as the forward-looking volatility.

Elaborate empirical indicators of volatility which are a *proxy* of the theoretical interpretation of uncertainty, which captures the evolution of volatility along time and is free of anachronism[6].

Discuss if complex indices improve upon the information content about how the volatility evolves through time.

Another contribution is the comparison of indicators of volatility with different approaches, evaluating if there is one that can be chosen as a preferable in portraying the different aspects of volatility. These properties will be useful for the econometric estimation of the volatility-growth links.

[5] Dehn (2000), Wolf (2005).

[6] See Section II.

Contribute to scientific language. A feature of science is the use of technical unambiguous language that is the precise vehicle of the transmission of knowledge among members of the scientific community. The requirement certainly fails to be satisfied in the case of the meaning of the widely used term “volatility”. We shall show here the evolution of the expression and how it is used in diverse empirical measures. Further, we will suggest the properties of the phenomenon that may provide the precision required.

Perform estimations of TOT and GDP volatility under different approaches for Argentina and other land-abundant countries, and compare the indicators of volatility to evaluate how robust the empirical findings are to the use of different definitions.

In the rest of this paper, Section II addresses selectively the discussion about the analytical implications over traditional theorems of the introduction of *uncertainty* in general trade models, and the main results emerging from this literature are compared with papers that stress TOT *volatility*. The purpose is to show the change towards a new perspective more akin to the use of time series econometric applications. It also handles methodological issues which drive to a proposal to measure volatility that contains desirable properties. Section III reports empirical results of our estimations of volatility, and other features of importance for Argentina. The temporal patterns of volatility which results from using standard and more sophisticated indices are compared. Section IV addresses the comparative study of volatility in the land-abundant countries. Section V closes with a synthesis. Section VI contains the references.

II. From comparative statics shocks uncertainty to dynamic volatility

1. What is volatility? A critique of usual empirical indicators

Let´s now address the issue of uncertainty on international trade models and the specific case of terms of trade volatility.

Two strands of research deal with the presence of uncertainty in international trade; one is the general equilibrium long-run theorems of real trade models, the other one the dynamic effects related with the notion of a volatile variable.

Even when the limits are blurred, we may distinguish periods with different weight to both problems. Along approximately the decades of 1950s and 1970s the role of uncertainty was posed in terms of the problem of distortions in factor allocation and the validity of theorems and predictions from the traditional theory: the costs of uncertainty are a lower GDP and a welfare loss. The framework of this literature was a static, atemporal general equilibrium, subject to once-and-for-all shocks.

After a transition in the 1970s and 1980s attention has shifted to a more dynamic perspective. Volatility is indeed associated with the evolutions of the variables along time, and the costs are related to those of impairing growth, rather than the static inefficiency from resource misallocation.

The rest of this section addresses the following topics: we present some representative works of the early literature with uncertainty in trade models, point out that there is transition both in modeling agents behavior, together with increasing importance attributed to volatility. And we provide a critique of standard statistical measures, and a consensus that if regularities in the evolution of economic variables along time are perceived by people, this component of movements along time is not volatility. Last, we address a critique about the information set.

The early literature: uncertainty in trade models

The general characteristic of the early literature is a comparison of models of international trade under certainty, and under uncertainty. Some of the authors that can be mentioned in this group are Harry Johnson (1972), Batra (1975); Eaton (1979), Dumas (1980), Brander (1981), Newbery and Stiglitz (1981), Pomery (1984), Dixit (1991); Winters (1998), Gandolfo (1994), Helpman and Razin (1978); Shackley (1968), Hu (1975).

In a survey published by Jones and Kenen[7] in the first half of the 1980s, Pomery (1984) discusses models of trade with uncertainty. Uncertainty appended to traditional trade models may alter basic results. And also specific results may arise because of the presence of uncertainty.

He mentions examples of new results such as the possibility of gains in the absence of explicit differences in autarky prices (Krugman, 1975), or inefficient trade (Brander, 1981; Newbery and Stiglitz, 1981).

A key feature in this extended framework is whether, with random TOT, production or trading decisions can be postponed until after the realization of the TOT, what he calls the *fluctuation model*. "The major topic in fluctuation models is whether the economy is better off with fluctuating TOT compared to some benchmark level of the TOT with certainty" (Pomery, 1984, p. 433-434). Alternatively, in *commitment models* decisions to trade are made before knowing the terms of trade. Pomery concludes that the role of uncertainty and its policy implications vary with the models and, in particular, there is not an unambiguous result concerning the desirability of free trade. He warns that the implications for policy vary with the type of models. "One must forego the comfort of strong conclusions, either positive or normative", depriving the analysis of strong conclusions either positive or normative.

Harry Johnson's (1972) makes a general assessment at the beginning of the 1970s, arguing that "international economics has flourished in the period since 1945 without the benefit of large admixtures of the theory of decision-taking under uncertainty". The reason in his view was that the theory of decision-making is in a partial equilibrium setting, while the equilibrium models of international trade are grounded on general equilibrium. Regarding economic policy, uncertainty might be seen as a distortion but one that in contrast with other distortions like taxes, may be costly to remove.

The Gandolfo (1994) text on International Economics notes that uncertainty in trade models can be introduced by randomness of any of the three basic determinants of international trade: technology, factor endowments, and demand[8]. Helpman and Razin (1978) on turn, mention three types of uncertainty found in the literature: in prices, technology and preferences.

A critical question is to what extent the same results of traditional trade theory are altered (or which new results arise) by the introduction of uncertainty (Pomery, 1984; Gandolfo, 1994).

Consider, for instance, a Ricardian model with production functions following the usual notation $y_i = \left(1/a_i \right) . L_i . \varepsilon$, $i = 1,2$, where ε is a stochastic variable with expected value equal to one. Note that the ratio of (y1/y2) is unchanged by movements of ε. In this case, called "scalar uncertainty", all the traditional theorems remain valid. But in the more general cases some results may not hold (Gandolfo, 1994[9]).

One case of discrepancy with the general assertion that trade is good, is that trade is good when future fluctuations are known, but under uncertainty trade could conceivable

[7] Jones and Kenen (1984).
[8] Or by random exogenous prices.

[9] Cfr. References from Gandolfo: Dumas (1980), Helpman and Razin (1978), Eaton (1979).

be harmful. In another example from Winters (1998) [10] when producers cannot insure against output and price fluctuations because of the lack of a full insurance market, the economy cannot reap the benefits of international trade.

Uncertainty in general equilibrium

Helpman & Razin (1978) [11], note that even when the importance of uncertainty was recognized, "the main body of the theory of international trade was confined to nonstochastic environment" i.e. to models which did not include any random variables explicitly. And the theory of international capital flows which relies largely on uncertainty does not offer an explicit interaction with commodity trade issues. They survey the earlier literature on international trade under uncertainty[12], and move on to develop their own model.

In a world of uncertainty it is peculiar that an action taken before the resolution of uncertainty does not uniquely determine the outcome, that depends also on the state of nature that realizes. "The meaning of uncertainty is that the individual does not know the state of nature". We leave it to the interested reader to fill in the details of the authors´ exposition and references thereof. But a major conclusion they draw is that under price uncertainty there is more diversification in production and less production of the export good, or less export. Further, free trade may be worse than complete autarky.

Eaton (1979) depicts uncertainty in TOT by the Geometric Mean Preserving Spread (GMPS). Factors of production differ on their ability to move between sectors. Prices are random variables and labor can move after the TOT are known. Capital instead cannot reallocate, and this restriction is the cause of welfare loss from uncertainty.

Hu (1975) discusses the role of uncertainty: he shows that the effect of export price uncertainty changes according to the flexibility to make reallocations, the cost structure, the demand conditions and the attitude toward risk.

In synthesis, the analysis in the first wave of research was largely theoretical, the introduction of uncertainty in static general equilibrium; effects on the level of GDP or GDP *per capita* and welfare. The analysis is mainly theoretical, not empirical. And the role of markets is related to the best static resource allocation rather than the dynamic process of economic development.

Note a general characteristic on the way these models portray uncertainty. They are models with two-period comparative statics, where uncertainty is generated by randomness of one or more of the variables. Comparing these early models with uncertainty with the literature on volatility, the current and past periods prices do not carry information about the future prices; the literature on volatility on the contrary makes an explicit assumption about future prices as partly explained by a data generating process that carry regularities.

Our current interest in volatility measures has a markedly orientation towards empirical estimation, which we handle with three approaches.

2. The transition from uncertainty to volatility

A new perspective emerges associated with the econometric developments in time series in the 1970s and 1980s, with the Lucas (1976) "econometric policy evaluation, a critique", and Sims (1980) critiques, the new methodology VAR, the Granger causality and cointegration (Navarro, 2005, p6,7). The new methods have emphasis on the analysis of time series and the dynamics of economic activity along time.

[10] See pages 83, 146, 378.
[11] See the introduction.
[12] Chapter four.

The Basu and Mc Leod (1992) paper is representative of the more modern perspective regarding the effects of uncertainty. Rather than formulating the conditions for static allocation efficiency, the attention shift toward the problem of the determinants of growth. To explore the link between export prices and export drops they work on a time series framework. They find that: a) transient TOT shocks may have persistent effects on output levels; b) a mean preserving spread in export prices may lower export growth.

The influential Ramey and Ramey (1995) is one of the leading papers in the shift in focus around the mid 1970s and the concept of volatility based on the distinction between predictable and non-predictable events.

“The development of unit root tests has been the basis for most of the recent terms of trade studies […] which have offered far more sophisticated treatment of the time series, but have excluded economic variables that might help explain relative price behavior and its impact.

Statistical approach. Volatility measured by the standard deviation of the “original time series”. Other methods.

We have on the one hand the type of merely statistical indicators that some authors call “variability” such as the variance, the SD of the raw time series, or the coefficient of variation (CV). These indicators are useful as benchmark, either a unique average, or calculated through a rolling window; or else of the log differences. There is not modeling of expectation[13].

Gillitzer and Kearns (2005) and Borkin (2006) calculate the absolute value of the differenced logarithm $\left|d\log(tot)\right|$ for Australia and New Zealand respectively and test for structural breaks in the mean. After finding the breaks they explain that the reduction of the TOT “volatility” has been reached as a consequence of the diversification of exports.

Díaz Cafferata and Mattheus (2010) do the same for these two countries and Argentina; the figures showing the profile of volatility in Argentina, New Zealand, and Australia are included as Appendix 5.

Moledina et al. (2004. p5), the most frequent indicator of volatility in the literature is the standard deviation (SD) of the logged variable. Most of the time there is not an explicit behavioral model.

In the new vision, one type of approach is modeled-residual associated with volatility. [14] Mendoza (1997); Bleaney and Greenaway (2001); Haddas and Williamson (2001, 2003); Blattman et al (2003, 2004, 2007); Basu and McLeod (1992); Wong (2010). Recent empirical papers have renewed the study of fluctuations in the TOT, with measurement refined in order to capture unpredictable movements. Also focus has changed from an atemporal static point of view to a time-related perspective. The term “volatility” began to be generally used, and Ramey and Ramey (1995) argued that the way in which this component is measured should reflect “the notion of uncertainty”. The current consensus defines volatility as the component of fluctuations that is a non-modeled residual.

Critiques to the statistical approach

The raw SD is criticized as a *proxy* for uncertainty, arguing that it is necessary to distinguish in the variability measures a predictable and an unpredictable component.

[13] Examining descriptive statistics of raw data it is worth warning that the mean, median, maximum and minimum, rank and standard deviation depend on the year chosen as the base of the index.

[14] There is a related literature concerned with the Current Account equilibrium, the exchange rate regime and fiscal issues. See Broda (2001)

Measures of mere variability, in spite of being commonly used, may lead to misleading interpretation. Given other properties, a variable is intuitively more volatile when its movements are irregular and hence less predictable.

Several authors recognize that *uncertainty* is an ex ante concept different from "variability". This latter is made up of components that are predictable and some other unpredictable ones by producers. Wolf (2005) draws a distinction between "realized" and "expected" volatility.

Another important reference to discuss alternative indicators of volatility is given by Mansfield and Reinhardt (2008) who argue that the calculation of volatility as the variance within a time series for a given country over a long period conflates predictable changes in trade with unexpected shocks. Consequently they suggest different measures of volatility. One of them, a measure of "exports drops", t is a dummy variable which takes on a value of 1 if the drop is greater or equal than 50%, and zero otherwise. This index provides a formal quantitative answer to the question of whether or not TOT upward movements are smoother than TOT downward movements[15]. What makes this approach appealing is that large negative shocks are likely to be especially disturbing.

Volatility as the fluctuations of the "residuals"

In contrast with the "standard" statistical indicators of "variability", that measure observed fluctuations, volatility, an *ex ante* concept, discriminates between predictable and unpredictable components and measures "uncertainty". This new type of indicator emerges when volatility is associated with the presence of "surprise".

Two alternative approaches are based on the representation of the signals perceived by the agents.

(i)One of the "expectations based" indicators includes the decomposition of fluctuations in an explained component, and residual variability.

(ii)Other expectation based index provides a forecasting error; a forward-looking procedure that rests on prediction uncertainty.

This is a family of indicators which portray volatility as related to uncertainty, and they are in consequence built by proceeding first to remove the components of fluctuations that are predictable, since they can be anticipated by economic agents (and are not cause of surprise), leaving the residual as the unpredictable movements of the variable. "Volatility" is in this case the standard deviation of the residuals or innovations. There is a family of indicators which remove predictable components of fluctuations, measuring "volatility" as the SD of the residuals.

Dehn (2000) argues that the SD in spite of being commonly used, may lead to misleading interpretation: SD is the mere variability of TOT, which includes a predictable as well as an unpredictable component and must be distinguished from volatility which leaves aside the regular part. 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.

[15] The other two measures that we are not going to use are the following. One is the absolute value of the change in the supplier's export share in the importer's market. The other is a GARCH estimate to assess the influence of trade agreements on exports volatility.

Volatility modeling and econometric properties: the time-invariant conditional expectation

Specific features of the evolution for the different countries may be explored, such as the presence of thresholds, asymmetry, or the degree of persistence. About the general pattern, Plasmans (2006)[16] points out that variances and covariances routinely assumed to be time invariant, have to be approached from a more general standpoint: it seems to be rather that the variance is conditional on time **t** and also volatility clustering (or conditional heteroskedasticity) with some periods of high followed by others of low volatility. Significantly high autocorrelation may cause episodes of acceleration in volatility in some subperiods.

As a proxy for the unexpected component of the TOT variability Díaz Cafferata and Mattheus (2010) estimate two alternative measures**:** deviation from trend using a Hodrick-Prescott filter and the conditional standard deviation from an ARCH type model, applying two detrending procedures. Volatility can be measured as the conditional standard deviation since, as we read in Enders (1995) "Rational expectation hypothesis asserts that agents do not waste information. In forecasting any time series, rational agents use the conditional distribution rather than the unconditional distribution". Díaz Cafferata and Mattheus follow two steps. First, look for the best fitting ARMA following the Box Jenkins procedure. Second, a model for the conditional variance is included. Since the ARMA models assume stationarity the estimation is made with the detrended series. [17]

Following Ramey and Ramey (1995), the components may be modeled as a function of explanatory variables, such that the variance of the residuals may be taken as the component of "uncertainty". "We now investigate the relationship between growth and the variance of innovations to a forecasting equation for growth. This latter measure corresponds more closely to the notion of uncertainty …".

We deem the distinction makes economic sense when trying to identify empirically the degree of volatility of a variable, since the use of "variability" can be reserved as just a description of movement, in contrast with the idea of "volatility" which is related to uncertainty.

On this approach to volatility a few authors (out of a large related literature) can be mentioned.

The Center for Global Development www.cgdev.org defines volatility as the standard deviation of GDP per capita from its trend. A question to decide in this instance/case is how the trend is estimated[18]. Total volatility is decomposed into the effects of fiscal volatility, TOT volatility, money growth volatility, financial development, and oil price volatility.

We shall insist that it is a state of affairs that it happens that authors use more than one measure of volatility, or compare results between different studies which provide estimations with different procedures. But the translation of one result to the other is lacking.

Aizenman and Marion, three alternative measures of volatility

Aizenman and Marion (1999) is illustrative of the existence and implications for research of different definitions and measuring methods. They argue that in principle *volatility* refers to the tendency of a variable to fluctuate, while *uncertainty* is present only when those fluctuations are unpredictable (Aizenman and Marion, 1999, n1, p. 175) and that since

[16] Plasmans p.199; see discussion on page 200 and following on GARCH models.

[17] Dehn (2000) follows a different approach because he estimates a homogeneous GARCH (1,1) model for all the countries in his data set.

[18] On this see the discussion in Canova (1998).

volatile variables are frequently unpredictable, they can use both concepts interchangeably.

The authors mention three alternative measures of volatility (page 158, 163):

a. The standard deviation of residuals, with annual data;

b. An index of volatility, equal to a weighted average of the standard deviation of residuals;

c. The standard deviation of innovations to a forecasting equation for growth.

The SD of the residuals are calculated from a 1st order autorregresive process (AR1)[19]. Besides, they indicate without further explanation that they "refrain from more complex constructions of volatility measures". (A & M, 1999, n6)

Comparing their estimations with those of Ramey and Ramey (1995), they note regarding the latter that "their particular measure of volatility lowers growth and is not significantly related to investment" contrary to "our measure of volatility". The reference to "their" particular and "our" measure depicts a clear picture of a variety of definitions of volatility. Different measures are admissible, and as a consequence the outcomes in the analysis of causality may differ without a criterion to prefer one over the others. This particular state of affairs is clearly unsatisfactory and may be improved upon by an analysis of the relationship between the different measures and their implication for the formulation of stylized facts and estimation of effects.

Some authors such as Mendoza (1997) and Blattman *et al*. (2003) recur to "traditional" measures of volatility (variance or standard deviation). Many alternative ones are found in the literature.

Turnovsky and Chattopadhyay (2003) use annual data to estimate the first order AR process of the logarithm of TOT for each country over the period 1975-1995. The TOT volatility is the standard deviation of residuals.

Blattman *et al*. (2004) decompose annual disturbances in TOT into a secular trend and a variance around this trend. The latter is what they call volatility. The estimations were done for three 20-year periods: 1870-1889, 1890-1909 and 1920-1939.

Dabús *et al* (2012) in a study of Latin American countries measure the degree of volatility of output estimated as the standard deviation of the cyclical component of log GDP, using the Baxter-King filter.

Bleaney and Greenaway (2001) estimate volatility from a GARCH (1,1) model using a regression of a change in the log of the variable on a constant. They analyse annual data from 14 sub-Saharian African countries for the period 1980-1995. Grimes (2006) uses quarterly data (1950I-2004-III) from New Zealand and measures volatility as the 10-year moving standard deviation to the relevant quarter.

3. <u>Other methods: the best one can do</u>

Note that if one adopts a "purely statistical" approach variability and volatility are equivalent indication of *ex post* fluctuations. Not so 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). Decision rules, and an empirical procedure, are needed to determine when one or the other principle is appropriate. We claim that the "expectations approach" to volatility is relevant when the decision process is the object of analysis.

[19] For example: government consumption volatility is measured as the standard deviation from an AR1 process of government consumption as share of GDP, 1970-1992.

In a nutshell, the state of the art concerning estimation of volatility by first modeling and second measuring the residuals is subject to an important caveat, that of paying particular attention to the nature of the relevant information set.

Methodological critique

As stated above, the previous methods of estimating volatility are subject to an important methodological critique: fluctuations of the residuals are based on a previous modeling effort. The standard general procedure is to estimate the trend using information on the whole data set for the period t= 1, …,T. The quintessential feature of our critique is that on logical grounds it is not admissible to assume, that the residuals at any point in time t<T are estimated using the total data set. In usual analysis 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. This contradicts a basic logical rule: all data points relating to observations at any time t < T cannot be known in advance for the years between t + 1 and T.[20] It can be said that they know all the past and have the gift of prescience. It is clearly impossible for an agent that at each point in time he relies on information about a future which, by definition, 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 from future events.

To overcome this limitation, we put forward a measure of volatility, following Cavallo (1977) and B. Friedman (1979), which is based on the standard error of predictions (SEP) and the use of rolling windows. We proceed by means of a recursive estimation algorithm, which incorporates sequential learning by drawing a temporal window, to account for the fact that individuals´ data set contains information from some limited period in the past[21].

Besides, the standard error of prediction SEP is computed for one, two, three, and four periods ahead. The rationale for this is that different time horizons may be relevant to measure the future uncertainty level applicable to investment projects with varying maturity periods and which are liable to irreversibility of various kinds.

Another strand of literature is grounded on a different approach. Since the seminal contributions of Bates and Granger (1969), a unique forecast value may be obtained by weighting individual forecasts based on different procedures. This approach may be promising but we have not pursued it here because we are mainly concerned with an-ante measure of uncertainty.

A key feature of our chosen representation is the assumption regarding the economic agents´ information set.

Agents are assumed to form expectations through a learning process, which we approximate by extracting information on perceived regularities in the data. ”Volatility” is associated not with perceived regularities but rather with the unexpected movements of the time series.

Agents are portrayed implicitly as both recognizing regularities in the evolution of TOT and being “surprised” by unexpected events related with uncertainty.

[21] Antonovitz and Green (1990) is a useful reference to a very significant body of empirical literature which attempts to model the role of risk as a (potentially) important explanatory variable in the estimation of supply functions of agricultural goods. They pose also a very important question: do all market participants use the same model to compute their expectations, or, on the contrary, do they rely on different models? We do not address this latter issue.

Last, we calculate an index that captures the expected volatility (compared with realized volatility).

III. Empirics: log TOT volatility, the Argentine experience

Having laid out the main features of what we regard as a proper way to measure uncertainty, in this section we provide a succinct guide to the algorithms we have employed.

Friedman - Cavallo and the best one can do

The practical implementation of the Friedman-Cavallo "the best one can do" follows several steps:

First step: remove the predictable components by means of: i) detrending only; ii)detrending plus decycling. Other approaches could have been implemented, such as estimating time varying detrending (local level model); or ARIMA models. No results are given here in connection with these two approaches.

Second step: we emphasize that the assumed forecast (either detrending only or detrending plus decycling) are made explicitly dependent of the information set available to the agent at moment **t** when the forecast is made. In order to achieve this, we resort to the use of fixed-window rolling samples of length **m**. In this way we make sure that our estimations are free from anachronism.

Third step: once the unpredictable component (usually as a "residual") has been correctly estimated as described in the previous steps, there are two alternative ways to measure volatility: (i) the standard deviation of the residuals (in-sample volatility); (ii) the **h** step-ahead standard error of prediction, with values of **h** ranging from 1 to 4.

We address the expectations formation exercise by relying on an admissible information set. We use a rolling window, assuming that agents form their expectations about log TOT based on m=30 years information: an agent in 1899 making inferences about future TOT uses for his estimations the data from 1870-1899 only. This process is repeated for every year. That is, estimations in 1900 will use data from 1871 to 1900, and so on.

Two basic models are used: detrending only and detrending plus decycling.

1) "Detrending only": economic agents form expectations on the basis of least squares regressions based on an intercept, a linear trend and a quadratic trend[22].

2) "Detrending plus decycling": in addition to the former type of model, an algorithm was implemented to identify up to a maximum of "c" cycles which may be isolated by means of a Fourier-type regression.

The iteration process

The estimation algorithm we implemented for the calculations is sufficiently general so as to allow the researcher to choose: a) the size of the window (from m=20 to m = 34, m being in all cases an even number; b) the number of the most important cycles to be taken into account (from c=2 to c=5).

With regard to a) the estimation algorithm is straightforward: only a single OLS estimation is required. By way of contrast, in b) an iterative algorithm has to be implemented. On the first stage, a trend only model is estimated. This is followed by a second stage estimation in which the first stage residuals (detrended values) are regressed on cosine and sine functions of different frequencies (or periods) to isolate all cycles present in the data. We

[22] Note that there is no change in the curvature of the trend, and in consequence this detrending does not removes cyclical movements of the series.

chose a number c of the most important cycles in decreasing order of importance. On the third stage we estimate a new trend plus cycles model using the original data.

At this stage we checked whether these new trend estimates were reasonably close to the ones obtained in the first estimation. If we obtained a positive answer we stopped the iterations at this point. Otherwise the iterations were extended until the resulting trend estimates were close, as measured by the absolute value of the difference between each parameter estimate as obtained in two consecutive estimations. The tolerance value is tol = 1e-004. To guard against the danger of the number of iterations getting too big, a maximum number for them was set (maxiter = 1000). Our iterative algorithm achieved convergence fairly quickly; the maximum number of iterations needed was equal to 6 for all the combinations of values of m and c.

Although the implementation of this iterative approach bears some distant resemblance to Aghion and Howitt (1998), the actual purpose is very different here: we adopt it merely to ensure the internal consistency of the parameter estimates related to the trend and cycle components[23].

Computation of the Standard Deviation of Residuals (SD) and the Standard Error of Prediction (SEP)

For each of the previous forecasting models, we build log TOT volatility indices by estimating the Standard Deviation (SD) of the in-sample residuals and the h-step ahead Standard Error of Prediction (SEP).

In connection with the first basic model, $\hat{\sigma}_T$ and $\hat{\sigma}_{f+h,T}$ are derived. The former is the SD of residuals over the sample period (usually called the square root of the residual variance of the model, computed as the sum of squared residuals divided by the appropriate degrees of freedom), and the second one $\hat{\sigma}_{f+h,T}$, stands for the **h** period-ahead *standard error of prediction* (SEP), **h** being the length of the forecasting horizon, **f** the particular point in time when the forecast was made, and the subscript **T** denotes that the estimations rely on the residuals stemming from the trend only model. The subscript **TC** is used for the detrending plus decycling model.

The h-period ahead SEP from the detrending only model is computed as follows:

$$\hat{\sigma}_{f+h,T} = \hat{\sigma}_T \sqrt{1 + x'_{f+h} \left(X'X \right)^{-1} x_{f+h}} \qquad (4)$$

Details concerning the derivation of this formula may be found, for example, in Theil (1971, pp 134-137) or Johnston (1984, pp 195-196).

The vector x_{f+h} stores the values of explanatory variables to be used for out-of-sample forecasting.

In the usual textbook presentation, in which only one, monotonically increasing, explanatory variable is present, it is straightforward to show that the farther away into the future one goes, the greater the value we obtain from the use of formula (4).

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[23] These authors argue that cyclical variations in output may have an important bearing on its trend growth rate. Take, for example the case of a slump in production which triggers, as a policy response to counteract the ensuing recession, a drop in the rate of interest. This makes it more profitable to invest in more productive technology which can be used once the temporary drop in demand is over.

In Appendix 1, we present simple numerical examples that illustrate the way in which the square root in (4) behaves, for cases in which the linear trend only is enlarged by adding two cycles. Also shown there are the more complex cases of linear and quadratic trend, and linear and quadratic trend plus two cycles.

X is an mx3 matrix made up of the historical values of the explanatory variables employed in the OLS estimation (three being the total number of parameters associated with the intercept, the linear time trend, and the quadratic time trend). As stated above, our exercises rely on windows of size **m**, with **m** taking on the values 20, 22, 24 26, 28, 30, 32, and 34.

With regard to the **m**x3 matrix, its first column is made up of ones, the second by values of t, taking on consecutive integer values ranging from 1 to m. The third column is analogous to the second, the difference being that the squared values of t, that is (t^2), is used. Obviously, since the 3 columns of X are not linearly dependent, its rank is equal to 3 for **m** greater than 3. In the framework of OLS estimation, **X**'**X** is a 3x3 matrix which is symmetric, positive definite and non-singular, i.e. its inverse exists and is also symmetric and positive-definite.

In the case of the second estimation model, we obtain the SD of the residuals, $\hat{\sigma}_{TC}$, and the **h** period ahead SEP, $\hat{\sigma}_{f+h,TC}$, using a similar procedure but considering that now the matrix **X** and the vector x_{f+h} contain also the cosine and sine variables needed to take into account the cycles included in the proposed model. As stated above, the estimation process relies on an iterative algorithm to ensure convergence of the parameter estimates for the trend variables.

Stylized facts; estimation of TOT volatility for Argentina

The following example may be useful to clarify how the algorithm works. Starting from 1870 and up to 1899, a sample spanning a 30 year-period, the OLS estimation is carried out and $\hat{\sigma}_T$ and $\hat{\sigma}_{f+1,T}$ are calculated.

$\hat{\sigma}_T$ is computed using the 30 yearly observations the model has taken into account to estimate the parameters of the simple linear and quadratic time trend we postulated. Then we compute $\hat{\sigma}_{f+1,T}$ on the basis of the Equation (4). The x_{f+1} vector is built by taking into account that the trend must be evaluated for the year 1900 when dealing with the one-period ahead estimation of volatility.

Since $\hat{\sigma}_T = 0.1070$, whereas $\hat{\sigma}_{f+1,T} = 0.1241$, the ratio between the latter and the former amounts to 1.1598 (the latter being roughly 16% higher than the former) reflecting the fact that the prediction of a future value for volatility must include an extra element of uncertainty directly related with the distance between the values of the explanatory variables in 1899 and those for 1900.

We also computed volatility measures for two, three and four-period predictions. We think that these may prove especially relevant when trying to model the influence of logTOT uncertainty on investment. For some types of capital goods, one-period ahead estimates may be particularly relevant. For other type, involving longer gestation periods to mature, however, it may well be the case that two, three, or even four-period ahead predictions might prove to be a sensible choice.

The following table points to a very significant increase in our measures of uncertainty as from the standpoint in 1899 we forecast our measures of uncertainty (volatility) for the years 1900, 1901, 1902, and 1903.

Table 1.a

Argentina. Estimated log TOT volatility: Standard Error of Prediction (SEP).
Detrending only (column 3), and detrending plus decycling (column 4).
Data set 30 years (m=30), 1870-1899 for an agent standing at year **f**=1899.
Changes in TOT volatility for different planning horizon **h**.

Year (1)	***h*** (2)	$\hat{\sigma}_{f+h,T}$ (3)	$\hat{\sigma}_{f+h,TC}$ (4)	$\frac{\hat{\sigma}_{f+h,T}-\hat{\sigma}_{f+(h-1),T}}{\hat{\sigma}_{f+(h-1),T}}$ (5)	$\frac{\hat{\sigma}_{f+h,TC}-\hat{\sigma}_{f+(h-1),TC}}{\hat{\sigma}_{f+(h-1),TC}}$ (6)
1900	1	0.1241	0.1043	-	-
1901	2	0.1286	0.1111	0.0368	0.0644
1902	3	0.1340	0.1183	0.0419	0.0652
1903	4	0.1403	0.1252	0.0467	0.0581

Table 1.b

Estimated log TOT volatility measures for Argentina, agent standing at year **f=1905**. Data period used for the estimations 1876-1905 (**m**=30). Different planning horizons **h**.

Year (1)	*h* *(2)*	$\hat{\sigma}_{f+h,T}$ (3)	$\hat{\sigma}_{f+h,TC}$ (4)	$\frac{\hat{\sigma}_{f+h,T}-\hat{\sigma}_{f+(h-1),T}}{\hat{\sigma}_{f+(h-1),T}}$ (5)	$\frac{\hat{\sigma}_{f+h,TC}-\hat{\sigma}_{f+(h-1),TC}}{\hat{\sigma}_{f+(h-1),TC}}$ (6)
1906	1	0.1403	0.1624	-	-
1907	2	0.1455	0.2281	0.0368	0.4046
1908	3	0.1516	0.3158	0.0419	0.3844
1909	4	0.1586	0.4203	0.0467	0.3309

It should also be emphasized that the estimation exercise assumed that the agents use only the data available at the time the forecasts are made. For the prediction exercise the values for t should be t+1, t+2, t+3, and t+4, which take on the values 31, 32, 33, and 34, respectively.

Tables 1.a and 1.b show that $\hat{\sigma}_{f+h,T}$ and $\hat{\sigma}_{f+h,TC}$ grow with **h**.

The longer the planning horizon, the higher the forecasting uncertainty (volatility). In Appendix 1 we present a numerical exercise showing that the relation between the number of years **h** and the measure of volatility is not necessarily monotonically increasing in **h**. The exceptions to the monotonic rule seem to be associated to the process of decycling.

Columns 5 and 6 display the growth rates of our volatility measures when the horizon enlarge .

So, for example, In Table 1.a, the growth rate of the **h**-step ahead SEP from the detrending only model $\hat{\sigma}_{f+h,T}$ in the period 1901 is 0.0368. Namely, an agent in year 1899 who relies on the trend only procedure will experience an additional 3.68% of uncertainty if the relevant horizon of planning is the year 1901 instead of year 1900[24].

Note that from the Table 1.a the volatility estimations from the detrending only model seems to be greater than the estimations from the detrending plus decycling procedure but this fact is not always true as can be appreciated in Table 1.b where $\hat{\sigma}_{f+h,T}$ is less than $\hat{\sigma}_{f+h,TC}$ for each **h**. In this latter table, we show the volatility evolution for the years 1906, 1907, 1908, and 1909, considering that those estimation are made at 1905.

The figures in column (5) are identical to the ones we reported in Table 1.a. It can be shown that these growth rates do not depend on the specific period that is chosen as the starting point for the prediction exercise.

However, with regard to the growth rates displayed in column (6), they certainly show a very different picture. Two points are worthy of notice. First, the figures are different from their counterparts in the previous table. Second, their magnitudes are bigger.

People are expected to be increasingly uncertain the more he tries to see into the future. Also, the rate at which the uncertainty rises is not constant. And when **h** increases, the increment in uncertainty is independent of the starting year for the detrending only model but this result does not hold for the detrending plus decycling procedure. Therefore the detrending plus decycling procedure appears to provide a rather different picture of volatility.

Figure 1

Argentina, logged TOT volatility; rolling window m=30. 1839-2008

Alternative methods: a) SD of residuals from detrending, $\hat{\sigma}_T$; b) SD of residuals from detrending plus decycling, $\hat{\sigma}_{TC}$; c) One-step ahead standard error of prediction (from the detrending plus decycling model), $\hat{\sigma}_{f+h,TC}$; d) SD of the logged TOT, $\hat{\sigma}_{\log TOT}$.

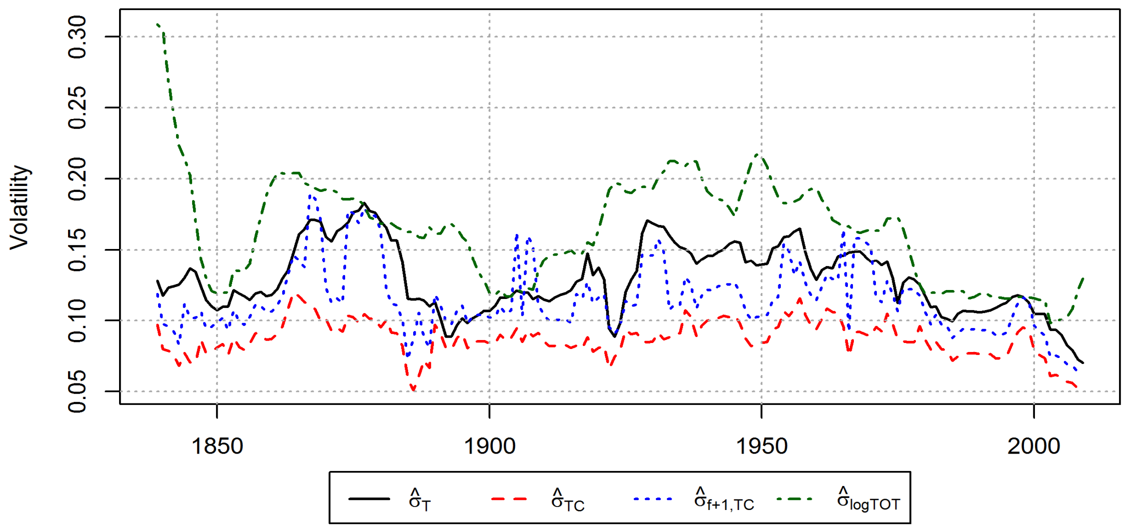


Figure 1 shows TOT volatility estimates for Argentina under four approaches. The reader is very likely to be struck by the fact that an unique underlying economic phenomenon, that of TOT historical evolution subject to important fluctuations, may give rise to such substantially different representations of TOT uncertainty both with regard not only to the

[24] The growth rate of the h-step-ahead SEP from the detrending only procedure (column 5) is always increasing but this result does not hold for the h step ahead SEP obtained for the detrending plus decycling model (column 6).

temporal patterns but also in connection to magnitudes. Which one of them, if any, provides a true representation of the economic nature of the phenomenon?

The upper line (d) is our benchmark. This is the Standard Deviation of the logged TOT, a widely used indicator of volatility in the literature. To make it comparable with other methods is estimated with a rolling window of **m**=30 years. As we discussed in Section II the Standard Deviation of the raw logged series tends to overestimate true "volatility" because it does not remove the predictable component which do not constitute a surprise to economic agents.

Further, the SD of the residuals from the detrended model (the time series a), is necesarily smaller than our benchmark (the time series d), for every point in time as the reader can see in Figure 1. The distance between the volatility calculated using the raw data and the volatility from the detrended series is not constant, and in consequence one and the other tell different stories.

If now the cycles are also removed, the SD of the residuals from detrending plus decycling (series b) ($\hat{\sigma}_T$ > $\hat{\sigma}_{TC}$) is below the SD of the residuals from the detrending only model (series a), since the former has removed additionally the variability due to cycles. The difference between both series is again not constant, the underlying reason being that in certain periods the cyclical components account for a smaller proportion of the total variability than in others.

Up to this point the SD from the logged TOT seems to overestimate TOT volatility. However this is not necessarily true if we consider the additional uncertainty faced by agents when they look forward to the future. That is, the main costs for producers and consumers arise from errors in forward looking plans. In order to represent this kind of volatility, we calculated the one-step ahead standard error of prediction from the detrending plus decycling model (line c). Figure 1 shows that the widely used SD from the raw series (line d) does not always overestimate TOT volatility if it is compared with the series (c).

Also, the one-step ahead standard error of prediction from the detrending plus decycling aproach is more unstable than the SD of the residuals from the same model, and $\hat{\sigma}_{TC}$ < $\hat{\sigma}_{f+1,TC}$, provided $\hat{\sigma}_{f+1,TC}$ incorporate the forecasting uncertainty.

$\hat{\sigma}_{f+1,T}$ is not included because it is perfectly correlated with $\hat{\sigma}_T$. This fact can be appreciated in Table 2.

Another piece of information that maters for the relevance of the choice between definitios of volatility is their correlation. If different measures were perfectly correlated both would provide similar indication of the sign and the significance of causality. On the contrary, if the most accurate expression of the true volatility is one from the detrending plus decycling model the mechanical use of the SD from the raw series would bring an inaccurate picture of the effect of volatility on growth. This is most likely the case since the correlations, even when they are positive, are fairly bellow one in our estimations in Table 2.

Table 2 shows that the estimations of volatility from the "detrending only" model are more (linearly) correlated with the 30-year rolling window SD of the raw data, $\hat{\sigma}_{\log TOT}$, than the estimations of volatility obtained from the "detrending plus decycling" model. Hence, if agents can perceive the main cycles, $\hat{\sigma}_{\log TOT}$ will exhibit a quite misleading representation of the "true" uncertainty.

Table 2

Pearson Correlation Coefficient among the alternative volatility measures estimated for the logged TOT of Argentina. 1839-2008.

			$\hat{\sigma}_T$	$\hat{\sigma}_{f+h,T}$	$\hat{\sigma}_{TC}$	$\hat{\sigma}_{f+h,TC}$	$\hat{\sigma}_{\log TOT}$
Detrending only model	SD	$\hat{\sigma}_T$	1	1	0.60	0.61	0.55
	One step ahead SEP	$\hat{\sigma}_{f+h,T}$		1	0.60	0.61	0.55
Detrending plus decycling model	SD	$\hat{\sigma}_{TC}$			1	0.52	0.37
	One step ahead SEP	$\hat{\sigma}_{f+h,TC}$				1	0.26
Log TOT (benchmark)	SD	$\hat{\sigma}_{\log TOT}$					1

Additional information is provided in four scatter plots in Appendix 2. No clear cut pattern of correlation, linear or nonlinear, appears.

Sensitivity analysis. Changes in the size of the window. Changes in the number of cycles.

We need to assess the impact, on our measures of volatility, of the methodological choices made.

In the first place there is a choice about the definition of volatility (for example, measures of fluctuations of the raw data, or detrending only, or detrending plus decycling, etc.). Then, we have to take a decision about the parameters, (such as window sizes adopted and the number of cycles taken into account).

Next, we address the question of how sensitive the volatility estimations are to changes in the size **m** of the windows, and of the quantity **c** of cycles.

Since we do not know how long the horizon of the agent's information set is we can estimate the consequences of making different assumptions on the temporal profile of volatility.

This analysis is made for $\hat{\sigma}_T$, $\hat{\sigma}_{f+1,T}$, $\hat{\sigma}_{TC}$ and $\hat{\sigma}_{f+1,TC}$ with different window sizes, and for $\hat{\sigma}_{TC}$ and $\hat{\sigma}_{f+1,TC}$ with different number of cycles.

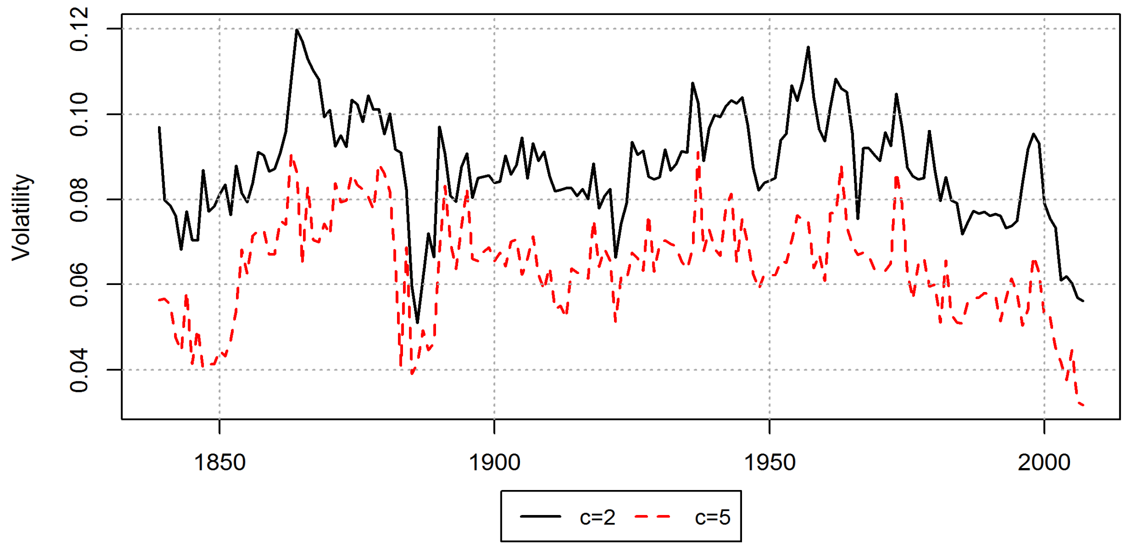
As a first exercise, we examine what happens with the temporal profile of volatility when the number of cycles is modified (**c**=2, 3, 4 and 5) given the size of the windows (**m**=30). In Figure 2, for convenience of exposition only the cases for two cycles **c**=2 and when five cycles **c**=5, are reported.

Figure 2, panel (a), shows that when it is assumed that more cycles are perceived by people, the uncertainty $\hat{\sigma}_{TC}$ (i.e. the SD of the residuals from the detrending and decyling approach) decreases, as one could reasonably expect, because those extra cycles in the expectation formation model used by the agents now are not a surprise. And the residuals do not include the variability due to those additional cycles.

Since the number of cycles assumed to be perceived by agents is arbitrary, care must be taken not to assume too much about the knowledge of the Data Generated Process: the incorporation of too many cycles can lead to include excessive knowledge of the economy, such that assuming that all fluctuations of the TOT are expected would give rise to an underestimation of true volatility.

Figure 2
Comparison of volatility indices for the logged TOT of Argentina, 1843-2008.
Window size **m**=30. **Detrending plus decycling model**.
Compared predictions with two cycles or five cycles.

(a) Standard Deviation ($\hat{\sigma}_{TC}$)



(b) One-step ahead Standard Error of Prediction (SEP) ($\hat{\sigma}_{f+1,TC}$)

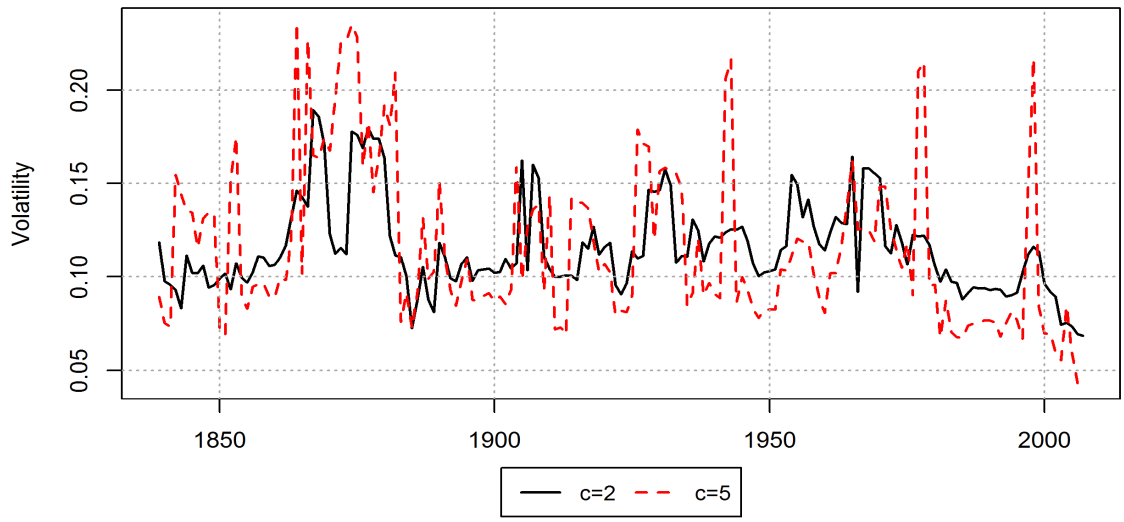


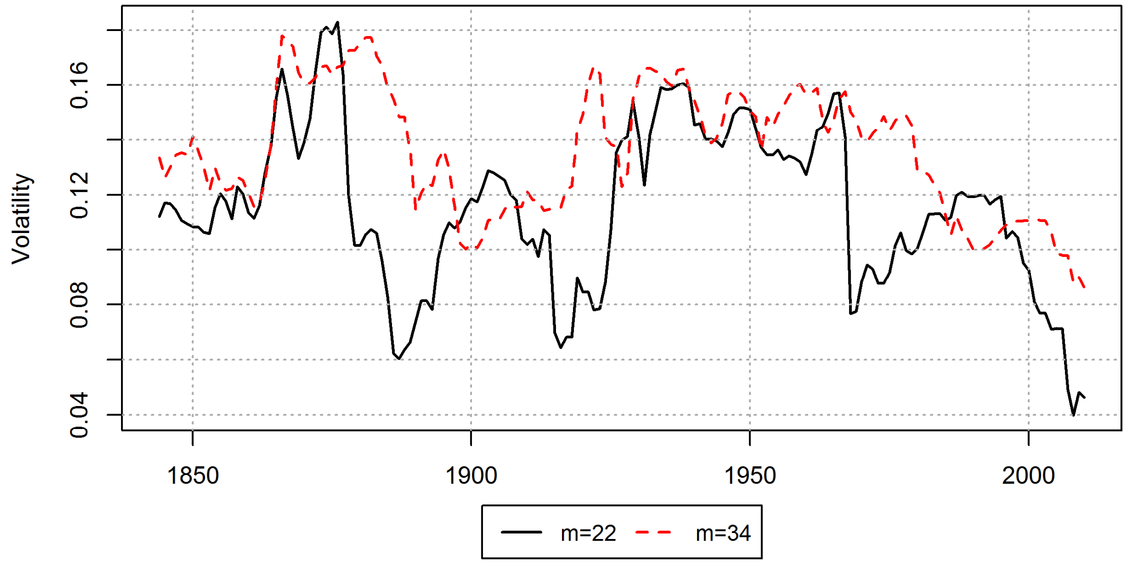
Figure 3

Patterns of volatility: detrending only model and the detrending plus decycling model. Comparison of volatility indices; logged TOT of Argentina, 1843-2008, with **two cycles**. Alternative window size **m**=22, and **m**=34.

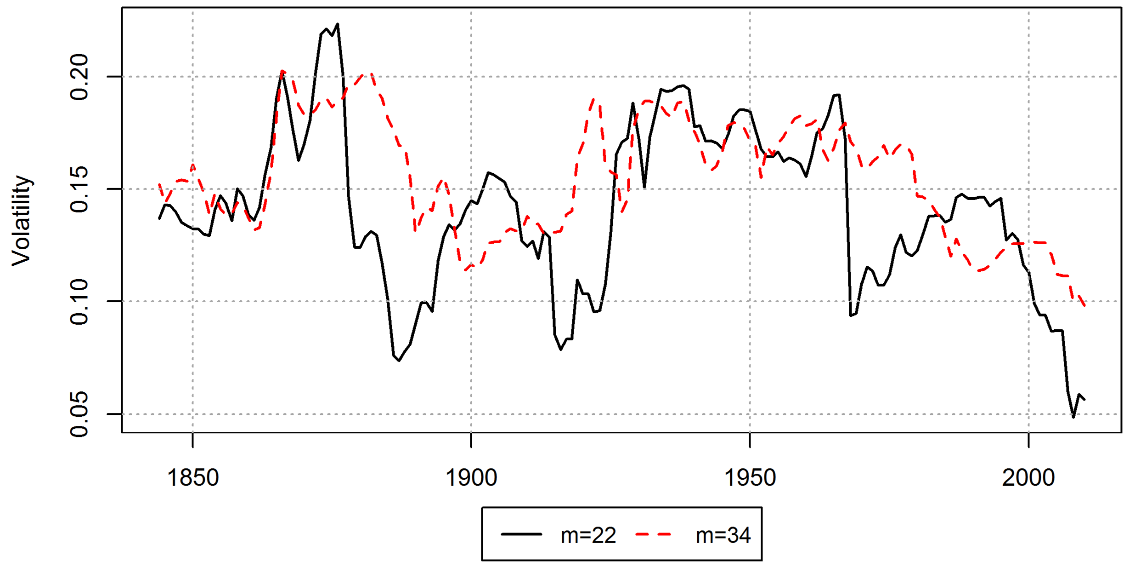
(a),(b) Detrending only model; (c),(d) Detrending plus decycling model.

(a),(b) Detrending only model

(a) Standard Deviation ($\hat{\sigma}_T$) in the detrending only model.

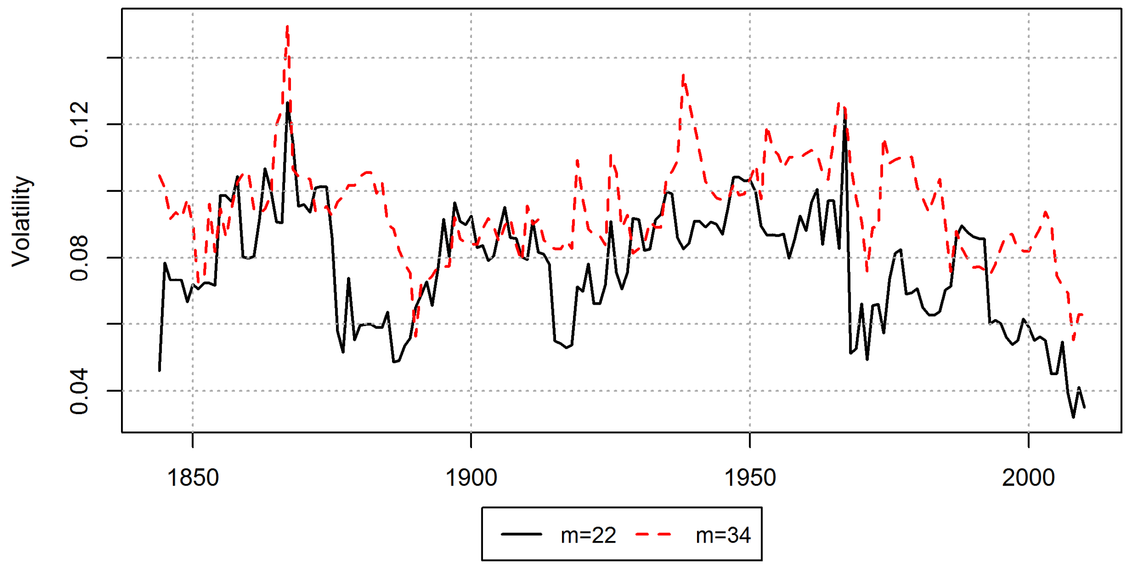


(b) One-step ahead Standard Error of Prediction (SEP) ($\hat{\sigma}_{f+1,T}$)

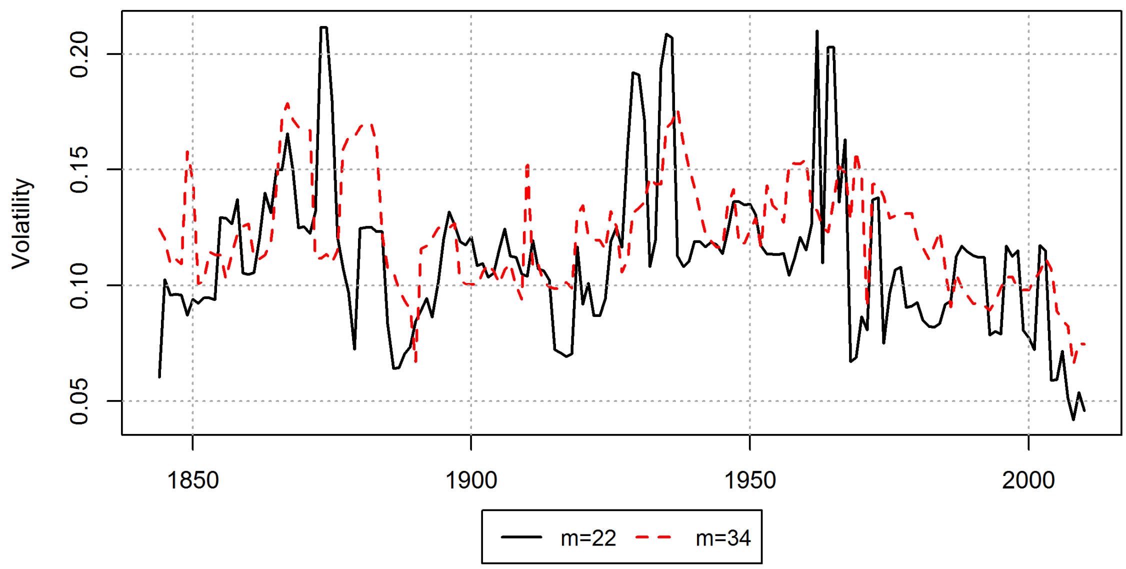


(c),(d) Detrending plus decycling model.

(c) Standard Deviation ($\hat{\sigma}_{TC}$)



(d) One-step ahead Standard Error of Prediction (SEP) ($\hat{\sigma}_{f+1,TC}$)



In Figure 2, panel (b) one can see that the previous results do not hold for $\hat{\sigma}_{f+1,TC}$, that is, increases in **c** do not necessarily generate a decrease in $\hat{\sigma}_{f+1,TC}$.

The <u>second exercise</u> consists of modifying the size **m** of the windows (**m**=20, 22, 24, 26, 28, 30, 32, 34) given the number of cycles equal to **c**=2. In Figure 3 the cases for **m**=22 and **m**=34 are reported.

It should be clear by now that we are building time series of volatility which are admissible and we do not have a formal criterion to choose one of them as superior. In some cases the relevant parameters may be obtained from estimation, for example Arrufat *et.al.*

(2011) find that the most important cycles in Argentina is 30 years. In other cases, the number should be an educated guess as in the size of the windows. To have a feel for the order of magnitude on the Cartesian product we have eight different window sizes (in our case **m**=20, 22, 24, 26, 28, 30, 32, 34), times four parameters for the definitions of cycles (**c**= 2,3,4,5), that is to say, 32 admissible paths of volatility.

Figure 3 shows that the estimations based on shorter windows react faster because in this case the last data has larger weight. This pattern is more evident for the "detrending only" based estimations ($\hat{\sigma}_T , \hat{\sigma}_{f+1,T}$) than for the "detrending plus decycling" based ones ($\hat{\sigma}_{TC} , \hat{\sigma}_{f+1,TC}$). Also the correlations between the former estimations are lesser than the latter ones. The correlation matrices for the analyzed volatility series are reported in Appendix 3.

Although for sake of brevity a similar analysis for $\hat{\sigma}_{\log TOT}$ is not shown, it can be proved that this measure behaves in a similar way than the "detrending only" based estimations.

IV. Comparison of land-abundant countries TOT volatility

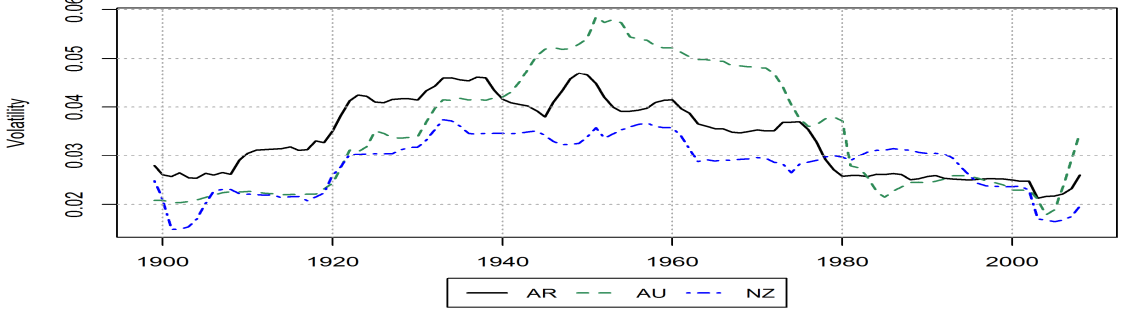
Estimations were performed for five countries: Argentina, Australia, Canada, New Zealand, and Uruguay. Annual data for 1870-2007 are from and Arrufat, Díaz Cafferata and Viceconte (2011).

The Coefficient of Variation was used to compare TOT volatility in land abundant countries, in order to avoid the dependence in the Standard Deviation of the average magnitudes. As regards the size of the rolling window, we use as before an amplitude of 30 years, and the Coefficients of Variation are calculated using the average of those 30 years.

Figure 4 shows the rolling window Coefficient of Variation for the selected countries. It is interesting to note that the TOT volatility paths are roughly similar for Argentina and New Zealand. Also similar is the case of Uruguay and Australia, except for the years between the late 1970's and the early 2000's when Uruguay's TOT volatility almost doubles, and for the period between the 1940's and the 1970's when Australia faces a TOT volatility peak. Also striking is the case of Canada. Its TOT volatility measure hovers around or below 0.02 for most of the 20th century, being clearly lower than the other countries TOT volatility in this period. It is also useful to take the results as facts to be explained; for example: why do the TOT variability of Canada and Uruguay show the inverted U shape between the 1970s and the early 2000?

Figure 4

Rolling window Coefficient of Variation (CV) from the logged TOT. Argentina, Australia, Canada, New Zealand and Uruguay. Period 1899-2007.



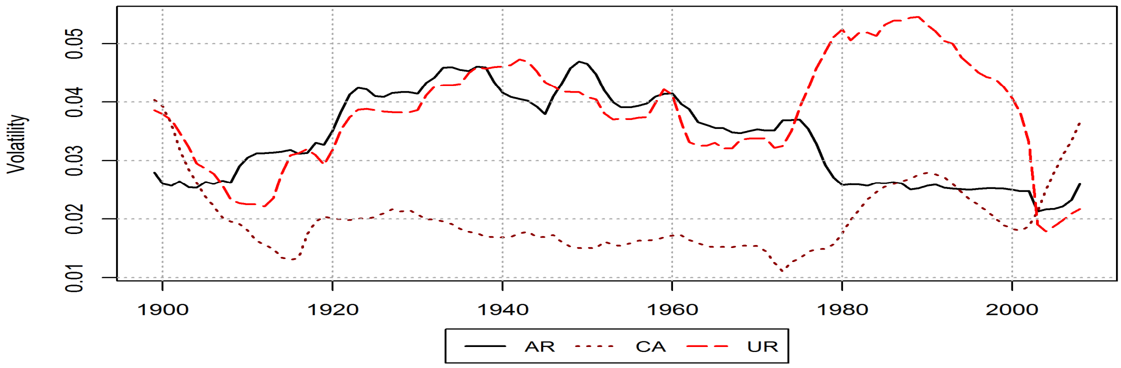


Figure 5
Log TOT volatility index for Argentina, Australia, Canada, New Zealand, and Uruguay. Annual data 1899-2007.

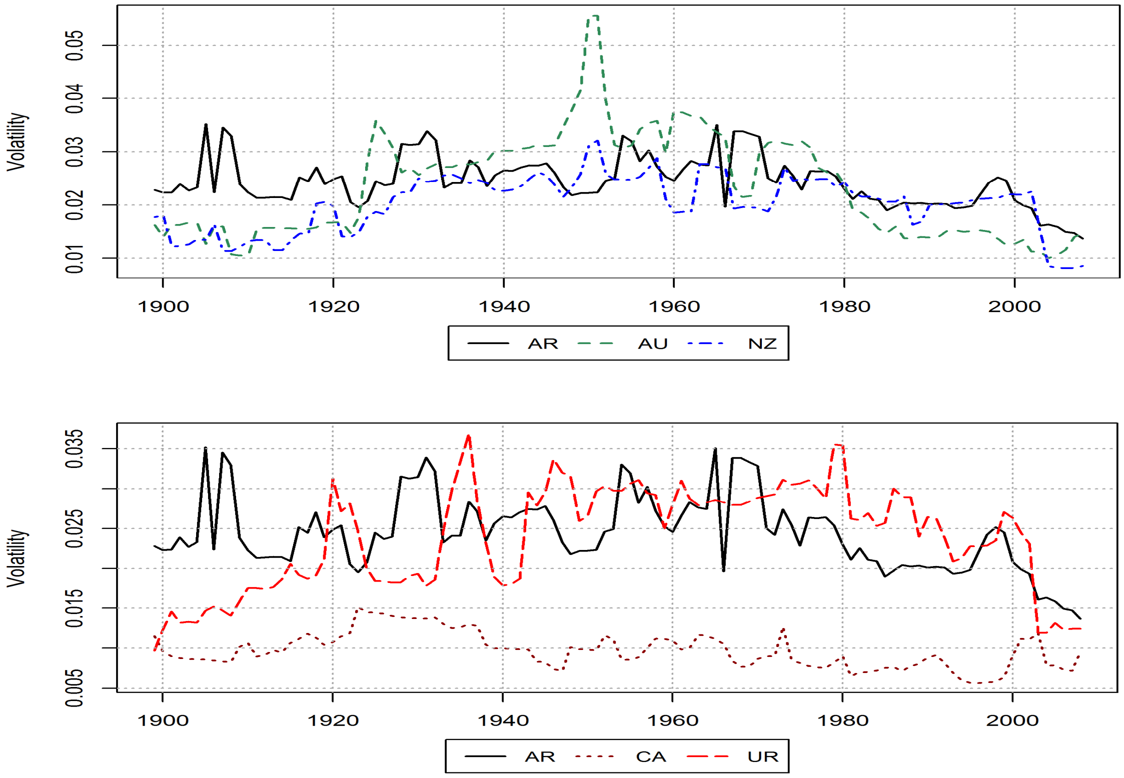


Figure 6 shows the rolling window “Coefficient of Variation like” index based on the one step ahead SEP for the detrending plus decycling model. As the coefficient of variation is the ration between the SD and the mean of a given statistical series, we deemed it appropriate to standardize the indices to take into account the heterogeneity among countries. The temporal evolutions are quite different compared with the previous ones.

In this case, Canada faces consistently the lowest TOT volatility whereas for the remaining countries no clear-cut differences emerge. Now, the TOT volatility for Uruguay is not different to the TOT volatility of Argentina, Australia and New Zealand for the period between the late 1970’s and the early 2000’s. Also the Australian TOT volatility’s peak only remains for a shorter period between the late 1940’s and the early 1950’s.

If we compare both figures, the conclusion that the selection of the appropriate index is not trivial arises. Therefore, if agents can perceive trends and the most important cycles, using the cv of the raw series as an indicator of uncertainty will conduce us to quite misleading conclusions. In Appendix 4 similar figures for alternative "coefficient of variation like" measures are shown.

V. Synthesis and conclusions

Remember for causal analysis that the measure of volatility is not observable. Rather, it is a constructed variable.

A distinction between expectations based and purely descriptive statistics help highlight the distinction as a guide for the formulation of a proxy for volatility.

A usual practice is to estimate the statistical data generating process using a sample with the whole range of data. A desirable property of modelling is that, as economic agents do not know future prices, their assumed data set cannot include information that is beyond their experience in time, a problem we call anachronism. To avoid this problem we use rolling windows to build the volatility time series. The use of a rolling window is also useful to portray that the people are assumed to use information from a limited time span: they incorporate new information, and forgets the oldest one.

If, as we have argued, the proper measure of volatility must reflect the underlying uncertainty of an economic variable, some typically used indicators, based on a purely statistical approach that take only variability into account, might give rise to an overestimation of true volatility. An important policy implication is that this may, in turn, lead to a distorted evaluation of the potential gains a given country may be expected to reap if it successfully manages to reduce volatility.

We agree with the assertion in the literature that "there is no universally accepted measure of volatility"[25]. In some empirical studies, variability was measured by comparing values located at substantial chronological distance, of, say, 10 years. This decade-long measure of uncertainty has obviously been regarded as appropriate in many instances by researchers. After all, their modeling effort is directed to the estimation of panel data models in which an important source of variation stems from the inclusion of many countries. For our purposes, on the contrary, we have placed a special emphasis on obtaining annual time series over a very long period (1899 – 2007) for five land-abundant countries: Argentina, Australia, Canada, New Zealand, and Uruguay. To the best of our knowledge such measures of TOT uncertainty, if they exist, have not been published.

For the generation of the TOT volatility series, a very important feature we have adopted is the use of the "best one can do approach" which is based on a very strong logical, and also practical, principle: agents´ forecasts made in period **f** can not be based on information not available at that moment in time, because they can only be observed at a future time. This is what we have often referred to as the Friedman-Cavallo approach to expectations formation or, alternatively, as the use of expectations which are "anachronism free".

We need a reasonably long time series estimate of TOT volatility to be used in future research to estimate econometric models to capture the causal effects of said volatility on growth rates. It is therefore essential that we have accurate measures of the variables involved. For this reason, a significant research effort has been devoted to discuss the relative merits of alternative measures of volatility, and to check how robust they are to assumptions about values of some key parameters involved.

Three such parameters are: the size of rolling windows **m**; the number of cycles **c**; and the length of the planning horizon **h**.

First, the length of time frame used for sequential estimation, labelled **m**, ranging from **m**=20 to **m**=34. Second, the number of cycles that economic agents take into account to

[25] See Mansfield & Reinhardt (2008)

predict future uncertainty, labelled **c**, with values chosen in the range from 2 to 5. Also of interest is to consider different lengths in connection with the planning horizon that agents may have in mind. To this effect, standard errors of prediction were computed for one and up to four-period ahead TOT forecasts. Although no attempt has been made to provide a single value that embodies the degree to which uncertainty is present, we pointed out that, for example, one-period ahead prediction errors may be the most relevant to reflect people´s perceptions that matter for investment projects with a short maturity period. On the other hand, two, tree, or even four-period ahead measures may be the most appropriate choice when investment projects with longer maturity periods are at stake. Finally, we made estimations of how the uncertainty changes when the period of planning moves into the future.

The statistical properties of alternative procedures are important as we wish to portray dimensions of the agents' economic behavior under uncertainty.

Some other characteristics related with volatility may be of interest, such as asymmetry, non-linearities, maximum and minimum or the existence of thresholds. In consequence more than one index may be appropriate for specific analyses. Further, the predictions of effects may depend on the model of expectations formation.

Wolf (2005, p50) lists seven "operational choices":the sample length, frequency, symmetry or weighting, realized versus expected volatility, thresholds, persistence and bunching, and the level of aggregation.

In order to tackle specific economic problems, desirable properties of volatility indices are:

a. To proxy the uncertainty *ex ante*.
b. To capture heteroskedasticity
c. To be free of anachronism.

To ensure this, firstly we decomposed between predictable and unpredictable components; secondly, we have used fixed size rolling windows. Further, data should be of a proper frequency for the economic problem at hand. Our discussion provides an interesting new ingredient to the idea that export diversification increases welfare by reducing the magnitude of aggregate TOT shocks (Kenen 1969). In certain countries this strategy may be associated with rising costs of diversification in terms of the loss of benefits when the economy moves away from comparative advantages.

Similarities found between countries that are otherwise different would suggest peculiar properties and effects of TOT volatility of how this type of economy (land abundant) works: in particular, the more general economic policy lesson from this perspective is a warning that standard recommendations regarding how to cope with TOT volatility may not be universally valid.

We agree with Haberler's (1963) warning about the danger of concentrating efforts to control the highly cyclical fluctuations of prices of primary products at a high cost in terms of loss of beneficial trade, bureaucratic intervention and high administrative costs[26].

In synthesis, we address the question of estimating volatility measures for Argentina and other land abundant countries, which are related with their external sector[27]. To perform and compare alternative estimations we rely on a general method which consist of decomposing the evolution of the variable in a modeled component representing the perception of regularities perceived by economic agents, and a residual associated with uncertainty. The robustness of volatility estimates has also been examined in the text;

[26]See Arrufat et al. (2013).

[27]Cerro and Meloni (2004) concludethat the mostimportant sources of fluctuations areattributabletodomesticvolatility.

there are several specific routines to estimate volatility which make it difficult to rank on an unambiguous “degree of volatility”.

Since many different measures of volatility used in empirical studies are found in the literature, the question is raised regarding the choice of the best one. This would provide the best proxy of the agent’s expectations formation model: i.e. a plausible empirical solution for causality analysis is to use different measures of volatility.

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Appendix 1

a) Linear trend only, and linear trend with two cycles

Linear trend.

The length of the window is **m** = 16 (years),

hh = 4 is the maximum number of out-of-sample forecasting periods imposed in the algorithm i.e. the assumed length of the agent´s forward looking horizon.

To keep matters simple the number of cycles taken into account for the decycling component, was chosen as **c** = 2.

The periods are pi=m/i where i is the number of times a complete cycle is observed.

Each complete cycle is observed **i** times in the time taken by the **m** data points of each window observed. When **m** = 16 and **i** = 6, for example, the period of the cycle is m/i=16/6. Only the cosine components were taken into account in both cases according to the following formula:

Cosine (2 * i * Π * t / m) ; t = 1, 2, 3, 4,...,m.

In the expression **i**=6 and **i**=3, such that the length of the periods (distance between two consecutive peaks and two consecutive troughs) associated to the two cycles are:

p1= m / i= 16/6= 2.67 years; p2= m / i= 16/3= 5.33 years.

In-sample predictions: observations 1 to 16.

Out of sample predictions: Observations 17 to 20.

b) Linear and quadratic trend (trend only) and trend plus two cycles.

m = 16, hh = 4
cy = 2 with periods

p1= m / i= 16/6= 2.67 years; p2= m / i= 16/3= 5.33 years.

as before.

The first column shows the observations corresponding to a rolling window of size **m**=16.

For ease of reference, we define a new variable as follows:

$$\text{Ratio} = \sqrt{1 + x'_{f+h} \left(X'X \right)^{-1} x_{f+h}} \qquad \text{(A.1)}$$

This is a proxy for the increase in volatility when the consumer or the producer looks into the future, i.e. when the estimation deals with out-of-sample prediction. This formula, obtained from Equation (4) (section III) in an obvious way, will prove useful to discuss the extra degree of uncertainty an agent may suffer as a function of **h**.

In Table A.1 Ratio1 is computed for the trend only model, and Ratio2 for the trend and cycles model.

As a general rule both ratio 1 and ratio 2 are monotonically increasing functions of **h**, the only exception being the figures for ratio in column 3.

The minimum is in observations 8 and 9. Note that standard errors of prediction for observations 17 to 20 are related to out-of-sample observations.

Table A.1

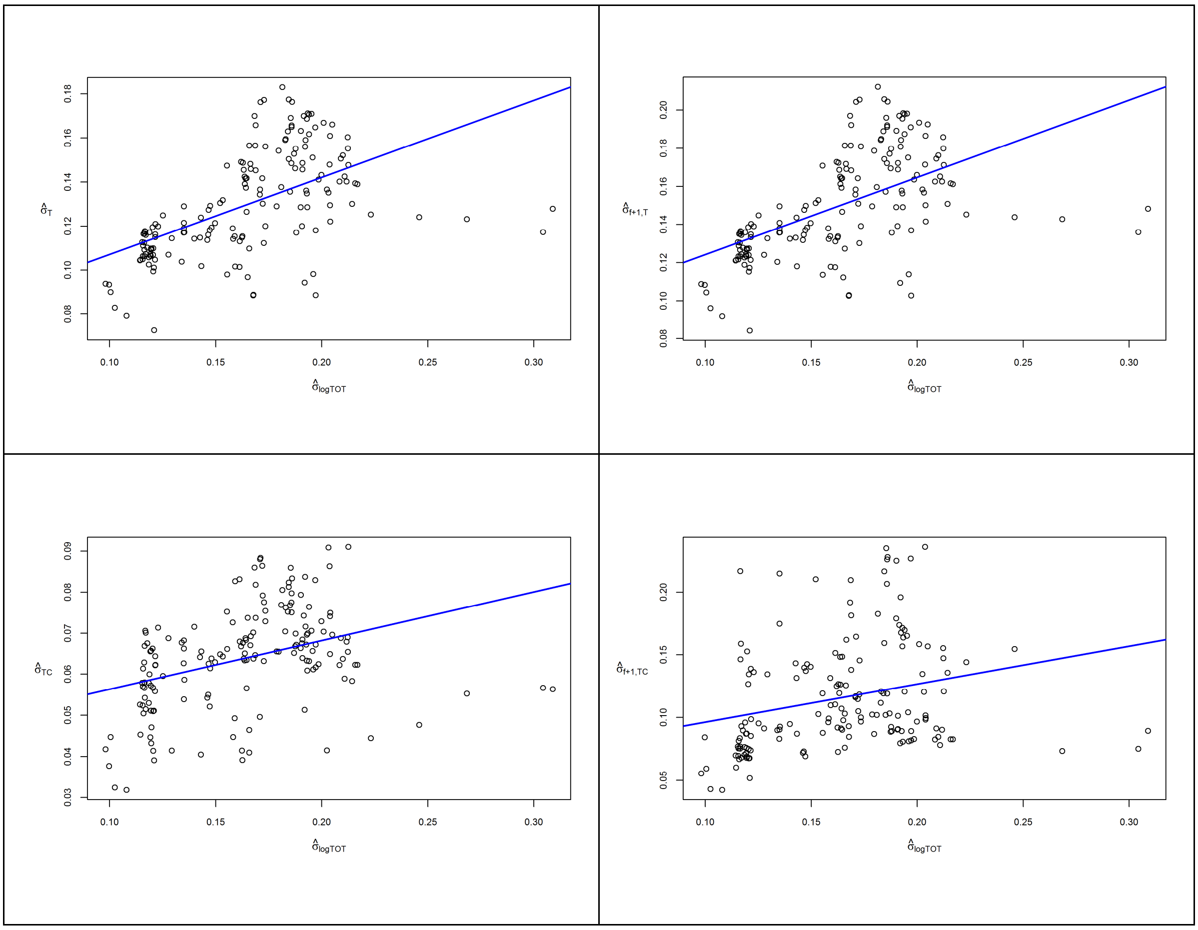
"Ratio" in sample and out of sample evolution under four alternative procedures

Observation	**(a)Linear trend only and linear trend with two cycles**		**(b) Linear and quadratic trend (trend only) and trend plus two cycles**	
m=16	RATIO 1	RATIO 2	RATIO 1	RATIO 2
(1)	(2)	(3)	(4)	(5)
In-sample				
1	1.1081	1.1882	1.2010	1.2648
2	1.0894	1.1830	1.1243	1.2185
3	1.0731	1.1891	1.0797	1.1985
4	1.0593	1.1809	1.0594	1.1809
5	1.0481	1.1960	1.0549	1.2039
6	1.0397	1.1499	1.0584	1.1748
7	1.0340	1.1463	1.0641	1.1742
8	1.0311	1.1460	1.0679	1.1733
9	1.0311	1.1460	1.0679	1.1733
10	1.0340	1.1463	1.0641	1.1742
11	1.0397	1.1499	1.0584	1.1748
12	1.0481	1.1960	1.0549	1.2039
13	1.0593	1.1809	1.0594	1.1809
14	1.0731	1.1891	1.0797	1.1985
15	1.0894	1.1830	1.1243	1.2185
16	1.1081	1.1882	1.2010	1.2648
Out of sample				
17 (h=1)	1.1292	1.2940	1.3154	1.4464
18 (h=2)	1.1524	1.3034	1.4702	1.6014
19 (h=3)	1.1776	1.2923	1.6654	1.7727
20 (h=4)	1.2048	1.3076	1.8996	1.9889

Appendix 2

Figure A2.1

Scatter plots, alternative volatility measures against the benchmark (Standard deviation of the logged raw terms of trade).
Upper left panel: SD of residuals from detrending.
Upper right panel: one-step ahead SEP from detrending.
Bottom left panel: SD of residuals from detrending plus decycling.
Bottom right panel: one-step ahead SEP from detrending plus decycling.



The correlation matrix was also computed after dropping the four most significant outliers. No significant changes in the conclusions arise.

Appendix 3

Correlation matrices, different parameters (window m, and cyles c).

For the number of cycles "c"

1) Correlation matrix of the SD from the detrending plus decicling procedure, $\hat{\sigma}_{TC}$

	c=2	c=3	c=4	c=5
c=2	1.00	0.93	0.83	0.77
c=3		1.00	0.91	0.84
c=4			1.00	0.93
c=5				1.00

2) Correlation matrix of the one-step ahead SEP from the detrending plus decicling procedure, $\hat{\sigma}_{f+1,TC}$

	c=2	c=3	c=4	c=5
c=2	1.00	0.83	0.70	0.56
c=3		1.00	0.78	0.59
c=4			1.00	0.75
c=5				1.00

For the size of the windows "m"

1) Correlation matrix of the SD from the detrending only procedure, $\hat{\sigma}_{T}$

	m=22	m=26	m=30	m=34
m=22	1.00	0.81	0.62	0.48
m=26		1.00	0.82	0.64
m=30			1.00	0.84
m=34				1.00

2) Correlation matrix of the one-step ahead SEP from the detrending only procedure, $\hat{\sigma}_{f+1,T}$

	m=22	m=26	m=30	m=34
m=22	1.00	0.81	0.62	0.48
m=26		1.00	0.82	0.64
m=30			1.00	0.84
m=34				1.00

3) Correlation matrix of the SD from the detrending plus decycling procedure, $\hat{\sigma}_{TC}$

	m=22	m=26	m=30	m=34
m=22	1.00	0.64	0.50	0.46
m=26		1.00	0.57	0.46
m=30			1.00	0.63
m=34				1.00

4) Correlation matrix of the one-step ahead SEP from the detrending plus decycling procedure, $\hat{\sigma}_{f+1,TC}$

	m=22	m=26	m=30	m=34
m=22	1.00	0.50	0.34	0.41
m=26		1.00	0.63	0.41
m=30			1.00	0.60
m=34				1.00

Appendix 4

Alternative TOT volatility measures for Argentina, Australia, Canada, New Zealand, and Uruguay. Annual data 1899-2008.

Figure A4.1

Coefficient of Variation of the residuals from the detrending only model

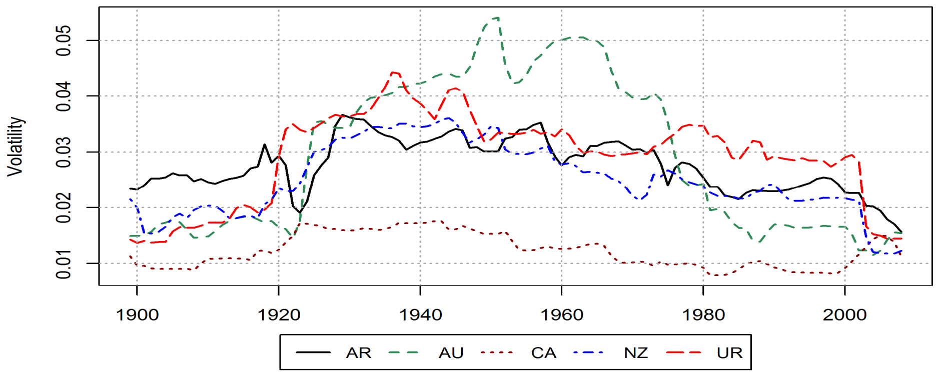


Figure A4.2

"Coefficient of Variation like". Based in the one-step ahead SEP from the detrending only model

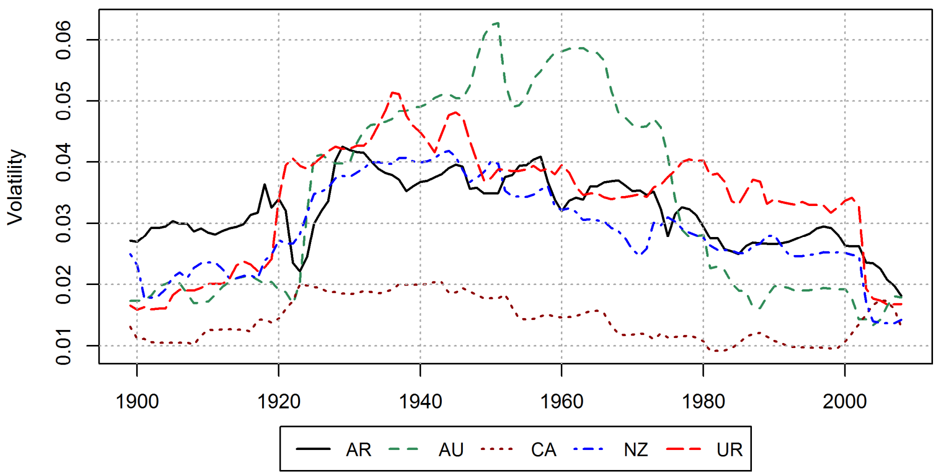
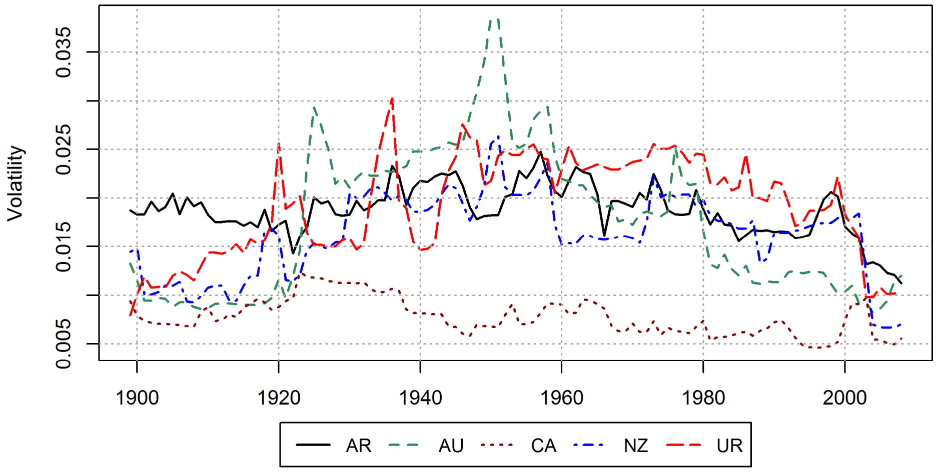


Figure A4.3

Coefficient of Variation of the residuals from the detrending plus decycling model



Appendix 5

Figure A5.1

Argentina, Australia and New Zealand

Terms of trade index 1951=100 (log scale). Left TOT, right $|d\log(tot)|$

Source: Diaz Cafferata and Matthews (2010)