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DOCTORAL THESIS IN ECONOMICS

Essays on Macroeconomic Vulnerability Financial Development and Economic Growth

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Abstract

Many studies identified financial market deepening as supporting macroeconomic stability and long-term growth. However, the role of the financial sector in increasing and propagating shocks has been considered only by few studies. The aim of this thesis is to empirically assess the effects of output volatility on growth and the limits of the financial sector in generating long-term and stable growth.

First, we reexamine the linkage between output volatility and economic growth, considering cross-section dependence and heterogeneity. By doing so, we use the common correlated effects mean group estimator which accounts for cross-section dependence and heterogeneity. Our study focuses on a panel of 85 developed and developing economies from 1975 to 2006. We confirm the negative relationship between output volatility and economic growth. Moreover, we show that, as cross-country interdependence increases, economies get synchronized, thus more vulnerable to common shocks. This is particularly true for advanced countries where the negative effect of macroeconomic fluctuations on growth seem to be stronger than in developing countries. Thus, the findings advocating a positive effect of volatility on growth may be spurious.

Second, we address the effects of financial development on economic growth for a sample of 64 developed and developing countries from 1980 to 2010. Our analysis using traditional GMM techniques and panel smoothing transition regression model (PSTR), suggests that the benefits from financial development crucially depend on the level of economic and financial development. Below a given level of income, financial development adversely affects growth. Also excessive finance tends to deter growth and increase macroeconomic instability.

Finally, we challenge the consensus of an inconclusive relationship through a quantitative assessment of the volatility-growth literature. We apply meta-analysis to 324 estimates from 39 studies that examine the effect of volatility on economic growth in linear models. We find that both research design and heterogeneity in the underlying effect play a role in explaining the differences in results. Studies that do not address endogeneity tend to find positive effects of output volatility on economic growth. Our findings support the negative effects of volatility on growth in poor countries with weak institutions and low human capital. Overall, the net effect of volatility on growth seems to be significantly negative. We find no evidence of publication bias in the literature.

Keywords: Macroeconomic volatility, Financial development, Economic growth, Cross-section dependence, PSTR
Code JEL: C24,C33, O43,G00, E32,

Thesis Introduction

"Economic development requires sustained economic growth. The process of development allows a society to adapt to the uncertainties created by changing environmental circumstances in such a way as to continue to improve the standard of living of its members. Development is therefore not only a result of high or positive growth rates, but also of the stability of that growth" (Mobarak (2005)).

" There are many reasons to believe that growth and volatility may be linked, either positively or negatively" Ramey and Ramey (1995).

The literature on the volatility-growth is quite controversial, however, it is widely accepted that developing countries tend to be more vulnerable to shocks because their financial markets are underdeveloped. Financial development is seen as shock absorber, dampening the negative effects of exogenous shocks on economic growth and leading to higher resilience to shocks. However, allowing financial liberalization to run ahead of financial regulation is an invitation to disaster (Rodrik (2000)).

The recent global financial crisis raised considerable concern about macroeconomic volatility and the effect of financial development on economic growth in advanced economies. Indeed, after decades of great moderation, their output volatility turned to increase and they fell into recession inspite of their large financial markets. Additionally, deeper financial and trade linkages (countries' interdependence) contributed to magnify the sensitivity of advanced countries to shocks.

Many studies use different methodologies to analyze the volatility-growth link leading to controversial results. Moreover, the uneven effects of output volatility on economic growth may be explained by differences in the level of economic and financial development.

To deal with the highlighted issues in the literature, this dissertation investigates the effects of output volatility and financial development on economic growth. Analysis of recent volatility trends and economic performance of developed countries raises at least two important questions. The first question deals with the link between output volatility and economic growth and the second one focuses on the potential non-linearity of the effects of financial development on economic growth. The third issue assesses the reasons of the inconclusiveness in the volatility-growth literature.

This thesis consists of three independent and closely linked studies covering the issues related to the impact of output volatility and financial development on economic growth. In the first chapter we examine the impact of output volatility on economic growth by considering cross-section dependence and heterogeneity. The purpose of this analysis is to identify which kind of shocks influence output volatility and hence the volatility-growth relationship. In the second chapter, we assess the nonlinear relationship between financial development and economic growth and whether the volatility-growth relationship changes with the level of economic and financial development. The third chapter attempts to investigate why the empirical literature on the volatility-growth link is so controversial. In what follows, we provide details about these three chapters.

In the first chapter, using common correlated effects mean group (CCEMG) estimator, we analyze the effects of output volatility on economic growth for a sample of 85 developing and developed countries over 1975-2006. Then we split the sample in developing and OECD countries. Our general findings suggest that output volatility is detrimental to growth. These negative effects are enhanced by the persistence of common shocks, which implies a propagation mechanism driven by international trade and financial co-movements. However, the main shortcoming of this analysis is the omission of potential nonlinearities in the volatility-growth relationship. Durlauf et al. (2008) suggest that linear growth models may be misspecified and more work needs to be done in systematically uncovering potential nonlinearities and heterogeneity in growth processes across countries.

In the second chapter, using panel smoothing regression (PSTR) models and a panel of 64 developing countries over 1980-2010 period, we find that the effects of the finance-growth relationship depend on the level of economic and financial development. Our main finding suggests that the finance-growth nexus can be influenced by output volatility. Indeed, when the volatility variable is omitted, we find an inverted U-shaped relationship of financial development on growth, confirming the existing literature. Nonetheless, the relationship becomes S-shaped once output volatility is considered supporting the findings of Favara (2003). The results also suggest that under a given threshold financial development tends to dampen the effects of output volatility on economic growth, however, beyond this threshold a further development of financial markets leads to higher output volatility and lower growth.

In the third chapter, we use meta-regression analysis and 324 t-statistics from 39 studies to explain the reasons of the heterogeneity across-studies. Our analysis find no evidence of publication bias in the volatility-growth literature. Moreover, the results suggest that the true effect of volatility on economic growth is negative and significant. Finally, the heterogeneity across studies is explained by the measure of volatility, country samples and econometric methodologies.

Contribution of the Thesis

Broadly speaking, this dissertation makes three major contributions to the existing literature. First, it considers cross-section dependence and heterogeneity in the volatility-growth relationship. Second it attempts to analyze how the effects of output volatility vary with the level of economic and financial development using panel smoothing regression models. Third, it challenges the consensus of an inconclusive relationship through a quantitative assessment of the volatility-growth literature. Thus, the novelties from the extant literature can be enumerate as follows:

1. The first novelty comes from the methodologies used to analyze the effects of macroeconomic volatility on economic growth. It includes the approach to measure output volatility and the introduction of cross-section dependence.

2. Secondly, using panel smoothing regression models the nonlinear effects of output volatility and financial development on economic growth are analyzed. The novelty comes from the fact that the volatility-growth link is analyzed in the context of nonlinear models. The empirical findings suggest that expanding financial market in low-income countries is risky, since it may increase vulnerability to shocks and lower growth.

3. Finally, the thesis contributes to the linear growth empirical literature by providing meta-regression analysis to explain why the volatility-growth relationship varies from one study to another. It suggests that both research design and heterogeneity explain the differences in results. To the best of our knowledge, analyzing the volatility-growth link is a novel in the context of meta-analysis.

Chapter 1

Cross-section Dependence, output volatility and economic growth

Introduction

How does output volatility influence growth? The literature on output volatility and economic growth is quite controversial. There are two main views on the impact of output volatility on growth. The first assumes that output volatility adversely affects economic growth whereas the second one (Schumpeterian/financial view) suggests a kind of trade-off between volatility and growth. The Schumpeterian thesis implies that innovations, that is, microeconomic shocks are predominant in macroeconomic fluctuations, which was questioned by (Lucas (1977)). Indeed he argued that "A new technology.... in a complex of modern economy will induce a large number of shifts in any given periods, each small in importance relative to total output...so that, there will be much averaging out of such effects across markets". Only, " ....shocks to supply which affect all, or, many sectors of the economy simultaneously...do not cancel... they induce output fluctuations in the aggregate". In other words common rather than idiosyncratic shocks significantly affect macroeconomic volatility.

Analyzing the relationship between volatility and growth is not so simple, due to cross-country heterogeneity and dependence. In fact, the potential cross-section dependence is particularly salient, given the interconnections of countries through geography, history and trade relations (Eberhardt and Teal (2011)). Thus, the independence assumption prevalent in cross-sectional econometrics are at odds with economic theory (Conley (1999)), ignoring this issue may lead to inconsistent and potentially misleading inferences.

The aim of this paper is to go beyond the traditional analysis of the volatility-growth linkage. Hence, besides assessing the effects of volatility on growth, our research focuses on cross-section dependence to identify which shocks influence output volatility and hence, the volatility-growth relationship. In that aim, we first run the cross-section dependence test of Pesaran (2004). Second, we run the unit root test of Bai and Ng (2004), which enables us to establish whether output volatility is driven by common or by idiosyncratic shocks. Finally, we investigate the sign of the correlation between output volatility and economic growth by the common correlated effect mean group (CCEMG) estimator.

This paper is structured as follows: the first section provides a brief overview of the literature. The second section presents some stylized facts. The third part illustrates the model and the econometric methodology. The fourth part provides the data and the empirical results. The fifth section summarizes the results of the regressions with additional variables and conclusions.

1 The relationship between output volatility and economic growth

1.1 Theory

Up to the early 1980s, economic growth and business fluctuations have been long treated as separated macroeconomic issues. For example, Friedman (1968) argues that output fluctuations around its natural rate arise from price misperceptions resulting from monetary shocks, whereas changes in the output growth rate are due to technology and other real factors. However, this perspective has been questioned by different authors. Indeed, Nelson and Plosser (1982) showed that movements in the GNP tend to be permanent. In other words, this means that fluctuations in the GNP are affected by business cycles. Moreover, Kydland and Prescott (1982) and Long Jr and Plosser (1983) proposed models that integrated growth and business cycle theory in order to analyze economic fluctuations. There are different views concerning the growth-volatility relationship: positive, negative, mixed or null.

Some economic theories predict that higher volatility could improve growth. Indeed, According to Black (1987), investments in riskier technologies are made if and only if the expected return is large enough to offset the extra risk. These investments could lead, if successful, to innovations and to the questioning of the established positions. Finance and innovations combine to increase growth and volatility simultaneously, by accelerating the destructive-creation process . The positive relationship could also arise from lower opportunity costs during recessions (Aghion and Saint-Paul (1998)), and from cleansing effects on inefficient firms (Schumpeter (1939), Caballero and Hammour (1994)).

Those who identify negative effects based their view on the theory of irreversibility of investments under uncertainty. Pindyck (1991) & Bernanke (1980) argue that irreversibility of investments which makes capital reallocation inefficiently expensive once installed, leads to higher volatility and much more uncertainty about long-term inflation, implying lower investment and consequently lower growth. In a similar way, Stiglitz (1993) explains that economic fluctuations negatively impact on future productivity because losses in the long run are far more significant than any temporary gains. Martin and Rogers (1995) argue that when the "learning by doing" is at the origin of growth, the long-term growth rate should be negatively related to business cycle fluctuations if human capital is increasing and concave in the cyclical component of production.

Finally the relationship could be mixed. Blackburn and Pelloni (2001) rely on a simple stochastic monetary growth model allowing for learning-by-doing. They concluded that long-run growth is negatively linked to the volatility in the presence of nominal shocks, but positively related in the case of predominantly real shocks. Furthermore they explain that the relationship is negative in the absence of nominal rigidities and either positive or negative in the presence of such rigidities. In a similar vein, Blackburn and Galindev (2003) explain that there is no fundamental reason for assuming that the relationship between volatility and growth should be positive or negative whatever the growth regime. They conclude that the correlation between growth and volatility may be positive when technological change is driven by internal learning (purposeful learning) or negative when it is driven by external learning (serendipitous learning).

From the theoretical view point, the relationship seems ambiguous. Indeed, it seems that the sign of the relationship depends on model assumptions. However, what can we learn from the empirical evidence?

1.2 Empirical evidence

There are three kinds of analysis of this topic: at sectoral, cross-regional and cross-country levels. Several empirical papers attempt to investigate the kind of relationship between volatility and growth with more or less mixed results .

One of the most influential empirical work on growth is Ramey and Ramey (1995). Using a panel data of 92 countries and a subset of 24 OECD countries over the period 1960-1985 and 1950-1988 respectively, they detect a strong negative relationship between volatility and growth. Firstly, they test the simple correlation between mean growth and volatility. The correlation is strongly negative for the whole sample nonexistent for OECD countries. Then they control for the important characteristics of these countries in order to test the robustness of their results. In that aim, Ramey and Ramey (1995) used control variables found to be significant for cross-country growth regressions. These variables are the following: the ratio of average investment to GDP, initial log GDP per capita, the average growth rate of population and initial human capital. The inclusion of control variables strengthens the negative link for the sample of 92 countries, but reverses the sign of the correlation for the sample of OECD countries. Henry & Olekans (2002), Tochkov and Tochkov (2009), Aghion and Banerjee (2005) and Badinger (2010) among others also find a negative correlation between growth and volatility. Asteriou and Price (2005), study a cross-country analysis for a sample of 59 industrialised and developing countries between 1966 and 1992. Firstly, they use traditional panel data techniques, fixed effects and random effects. Including the growth rate of capital per capita as control variable, they find output fluctuations to be harmful to both investment and growth. When they exclude investment from the regression, output volatility seems to be beneficial for growth. Which is in contrast with Ramey and Ramey (1995) findings for the sample of 59 countries. Furthermore, the results suggest that investment is one of the determinant of output uncertainty. Finally, they use mean group and pooled mean group estimates and confirm that uncertainty hampers growth. However, the negative relationship is not significant for a sample of industrialized countries. Hnatkovska and Loayza (2004) investigate the cross-country relationship between macroeconomic volatility and long-term growth. Using a sample of 79 countries over 1960-2000, they find growth to be negatively correlated to volatility. They try to answer four questions:

Does the relationship depend on country and policy characteristics such as the level of development and trade openness? Does the link reflect the causal effect from volatility to growth? if so, is this effect statistically and economically significant? Is this relationship stable over time? Has this relationship become stronger in the recent decades? Does the volatility-growth connection reveals the impact of crises rather than the overall effect of cyclical fluctuations?

The authors attempt to answer the first question, by testing whether there is a significant link between volatility and growth considering various country characteristics. In that aim, they followed the main strand of the growth literature in the choice of both the dependent and explanatory variables, to which they add two measures of volatility (the standard deviation of per capita GDP growth and the standard deviation of the per capita output gap). They start by using the baseline model for the whole sample and considering country characteristics, then they do the same regression by controlling for variables that affect a country's process growth. They find that the relationship actually depends on country and policy characteristics but not on country's international trade openness. Indeed, the poorer is a country, the more procyclical is its fiscal policy or the poorer its institutions are, the higher is the negative impact of volatility on its long-run growth. Concerning the second issue Hnatkovska and Loayza (2004) use an instrumental variable procedure to account for endogeneity in the volatility-growth trade-off so that they ascertain the causal effect from volatility to economic growth. Their instrumental variables are: exchange rate misalignment, frequency of banking crises, price volatility proxied by standard deviation of inflation rate and volatility of terms of trade shocks. They find that the global negative link between macroeconomic volatility and long-run growth actually reflects an even stronger, harmful effect from volatility to growth. They also find that this negative effect is not stable over time, it has become considerably larger in recent decades particularly for developing countries. They suggest that this harmful effect derives from large drops below the output trend.

? decompose the effects of volatility into short-term and long-term effects. By doing so, they focus on a sample of 24 OECD countries from 1961 to 1997. They use static and dynamic panels. Furthermore, they employ two measures of volatility: annual standard deviation of growth rates and time varying standard deviation. They find volatility to be detrimental to growth and conclude that the opposing results in the previous literature occurred because the authors do not allow for a time variation of volatility within national economies.

Other studies find no evidence of a relationship between volatility and growth. Indeed Dawson and Stephenson (1997) using maximum likelihood method and applying Ramey and Ramey (1995) to data from 48 contiguous US regions over the years 1970-1988, found no evidence of a relationship between volatility and growth. Moreover, they suggest that the Ramey and Ramey (1995) results may have been due to measurement errors in cross-country data. Thus the negative relationship is not a genuine casual relationship, rather an artefact of cross-country data quality variation. But this study can tell us little about the nature of the relationship since it is based only on US data. In a similar vein, in order to test Black's hypothesis, Grier and Perry (2000) using the GARCH method on a sample of US data from 1948-1996, do not confirm the result of a positive relationship between volatility and growth.

Caporale and McKiernan (1996) used monthly UK industrial production data and a GARCH-M model based on Black's hypothesis. They found evidence of a positive link between output growth and volatility on a sample over the period from 1870 to 1993. Kormendi and Meguire (1985) examine the cross-country relationship between the mean growth and the variables suggested in Levine and Renelt (1992). Furthermore they include the standard deviation of growth in order to test Black (1987) hypothesis, they used the same procedure as Ramey and Ramey (1995) however, they allow volatility to differ across countries but not across time. They find a positive relationship between real fluctuations and growth, confirming Black's hypothesis.

The third group of studies suggests a mixed volatility-growth relationship. Imbs (2002) uses a non-parametric method and test the relationship on aggregated and disaggregated data, in order to show that the same dataset used by Ramey and Ramey (1995) can be exploited to obtain both a negative and a positive correlation. Indeed he argues that "the negative link between aggregate growth and volatility masks a positive one at the purely disaggregated level". However, unlike Ramey and Ramey (1995) they only consider initial conditions as control variables. The author finds the evidence that output volatility is beneficial at disaggregrated level, and detrimental for growth at aggregated level. Imbs (2002) explains the discrepancy in the results as arising from cross-country heterogeneity in the sectoral composition of aggregate output.

Posch and Walde (2009), assess the relationship between volatility and growth using a panel of 20 OECD countries over 1970-2009 and the maximum likelihood method. The authors suggest that the Ramey and Ramey (1995) results are biased because of the omitted variables. Thus by adding further control variables to the conditional variance equation, the bias will be reduced. In that aim, they include taxes in the original equation of Ramey and Ramey (1995). They claim that the sign of the relationship depends on the purpose of taxes on wealth. If they are designed to promote R & D the relationship is positive. In contrast, when the taxes are used to encourage physical capital investment, then the negative link may occur.

2 Some Stylized Facts

Before going further it is necessary to begin by some facts which enhance the theory of cross-country interdependence. Let us start by considering the evolution of output growth for the whole sample and the subgroups of OECD and developing countries from 1975 to 2006.

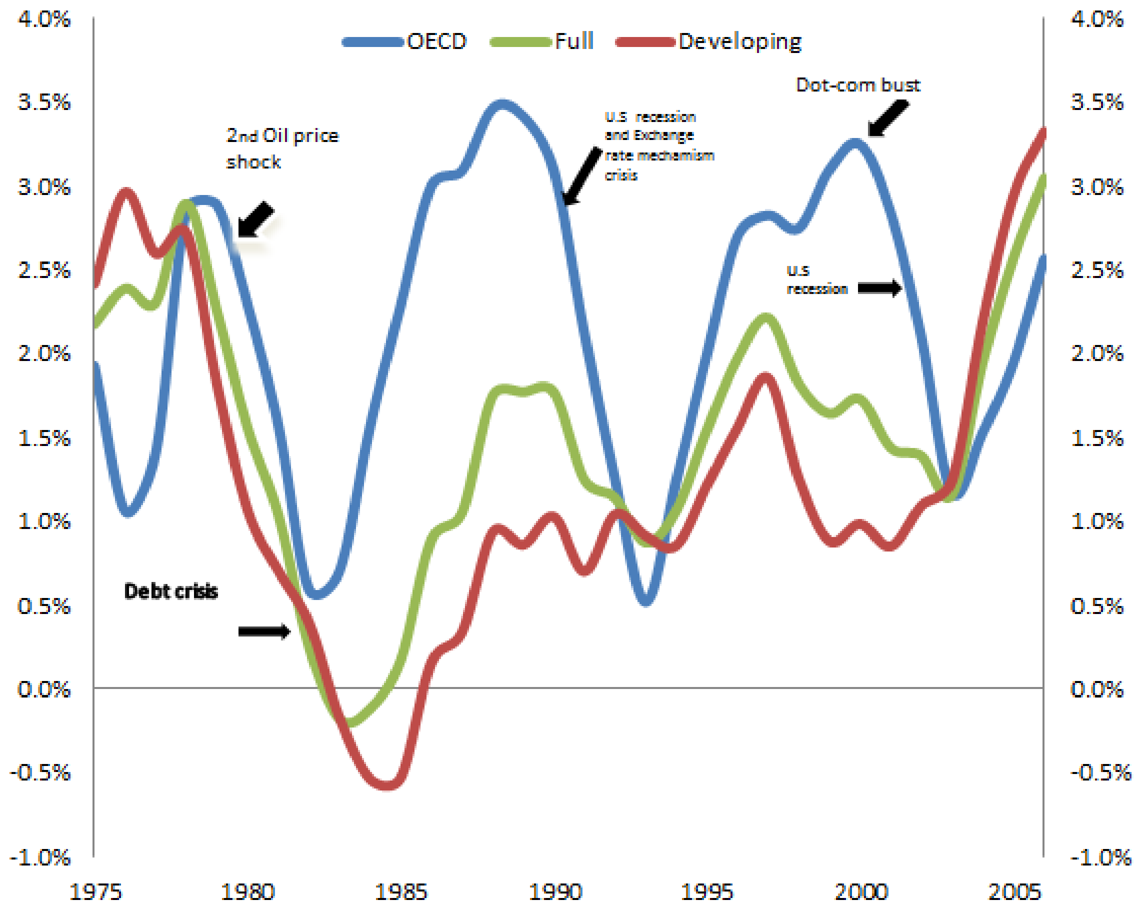

Figure 1: Real per capita GDP Growth Rates by region

Figure 1 shows that in the mid 1970s developing countries' output growth rates were higher than those experienced by advanced countries. However, they faced a sharp decline from the end of 1970s due to commodity price shocks and debt crisis, and a net acceleration from 2003. Conversely, advanced countries grow more than developing countries from the end of 1970s up to the beginning of 1990s culminating in 2000s. To sum up, developed countries grew more than the developing ones.

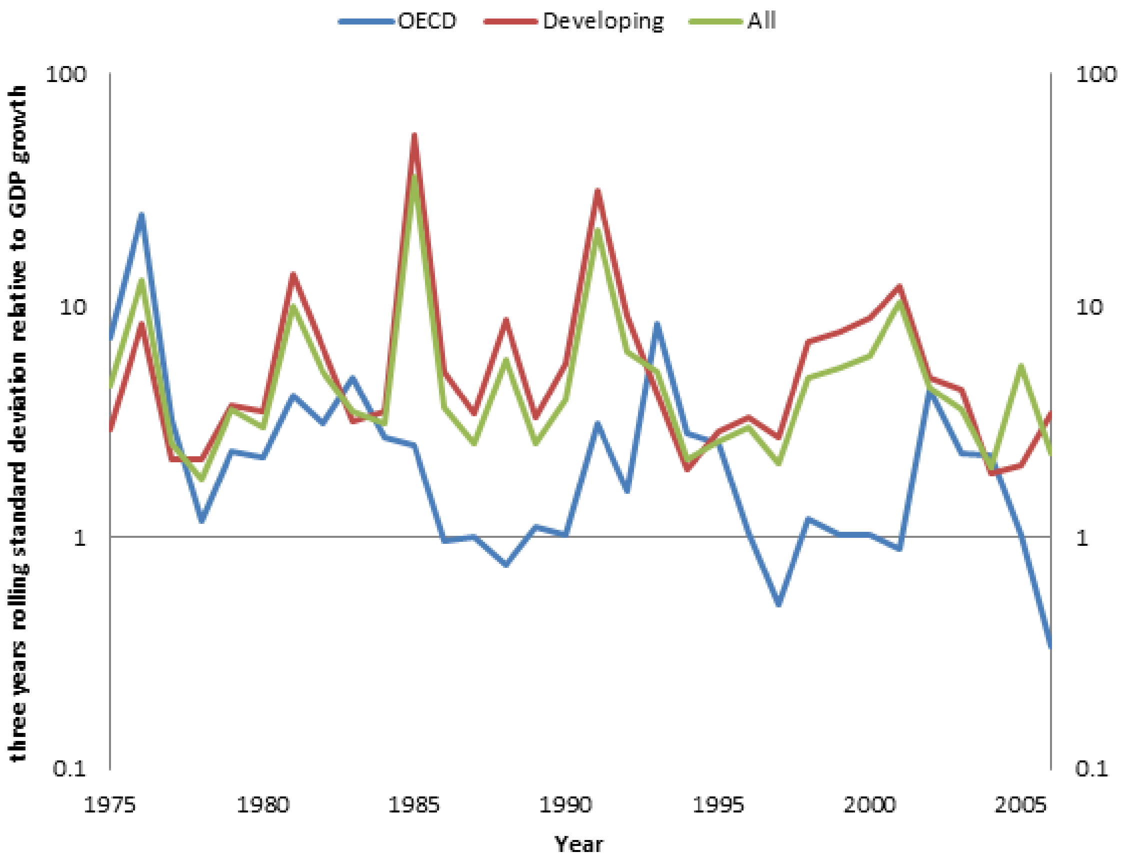

Figure 2: Evolution of macroeconomic volatility by region (Logarithmic scale)

There has been a decline on output volatility both in advanced countries and in the developed ones (Figure 2). Nonetheless, the decline has been sharper in OECD countries. While the shifts in the output volatility coincide with periods of common shocks in the latter, in the case of developing countries, they correspond to periods of high growth and common shocks.

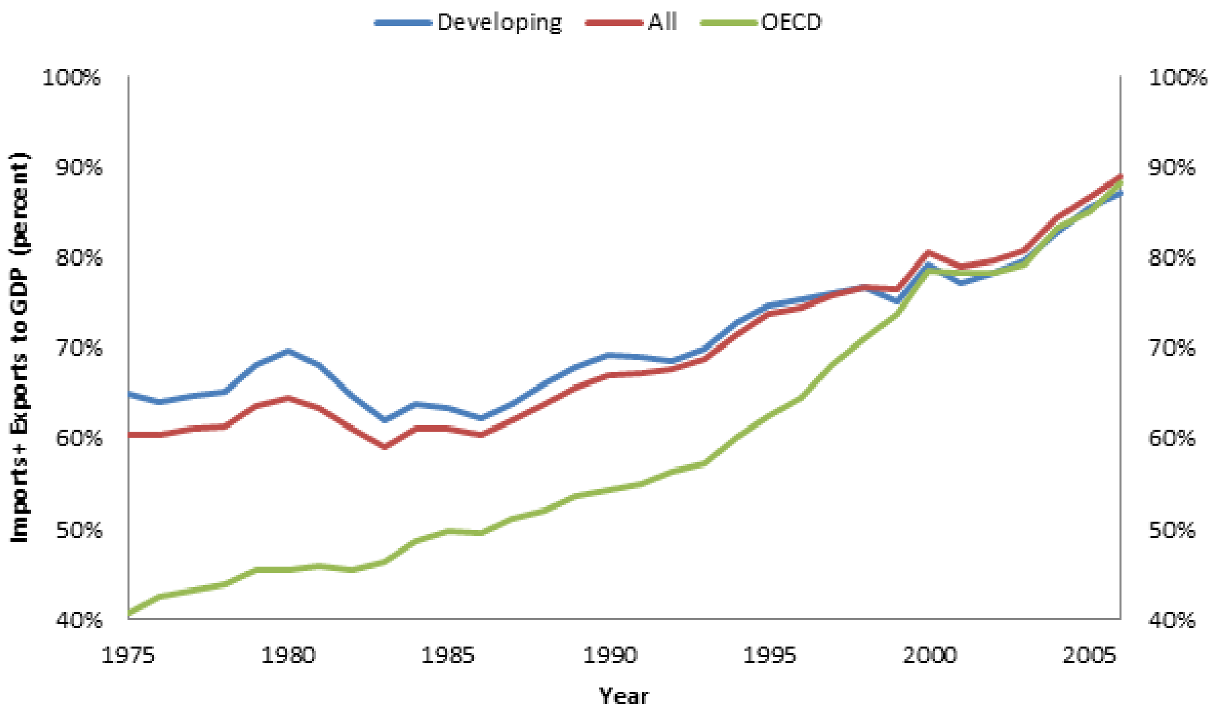

Figure 3: Openness to trade by region

We observe from Figure 3 that, before the year 2000, developing countries were more open than advanced countries. The ratio of trade openness increased unless it reached the level of developing countries. Therefore, trade linkages rose over time, making countries more synchronized and vulnerable to common shocks. In other words, the increase in trade linkages enhances interdependence of the economic activity, so that a shock to a given country could be transmitted to another. Therefore, conventional methodologies to estimate the effect of volatility on growth do not account for this issue, leading to potential biases related to endogeneity and error measurement. GMM method try to reduce the bias through instrumental variable, however it does not consider heterogeneity and cross-section dependence leading to biased inferences.

3 Econometric Model and Methodology

This subsection focuses on econometric analysis. We firstly run regressions assuming slope homogeneity, then, we account for cross-section dependence through the CCEMG (common correlated effects mean group) estimator.

3.1 Cross-section dependence

Before proceeding with cross-section dependence, based on Ramey and Ramey (1995) we estimate the following equation:

$$\Delta Y_{it} = \alpha_i + \eta_t + \theta\sigma_{it} + \beta^{'} X_{it} + \varepsilon_{it} \tag{1}$$

$$\varepsilon_{it} \sim (0, \sigma_i^2) \tag{2}$$

where, X_{it} is the vector of control variables where ΔY_{it} is the growth rate of real GDP per capita in country i at time t; X_{it} is the vector of control variables and includes: the average investment in percentage of GDP, the log of initial income, population growth rate and the log of average years of secondary schooling, σ_{it} is our measure of output volatility; β is a vector of coefficients which is assumed to be homogeneous, that is, common across countries. θ is the parameter of interest which links volatility to growth. α_i and η_t are respectively individual and time fixed effects. ε_{it} is the error term. The Results of the estimation are displayed in Table 1.

Table 1: Cross-section regression with homogeneous slope

	Full sample	OECD	Developing
Volatility	-0.0004**	-0.0002	-0.00038**
Investment	0.0007***	0.0013**	0.0006**
Initial income	-0.0009	-0.0101	0.0022
Population growth	-0.408**	0.053	-0.451
Education	0.002	-0.0008	0.0018

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The estimation method is Ordinary Least Square (OLS). The dependent variable is average growth rate of GDP per capita from 1975 to 2006, for a sample of 85 developed and developing countries.

We observe that, output volatility is significant (5%) and negatively correlated to growth for the whole sample and the sample of developing countries, but it is unrelated to growth in advanced countries. The estimated coefficients of investment and population growth have the expected sign, and are significant. Thus, confirming the findings of Ramey and Ramey (1995). Notwithstanding this methodology suffers from endogeneity, error measurement, cross-section dependence and so on. Therefore, to reduce/remove these limitations we employ the CCEMG estimator developed by Pesaran (2006) and extended to nonstationary variables by Kapetanios et al. (2011). Moreover, the latter proves that this estimator is consistent, regardless of whether the common factors are stationary or nonstationary.

Cross-section dependence test

Before incorporating the cross-section dependence in our regression, it is necessary to test its existence in the data. In that purpose we run the CD (cross-section dependence) test of Pesaran (2004). The latter proposes a test of the presence of cross-section dependence in the error term. The CD test is based on an average of all pair-wise correlations of the ordinary least squares (OLS) residuals from the individual regressions in the panel data:

$$y_{it} = \alpha_i + \beta_i^{'} x_{it} + u_{it} \qquad for \qquad i = 1, 2, ...N; t = 1, 2, ..T \tag{3}$$

where x_{it} is a vector of time varying regressors. The intercept α_i and β_i are allowed to vary across i.For each i, $u_{it} \sim iid(0, \sigma_{iu}^2)$, for all t. The CD test statistic is defined as:

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \right) \tag{4}$$

Where $\hat{\rho}_{ij}$ is the sample estimate of the pair-wise correlation of the OLS residuals, u_{it}.

Estimation Method

In our analysis we account for cross-section dependence in two ways: by testing the existence of cross-section dependence. Then by treating this issue in our regression through the CCEMG (common correlated effect mean group). The objective of this methodology is to filter the individual-specific regressors by means of cross-section aggregates. Pesaran (2006) considers the following equation:

$$\Delta Y_{it} = \alpha_i^{'} d_t + \beta_i^{'} X_{it} + \gamma_i^{'} f_t + \xi_{it} \tag{5}$$

where d_t is an $n \times 1$ vector of observed common effects(including intercept and trend) and ΔY_{it} is a 1×1 observation and X_{it} is a $k \times 1$ vector of regressors for the $i - th$ cross-section unit at time t, f_t is the $m \times 1$ vector of unobserved common effects which can be stationary or nonstationary (see Kapetanios et al. (2011)). ξ_{it} are the individual-specific (idiosyncratic) errors assumed to be independently distributed of (d_t, x_{it}). The common factors are allowed to be serially correlated and possibly correlated with regressors. To account for such possibility the regressors are specified as follows:

$$X_{it} = A_i d_t + \Gamma_i f_t + v_{it} \tag{6}$$

A_i and Γ_i are $n \times k$ and $m \times k$ factor loading matrices. v_{it} are the specific components of x_{it} distributed independently of the common effects and across i and assumed to follow general covariance stationary processes. ξ_{it} is assumed to be stationary, which means that nonstationarity could arise from f_t and/or d_t.

By combining $5-6$ Pesaran constructs the following system of equations :

$$z_{it} = \begin{pmatrix} \Delta Y_{it} \\ X_{it} \end{pmatrix} = B_i' d_t + C_i' f_t + u_{it}$$

The CCEMG estimator $\hat{b}_{ccemg}$,is a simple average of the individual CCE estimators, $\hat{b}_i$ of β_i (equation (5)):

$$\hat{b}_{ccemg} = \tfrac{1}{N}\sum \hat{b}_i$$

The CCEMG approach uses OLS to estimate an auxiliary regression for each country in which the cross-sectional averages of the dependent variable and the individual specific regressors are added , and then coefficients and standard errors are computed as usual.

Panel unit root tests

We start by looking at the CIPS test of Pesaran (2007). For a panel of observed data with N cross-sectional units and T time series observations, Pesaran (2007) proposes a cross-sectional augmented Dickey-Fuller (CADF) test where the standard Dickey-fuller regressions are augmented with cross-sectional averages of lagged levels and first differences of the individual series. He also considers a cross-sectional augmented IPS (CIPS) test, which is a simple average of the individuals CADF-tests where the standard Dickey-fuller regressions are augmented with cross-sectional averages of lagged levels and first differences of the individual series. Pesaran (2007) uses a simple dynamic linear heterogenous model:

$$Y_{i,t} = (1-\delta_i)\mu_i + \delta_i Y_{i,t-1} + u_{i,t}, \qquad i = 1, ..., N, \qquad t = 1, ...T, \tag{7}$$

with given initial values $Y_{i,0}$ and a one factor structure for the disturbance

$$u_{i,t} = \lambda_i f_t + e_{i,t} \tag{8}$$

Considering serially uncorrelated disturbances, the idiosyncratic components, $e_{i,t}$, $i = 1, ..., N$, $t = 1, ..., T$ are assumed to be independently distributed both across i and t, have zero mean, variance σ_i^2, and finite fourth-order moment. The common factor f_t is serially uncorrelated with mean zero and constant variance σ_f^2, and finite fourth-order moment. Without loss of generality, σ_f^2 is set equal to one. $e_{i,t}, \lambda_i$ and f_t are assumed to be mutually independent for all i and t. It is convenient to write (7) and (8) as:

$$\Delta Y_{i,t} = \alpha_i - (1 - \delta_i)Y_{i,t-1} + \lambda_i f_t + e_{i,t}, \tag{9}$$

where $\alpha_i = (1 - \delta_i)\mu_i$ and $\Delta Y_{i,t} = Y_{i,t} - Y_{i,t-1}$. The unit root hypothesis considered by Pesaran , $\delta_i = 1$ for all i is tested against the possibly heterogenous alternative $\delta_i \neq 1$ for $i = 1, ...N_1$, $\delta_i = 1$ for $i = N_1 + 1, ..., N$. Pesaran (2007) assumes that $\frac{N_1}{N}$, the fraction of the individual processes that is stationary, is non-zero and tends to some fixed value κ such that $0 < \kappa \leq 1$ as $N \longrightarrow \infty$.

It is important to notice that any non-stationarity of the observations of $Y_{i,t}$ in the setting considered by Pesaran (2007) is due to the presence of a unit root in the autoregressive part of (9). For the unit root null hypothesis considered by Pesaran (2007), he proposes a test based on the t-ratio of the OLS estimate $\hat{b}_i$ in the following cross-sectionally augmented DF (CADF) regression:

$$\Delta Y_{i,t} = a_i + b_i \cdot y_{i,t-1} + c_i \cdot \bar{y}_{t-1} + d_i \Delta \bar{y}_t + e_{i,t} \tag{10}$$

The averages, $\bar{y}_t = \frac{1}{N}\sum_{i=1}^{N} y_{i,t}$, $\Delta\bar{y}_t = \frac{1}{N}\sum_{i=1}^{N} \Delta y_{i,t}$, and $e_{i,t}$ is the regressor error. The cross-sectional averages $\bar{y}_{t-1}$ and $\Delta\bar{y}_t$, are included into (10) as a proxy for the unobserved common factor f_t. For analytical convenience when deriving the asymptotic properties, Pesaran (2007) replaces the usual estimator for σ^2 in the t-value for b_i by a slightly modified and also consistent one. He derives the asymptotic distribution of the modified t-statistic and shows that it is free of nuisance parameters as $N \to \infty$ any fixed $T > 3$, as well as for the case where $N \to \infty$ followed by $T \to \infty$. In line with Im et al. (2003), Pesaran (2007) proposes a cross-sectional augmented version of the IPS-test:

$$CIPS = \frac{1}{N} \sum CADF_i \tag{11}$$

where $CADF_i$ is the cross-sectionally augmented Dickey-Fuller statistic for the $i-th$ cross-sectional unit given by b_i in the CADF regression (10). Due to the presence of the common factor, the $CADF_i$ statistics will not be cross-sectionally independent[1].

Nonetheless, it is worth noting that Pesaran (2007) assumes that only the idiosyncratic component has a unit root. Given that, we are interested in investigating whether the nonstationarity depends either on idiosyncratic component or on common component or on both, we run the panic(Panel Analysis of Nonstationarity in Idiosyncratic and Common components)of Bai and Ng (2004).

This approach accounts for cross-sectional dependence given by the cross-cointegration relationship among variables. To estimate the idiosyncratic component they implement the ADF test for individual unit roots and the Choi type (Z_e^c) and Fisher type tests for the panel unit root hypothesis (P_e), which has standard normal distribution. They also use the mQ_c and mQ_f to determine the number of independent stochastic trends. The model of Bai and Ng (2004) describes the observed data $Y_{i,t}$ as the sum of a deterministic part, a common (stochastic) component, and the idiosyncratic error. In particular,

$$Y_{i,t} = D_{i,t} + \lambda_i' F_t + E_{i,t} \qquad i = 1, ...N, t = 1, ..., T \tag{12}$$

where as before λ_i is a $(K \times 1)$ vector of factor loadings, F_t is a $(K \times 1)$ vector of common factors, and $E_{i,t}$ is an error term. The deterministic component, $D_{i,t}$ contains either a constant α_i or a linear trend $\alpha_i + \beta_i t$. Bai and Ng (2004) consider a balanced panel with N cross-sectional units time series observations.

[1] Under the null hyptohesis of a unit root, $CADF_i$ converges to a functional of Brownian motions, say $G(W_f, W_i)$, where W_f and W_i are Brownian motions driven by the common factor and idiosyncratic error respectively

The common factors are assumed to be generated as follows:

$$F_t = F_{t-1} + f_t \tag{13}$$

where $f_t = \Phi(L)\eta_t, \Phi(L) = \sum_{j=1}^{\infty} \phi_j L^j$ is a $K-$ dimentional lag and rank $(\Phi(1)) = \kappa_1$. So, F_t contains κ_1 independent stochastic trends and consequently $K - \kappa_1$ stationary components. The shock η_t is assumed to be $i.i.d(0, \Sigma_\eta)$ with finite fourth-order moment. The idiosyncratic terms are allowed to be either $I(0)$ and $I(1)$ and are also modeled as AR(1) processes

$$E_{i,t} = \delta_i E_{i,t-1} + e_{i,t}. \tag{14}$$

where $e_{i,t}$ follows a mean zero, stationary, invertible MA process, such that $e_{i,t} = \Gamma_i(L)\varepsilon_{i,t}$ with $\varepsilon_{i,t} \sim i.i.d(0, \sigma^2_{\varepsilon_i})$. A series with a factor structure is non stationary if one or more of the common factors are non stationary, or the idiosyncratic error is non stationary or both. Bai and Ng (2004) do not assume an ex-ante cross-sectional independence of the idiosyncratic term, but impose it later to validate pooled testing. In this setup, the goal of PANIC is to determine the number of nonstationary factors κ_1, and to test for each $i = 1, ..., N$, whether $\delta_i = 1$. Bai and Ng (2004) suggest using principal components to consistenly estimate the unobserved components F_t and $E_{i,t}$. When the idiosyncratic component is stationary, F_t and λ_i' can consistently be estimated regardless of the order of F_t. Whereas, when $E_{i,t}$ is $I(1)$ the regression of $Y_{i,t}$ on F_t is spurious and the estimates are inconsistent. Consequently, to derive consistent estimates even if some elements of F_t and $E_{i,t}$ are $I(1)$, a suitable transformation of $Y_{i,t}$ is used. In particular, if the DGP does not contain a deterministic linear trend, the first differences of the data are employed, while in the presence of a deterministic linear trend, demeaned first-differences are used. So, in the former case $y_{i,t} = \Delta Y_{i,t} = Y_{i,t} - Y_{i,t-1}$, while in the latter $y_{i,t} = \Delta Y_{i,t} - \Delta \bar{Y_{i,t}}$ where $\Delta \bar{Y_{i,t}} = \frac{1}{T-1}\sum_{t=2}^{T} \Delta Y_{i,t}$. As the estimated common factors and idiosyncratic errors, denoted as $\hat{f}_t$ and $\hat{e}_{i,t}$ respectively, are derived applying the method of principal components to first-differenced or the de-trended data, Bai and Ng (2004) propose to re-accumulate them to remove the effect of possible overdifferencing. This yields:

$$\hat{F}_t = \sum_{s=2}^{t} \hat{f}_s, \tag{15}$$

$$\hat{E}_{i,t} = \sum_{s=2}^{t} \hat{e}_{i,s}. \tag{16}$$

These estimates are now individually tested for unit roots. For the idiosyncratic components, Bai and Ng (2004) suggest to compute an ADF statistic based on up to ρ lags. Denote the t-statistic to test the unit root hypothesis for each $\hat{E}_{i,t}$ as $ADF^{c}_{\hat{E}_i}$ or $ADF^{\tau}_{\hat{E}_i}$, depending on whether a constant, or a constant and linear trend is included in the DGP. Bai and Ng (2004) derive the limiting distributions, which are non-standard. For the case where a constant is present in the DGP given by (12), the distribution coincides with the usual Dickey-Fuller (DF) distribution where no constant is included in the estimation. the 5% critical value is -1.95. If DGP given by (12) contains a constant and a linear trend, the limiting distribution is proportional to the reciprocal of a Brownian bridge. Critical values for this distribution are not yet tabulated, and have to be simulated. Bai and Ng (2004) propose a Fisher-type test as suggested in Maddala and Wu (1999), using the correction proposed by Choi (2001). The test statistic, denoted as $P^{c}_{\hat{E}}$ or $P^{\tau}_{\hat{E}}$ depending on the deterministic specification, is given by:

$$P^{c}_{\hat{E}}, P^{\tau}_{\hat{E}} = \frac{-2\sum_{i=1}^{N} \log \pi_i - 2N}{\sqrt{4N}} \tag{17}$$

where π_i is the p-value of the ADF test for the $i-th$ cross-section. These two panel unit root test statistics have standard normal limiting distributions. Depending on whether there is just one, or several common factors, Bai and Ng (2004) suggest to use either an ADF test based on up to ρ lags, or a rank for $\hat{F}_t$. Denote the t-statistic for the unit root hypothesis as $ADF^{c}_{\hat{F}}$ when only a constant is accounted for, and as $ADF^{c}_{\hat{e}}$ in the linear trend case. Then, Bai and Ng(2004) derive their liminting distributions, which coincide with the DF distributions for the cases where only a constant, or a constant and a linear trend are included in the ADF estimation. The asymptotic 5% critical values are -2.86 and -3.41, respectively. If there are $K > 1$ common factors, Bai and Ng (2004) suggest an iterative procedure, comparable to the Johansen trace test for cointegration to select κ_1. They use demeaned or de-trended factor estimates, depending on whether (13) contains just a constant, or a constant and linear trend. Define $\tilde{F}_t = \hat{F}_t - \bar{\hat{F}}_t$ with $\bar{\hat{F}}_t = \frac{1}{T-2}\sum_{t=2}^{T}\hat{F}_t$ in the former case. In the latter, let $\hat{F}_t$ denote the residuals from a regression of $\hat{F}_t$ on a constant and linear trend. Further details on unit root and cointegration tests for multiple common factors can be found in Bai and Ng (2004).

4 Data and Empirical results

4.1 Data and sources

As mentioned above, we rely on Ramey and Ramey (1995) to construct our model, and implement the CCEMG estimator of Pesaran (2006) and extended to nonstationary variables by Kapetanios et al. (2011). Our analysis is based on a sample of 85 Developing and developed countries over the period 1975-2006. The sample is split into two subgroups: advanced(OECD) and developing countries . The data series included are real GDP per capita growth, the investment share of real GDP, the average population growth, the trade openness to GDP, the inflation rate and the government spending to GDP. We measure standard deviation accounting for growth differences across countries. Thus, we use the measure of standard deviation of Klomp and de Haan (2009): the relative standard deviation. Which is defined as follows:

$$Vol_{it} = \frac{1}{|\bar{y}_{iT}|}\sqrt{\frac{\sum (y_{it} - \bar{y}_{iT})^2}{n-1}} \tag{18}$$

Where Vol_{it} is our indicator of output volatility; y_{it} is the economic growth rate of individual i at time t; $\bar{y}_{iT}$ is the average economic growth rate in a three-year rolling window in country i at time T and n is the number of observations.

Data on real GDP, average investment, inflation rate, average population growth, trade openness and government spending are collected from Penn world table database, while data on average years of secondary schooling are from Barro and Lee (2010).

4.2 Empirical results

In this section, we report the results of the estimation for the whole sample, and for each subsample of countries. We start by implementing the cross-section dependence test of Pesaran (2004). Table 2 reports the results of the cross-section dependence test for the logarithm of real GDP per capita, the investment share of GDP, the inflation rate, the government spending, the average population growth and the output volatility.

Table 2: Cross-section dependence test

Variables	Output growth	Volatility	Investment	Initial income	Government size	Trade openness	Population growth	Inflation
CD test	26.62***	5.07***	21.63***	34.90***	58.05***	103.93***	34.74***	58.05***

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The null of cross-section independence is rejected at 0.01 for all variables which justifies the introduction of the cross-section dependence issue in our analysis.

Now let us investigate whether the variables are stationary. Tables 3 to 5 display the results of the CIPS test for the full sample and for each subgroup of countries. The null of unit root cannot be rejected for the following variables: real GDP per capita, trade and education. Whereas the unit root is rejected for the variables in differences as well as for volatility, inflation and government spending. Nonetheless, the results of the unit root test on investment and population growth are mixed because they depend on the lag order and on the group of countries considered. When we consider only the full sample the variables population growth and inflation seem to be stationary, however the results become ambiguous when we decompose the panel into OECD and developing countries.

Table 3: Pesaran's CIPS Panel Unit Root Test Full Sample

Variables	CADF(0)	CADF(1)	CADF(2)	CADF(3)
GDP per capita	2.7	-0.27	1.80	1.24
Inflation	-6.13***	-5.15***	-2.6***	-1.98***
Volatility	-27.03***	-17.28***	-9.62***	-4.38***
Education	4.65	5.1	4.28	2.43
Trade	-1.17	-1.01	-0.170	-0.796
Government	-6.13***	-5.15***	-2.67***	-1.99**
Investment	-5.25 ***	-4.33***	-1.433	0.46
Population growth	-3.21***	-6.78***	-1.54*	-3.51***
GDP growth	-2.55***	-7.74***	-6.42***	-9.39***
$\Delta Trade$	-32.90 ***	-18.90 ***	-9.58***	-7.72***
$\Delta Education$	-35.79 ***	-17.83***	-11.22***	-8.59***

Notes: The reported values are CIPS(p) statistics which are the mean of individual cross-sectionally augmented statistics (CADF, for more details see Pesaran (2007)). *** , ** , * indicates the rejection of the null at 1%, 5% and 10% level respectively.

Table 4: Pesaran's CIPS OECD countries

Variables	CADF(0)	CADF(1)	CADF(2)	CADF(3)
GDP per capita	-1.71 **	-1.51**	-0.30	0.59
Inflation	-0.288	-1.90**	-1.42*	-1.71**
Volatility	-12.21***	-11.74***	-5.12***	-3***
Education	1.71	1.7	1.04	-0.41
Trade	3.29	2.64	4.10	3.52
Government	-0.29	-1.91**	-1.427*	-1.71**
Investment	-1.46*	-1.14	0.612	-0.636
Population growth	-3.21***	-6.78***	0.757	2.29
GDP growth	-2.11***	-4.06***	-4.84***	-3.63***
$\Delta Trade$	-15.61 ***	-10.45 ***	-5.58***	-2.84***
$\Delta Education$	-18.02 ***	-17.83***	-4.23***	-1.86**

Notes: The reported values are CIPS(p) statistics which are the mean of individual cross-sectionnally augmented statistics (CADF, for more details see Pesaran (2007)). *** , ** , * indicates the rejection of the null at 1%, 5% and 10% level respectively.

Table 5: Pesaran's CIPS Panel Unit Root test Developing Countries

Variables	CADF(0)	CADF(1)	CADF(2)	CADF(3)
GDP per capita	1.12	0.87	-0.63	1.48
Inflation	-6.38 ***	-6.24***	-3.02***	-2.82**
Volatility	-23.13***	-13.62***	-7.96***	-3.9***
Education	4.22	4.61	4.06	2.77
Trade	-2.23 ***	-0.99	-0.22	-0.68
Government	-6.38 ***	-6.24 ***	-3.02 ***	-2.82***
Investment	-5.08***	-3.84 ***	1.65	1.4
Population growth	-0.56	-6.78***	0.757	2.29
GDP growth	-1.82**	-5.13***	-3.52	-6.11**
$\Delta Trade$	-27.76 ***	-16.08 ***	-7.58***	-4.82***
$\Delta Education$	-27.40***	-12.45***	-6.94***	-4.45**

Notes: The reported values are CIPS(p) statistics which are the mean of individual cross-sectionnally augmented statistics(CADF, for more details see Pesaran (2007)). *** , ** , * indicates the rejection of the null at 1%, 5% and 10% level respectively.

Given the ambiguity of the results from the CIPS test, we run the PANIC test of Bai and Ng (2004) to resolve this ambiguity and to investigate the different sources of non-stationarity. The results are reported on Tables 6-8.

Table 6: PANIC statistics full sample

Variables	Criterion	Estimated common factors ($\hat{r}$)	Idiosyncratic shocks Z_e^c	P_e	Common trends (r_1) MQ_c	MQ_f
GDP per capita	AIC3	5	-3.8	99.94	5	5
Volatility	AIC3	5	12.69***	404.09***	5	5
Investment	AIC3	5	1.71**	201.48**	5	5
Inflation	AIC3	5	2.018**	207.25**	5	5
Population growth	AIC3	5	1.39 *	195.66*	5	5
Education	AIC3	5	-5.52	68.066	5	5
Government	AIC3	5	-2.12	130.85	5	5
Trade openness	AIC3	5	-2.26	128.95	5	5
GDP per capita growth	AIC3	5	8.89***	333.98 ***	5	5
$\Delta government$	AIC3	5	23.85***	609.92***	5	5
$\Delta Trade$	AIC3	5	13.78***	424.11***	5	5
$\Delta Education$	AIC3	5	19.48***	529.24***	5	5

Notes: Z_e^c and P_e a standardized Choi's and Fisher's type statistics respectively. The number of common factors ($\hat{r}$) is estimated using the AIC3 of Bai and Ng (2002). When $\hat{r}$>1, the number of independent stochastic trends (r_1) is derived from MQ_c (intercept only model) or MQ_f (linear trend model). *** , ** , * indicates the rejection of the null at 1%, 5% and 10% level respectively.

Table 6 reports the results of the PANIC test for the full sample of countries. The results are quite similar to those found in the CIPS test except for the variable government. The non stationarity of the idiosyncratic components ((Z_e^c) and (P_e)) is rejected for volatility, population growth and output growth. However GDP per capita, education, government and trade openness are non-stationary in levels but difference stationary. It is worth noting that, in the Bai and Ng perspective, the rejection of the non-stationarity of the idiosyncratic component does not imply that the series are stationary, since it is not the unique source of non stationarity. Hence, the need to test the non-stationarity of the common factors. The number of common factors is estimated according to the AIC3 criteria (see Bai and Ng (2002)). On the basis of this criteria the estimated number of common factors is 5 for all variables. Furthermore whatever the test used, MQ_c or MQ_f, the number of common stochastic trends is equal to the number of estimated common factors.

Table 7: PANIC statistics OECD countries

Variables	Criterion	Estimated common factors ($\hat{r}$)	Idiosyncratic shocks Z_e^c	P_e	Common trends (r_1) MQ_c	MQ_f
GDP per capita	AIC3	5	-3.55	14.46	5	5
Volatility	AIC3	5	5.49***	104.91***	5	5
Investment	AIC3	5	2.15**	71.51**	5	5
Inflation	AIC3	5	-.3234	46.77	5	5
Population growth	AIC3	5	0.938	59.38	5	5
Education	AIC3	5	-4.35	6.5	5	5
Government	AIC3	5	-2.12	130.85	5	5
Trade openness	AIC3	5	0.646	56.46	5	5
GDP per capita growth	AIC3	5	1.51*	65.12 ***	5	5
$\Delta government$	AIC3	5	23.85***	609.92***	5	5
$\Delta Trade$	AIC3	5	7.44***	124.45***	5	5
$\Delta Education$	AIC3	5	7.336***	123.36***	5	5
$\Delta inflation$	AIC3	5	10.87***	158.77***	5	5
$\Delta populationgrowth$	AIC3	5	10.88***	158.69***	5	5

Notes: Z_e^c and P_e a standardized Choi's and Fisher's type statistics respectively. The number of common factors ($\hat{r}$) is estimated using the AIC3 of Bai and Ng (2002). When $\hat{r}>1$, the number of independent stochastic trends (r_1) is derived from MQ_c (intercept only model) or MQ_f (linear trend model). *** , ** , * indicates the rejection of the null at 1%, 5% and 10% level respectively.

Table 8: PANIC statistics Developing countries

Variables	Criterion	Estimated common factors ($\hat{r}$)	Idiosyncratic shocks Z_e^c	P_e	Common trends (r_1) MQ_c	MQ_f
GDP per capita	AIC3	5	-2.4	72.7	5	5
Volatility	AIC3	5	12.53***	292.13***	5	5
Investment	AIC3	5	2.67***	147.27***	5	5
Inflation	AIC3	5	2.17***	139.98***	5	5
Population growth	AIC3	5	0.7535	97.92	5	5
Education	AIC3	5	-2.51	70.99	5	5
Government	AIC3	5	-0.0028	107.95	5	5
Trade openness	AIC3	5	-0.7737	90.63	5	5
GDP per capita growth	AIC3	5	7.48***	65.12 ***	5	5
$\Delta government$	AIC3	5	23.85***	609.92***	5	5
$\Delta Trade$	AIC3	5	14.67***	363.64***	5	5
$\Delta Education$	AIC3	5	17.37***	123.36***	5	5
$\Delta populationgrowth$	AIC3	5	12.93***	298.03***	5	5

Notes: Z_e^c and P_e a standardized Choi's and Fisher's type statistics respectively. The number of common factors ($\hat{r}$) is estimated using the AIC3 of Bai and Ng (2002). When $\hat{r}>1$, the number of independent stochastic trends (r_1) is derived from MQ_c (intercept only model) or MQ_f (linear trend model). *** , ** , * indicates the rejection of the null at 1%, 5% and 10% level respectively.

Tables 7 and 8 report the PANIC test for OECD and developing countries respectively. We find interesting results. The tests on the idiosyncratic components ((Z_e^c) and (P_e)) do not reject the null hypothesis of unit root for trade, real GDP per capita, population growth, education and government in both cases. However, inflation seems to be stationary in developing countries and non-stationary in developed countries. Implying inflation convergence in developing countries and inflation divergence in advanced economies. The number of common components is five for all variables in each subgroup.

Panel error correction estimates

Having established that our variables of interest (output growth and volatility) are stationary, which means that the effects of output volatility on growth is only transitory, the present study focuses on the short-run effects of output volatility on economic growth. Thus, we now estimate the following model:

$$\Delta Y_{it} = \theta_j \sigma_{it} + \beta_j X_{it} + \phi_{j2} \Delta educ + e_{it} \tag{19}$$

Where Δy_{it} is output growth, σ_{it} is output volatility, X_{it} are I(0) control variables (inflation, government spending and population growth), educ is education. e_{it} is the regressor error. Table 7 reports the results of the regression applying the CCEMG estimator to the model of Ramey and Ramey (1995).

Table 9: CCEMG Estimates

Variables	Full sample	OECD	Developing
Volatility	-0.0023***	-0.0013**	-0.0022***
Investment	0.0024***	0.0032***	0.0021***
Population growth	- 0.87 **	0.35	-1.10*
$\Delta Education$	0.02*	0.015	0.0014
CD Test Statistics	1.81	-1.80	-0.45

Notes: CCEMG stands for Common Correlated Effects Mean Group. The dependent variable is GDP output growth. *** , ** , * indicates respectively 1%, 5% and 10% significance level.

The CCEMG analysis seems to confirm the detrimental effect of output volatility on economic growth. However developing countries seem to be the most affected by the detrimental effects of output volatility, supporting the existing literature. The CD-test on CCEMG residuals shows that the null of cross-section independence is accepted only for the subgroup of developing countries, whereas is only weakly rejected for the full sample and the subsample of developped economies. Which highlights the need to account for cross-section dependence in the growth regression models. In the next section we check whether the introduction of additional variables resolves the cross-dependence issue for both the whole sample and the sub-sample of developed countries and whether the negative relationship between output volatility and growth still holds.

5 Robustness check

Now let us examine the robustness of our results with additional control variables. The results are reported in Table 9.

Table 10: CCEMG Estimates

	Full sample	OECD	Developing
Volatility	-0.0018***	-0.0015***	-0.0023**
Investment	0.0026***	0.0033***	0.0019***
population growth	-0.139	–	–
$\Delta populationgrowth$	–	-0.83	-0.022*
$\Delta Government$	0.042 ***	0.013	0.052***
$\Delta trade$	-0.01	-0.036	-0.004
$\Delta Educ$	0.023	0.066***	0.002
Inflation	-0.07***		-.0517 ***
$\Delta Inflation$	–	0.002	–
CD test	-0.34	-0.32	-1.93

Notes: CCEMG stands for Common Correlated Effects Mean Group. The dependent variable is GDP output growth. *** , ** , * indicates respectively 1%, 5% and 10% significance level.

The introduction of additional control variables does not affect the direction of the relationship. However, the coefficient of output volatility has slightly increased, its significance as well. This is explained by the fact that advanced countries are so highly synchronized (through trade, financial exposures and so on) that a shock which hit a given country could extend to others. Moreover, the shocks which hit developing countries are mainly idiosyn-

cratic and domestic (such as natural disaster, political instability) rather than common. The variable investment is positive and significant for all the groups. Government spending seems to be beneficial to growth in the short-run as a whole and particularly in developing countries. In the short-run, trade openness seems to affect negatively (even if not significantly) output growth. Population growth seems to be detrimental to economic development only in developing countries. Education seems to promote growth only in advanced economies. Finally, inflation seems to be particularly harmful to growth in developing countries.
The test of cross-section dependence on residuals, shows that, the null can not be rejected for the sample as whole and the subset of advanced countries, however it is only weakly rejected in the case of developing countries.

6 Concluding remarks

The aim of the paper is to assess how output volatility influences economic growth and to identify the sources of shocks behind this relationship. In that aim, we applied recent panel data methodologies which account for the effects of cross-section dependence. We find that output volatility significantly hampers growth even in OECD countries. We also find that, the strength of this relationship is mostly due to the persistence of common shocks, which confirms Lucas (1977) theory and makes meaningless the Schumpeterian thesis of growth enhancing effects of output volatility. Indeed, the proponents of the Schumpeterian thesis claim that innovations could lead to higher output volatility and economic growth. However, Lucas (1977) highlights that only shocks that affect different sectors of the economy, simultaneously, have effects on output volatility. Since, it is difficult to assume microeconomic shocks occurring in many sectors simultaneously, the Schumpeterian thesis can not be validated at macro level. Thus, the theory of growth-enhancing effects of output volatility may conceal flaws particularly in the transition from micro to macro, because the effects of microeconomic shocks tend to vanish at aggregate level. Furthermore, aggregation introduces common components which are not present in disaggregate data (Byrne and Fiess (2010)).
Overall, our study points out that although developing countries remain more sensitive to macroeconomic fluctuations, the advanced countries' vulnerability also increased due to high economic integration. Thus, the predominance of common shocks implies that the propagation mechanism is driven by international trade and financial co-movements. However, it is the heterogeneity across countries which explains why developing countries are more vulnerable to output volatility than the advanced ones. Indeed, initially a shock could be common, but the differences in economic and social structures could lead some countries to be more sensitive than others to macroeconomic fluctuations. Antonakakis and Badinger (2012) underline the "potentially huge gains (in terms of stabilization and growth multipliers) from international policy coordination in the implementation of macroprudential stabiliza-

tion policies, which may result in a virtuous cycle of higher growth and lower volatility" mainly in advanced countries where common shocks are predominant.

Chapter 2

Financial development, macroeconomic stability and growth

1 Introduction

The fundamental concern in economic growth is to explain why growth rates are so different across countries. The empirical growth literature has mainly focused on factor accumulation, technical change, policies, religious diversity, geography, financial markets imperfections and macroeconomic volatility. Among these factors, the role of financial development and macroeconomic stability in economic growth has recently received a considerable attention. In this context, many economists claim that well-functioning financial markets spurs growth (the supply-leading view), and that there is a first order positive relationship between finance and economic growth. For instance, (Berthelemy and Varoudakis (1996)) believed that the persistence of cross-country growth difference occurs because of differences in the level of financial development. In particular, poor countries with underdeveloped financial systems tend to converge to the equilibrium of poverty trap in which the financial sector disappears and the economy stagnates (Berthelemy and Varoudakis (1996)). Whereas, countries with well-functioning financial systems tend to experience faster economic growth and tend to converge to the world frontier growth rate (Goldsmith (1959), McKinnon (1973), Shaw (1973), Levine and Zervos (1996)). On the other hand, Lucas Jr (1988) argued that "the importance of financial matters is very badly over-stressed", thus financial development was unrelated to growth. Finally, John Adams (1819) warns that "... banks have done more harm to the morality, tranquility, and even wealth of the nations than they have done or ever will do good".

On the other hand, the causality could also run from economic development to finance: the demand-following view. In particular, poor growth may contribute to financial market underdevelopment. For instance, Greenwood and Jovanovic (1989) associate the dynamics of economic development to the kuznet's hypothesis. They claim that, in the early stages of development, an economy's financial markets are virtually, nonexistent so that an economy grows slowly. Financial superstructure begins to form as the economy approaches the intermediate stage of the growth cycle. In other words, financial systems expand as the economy develops. Finally, Berthelemy and Varoudakis (1996) reconcile both theories by showing that, the causality runs both ways and suggest that, this relationship leads to the existence of multiple equilibria.

Although the non-linearity of the finance-growth nexus seems to have been integrated in the growth literature, controversies remain on the optimal level of financial development that promotes growth and macroeconomic stability, the sensitivity of this threshold to the methodology used and the sample of countries.

This paper attempts to explore the effects of output volatility on the finance-growth nexus by paying a particular attention to the potential non-linearity of this relationship. To the best of our knowledge, it is the first time that this type of exercise has been conducted in the PSTR models. Our study relies on a wide sample of countries, including both developed and developing economies. We first investigate the non-linearity of the finance-growth by estimating GMM and PSTR (panel smooth transition) models. In particular, following Arcand et al. (2012), we used dynamic generalized method of moments (GMM) that includes quadratic interaction terms in the growth equation. Next we split the sample into three subsamples (OECD, Africa, and other developing countries) to analyze the effects of financial development for each subgroup. Finally, we check whether financial development depends on the level of economic development.

The paper is organized as follows. The empirical literature is reviewed in Section 2. Section 3 provides the GMM and PSTR specifications and the data. The estimation results are presented in section 4. The final section comments and concludes on the main findings.

2 Literature Review

The first empirical work on the relationship between financial development and economic growth was pioneered by King and Levine (1993). They used several measures of financial development and implement a cross-country analysis for a sample of 80 countries over the period 1960-1989. They found that financial development predicts growth. Similarly, Levine and Zervos (1996) used a cross-country regression and data on 49 countries over the 1976-1993 period. They found that financial development influences current and future growth. Nonetheless, Arestis et al. (2001) raised doubts about the robustness of the econometric results derived from cross-country analysis. To overcome, this weakness, they reexamine the finance-growth nexus. In that purpose, they used time series method and data from five advanced countries. Their results support the view that financial intermediaries promote economic growth powerfully. Other studies such as Beck et al. (2000) recognize the potential biases induced by simultaneity, omitted variables, and unobserved country-specific effects that have plagued previous empirical work on the finance-growth link. The authors apply the GMM dynamic estimator on a sample of 63 countries from 1960 to 1995. They confirm the positive correlation between finance and growth and conclude that this result is not due to simultaneity bias. Deidda and Fattouh (2001) applied a threshold regression model to King and Levine (1993) dataset. They find that financial development does not have a statistically significant impact on output growth in countries with small financial sectors, whereas the relationship is positive and robust in high income countries. Finally, Loayza and Ranciere (2006) attempt to reconcile the empirical growth literature that studies the effects of financial depth on economic development and the literature that has found that monetary aggregates, such as credit growth are among the best predictors of banking and currency crises. In that purpose, they used a panel error correction model to jointly estimate the short and long-run effects of financial development. The authors point out that financial liberalization may generate short-run instability and long-run growth. Favara (2003) used a panel of 85 countries from 1960 to 1998 and a non-parametric specification that allows for heterogeneity across individuals and time. He find an inverted S-shape effects of financial development. In other words, his results suggest that financial development is beneficial only at the intermediate level of financial development. Moreover, the author states that, financial development does not have first order effect on growth, but excessive finance hampers growth. Rioja and Valev (2004) use a panel of 74 countries over 1961-1995. They find that financial development fosters growth only at intermediate level of financial development. Rajan (2005) claims that, despite the size of the financial sector contributes to dampen shocks, the risks that it generates are greater. Finally, he warns that the development of the financial sector raised the probability of a "catastrophic meltdown".

More recently Rousseau and Wachtel (2009) show that the positive finance-growth link is no more robust in recent data. Specifically, they use a cross-country and panel data of 84 countries observed from 1960 to 2004. They find vanishing effects of finance over time . The authors explain that the vanishing effects may be due to financial crises which are often associated with excessive and rapid financial deepening. In a similar way, Berkes et al. (2012) test whether the economies are experiencing "too much finance". Using different econometric methods: cross-country OLS, panel GMM, semi parametric. They find a non monotonic relationship between finance and growth; there is a threshold over which financial development start having negative effects on growth.

Masten et al. (2008) focus their study on European (advanced and transition) countries. They use threshold models to analyze the nonlinear effects of financial development on growth. Their study shows that less developed countries benefit from more finance than advanced economies, since the latter have already reached the threshold where financial development promotes growth. On the other hand, some authors as Arcand et al. (2012) emphasize the role played by the level of volatility on the finance-growth relationship. Indeed, their study suggests that financial development does not affect growth significantly in highly volatile economies. Easterly et al. (2000) use a panel data of developed and developing countries from 1960 to 1990. They find that deeper financial systems are associated with lower volatility, besides they suggest that this relationship is nonlinear; financial development reduces volatility up to a determinate threshold, beyond which, further finance increases macroeconomic instability. Finally, Dabla-Norris and Srivisal (2013) analyze the link between financial depth and output volatility, using a dynamic panel of 110 developed and developing countries over the years 1974-2008. They find a strong beneficial role of financial depth in dampening output volatility up to around 100% of GDP.

To sum up, the impact of financial development may depend on the level of financial and economic development. The traditional empirical literature on the finance-growth nexus found strong and statistically significant effects of financial development on economic growth. However, more recent studies suggest that this relationship may be nonlinear. Indeed, there is evidence that the effects of financial development are strongest in middle-income economies and negative in high-income countries when the level of financial development reaches the threshold of around 100% of GDP.
A large number of recent studies has attempted to estimate the optimal level of financial development that promotes growth without distinguishing between developed and developing countries. Moreover, the role of macroeconomic stability in the finance-growth nexus is often ignored. However, only the paper of (Arcand et al. (2012)) investigates how output volatility may affect an economy as financial markets develop. The main shortcoming of this study is the use of GMM methodology, which, although treating the endogeneity issue neglects cross-country heterogeneity. Moreover, the square term of the financial development variable used to capture the threshold impact of finance and growth imposes an a priori restriction that the effect of finance on growth monotonically and symmetrically increases and decreases with the level of financial development (Law and Singh (2014)). In other words this methodology inevitably conducts to an inverted U-shaped curve, whereas the curve could be S-shaped which is not possible to find with the square term. To overcome these shortcomings, we use PSTR models to investigate the nonlinear relationship between financial development and economic growth and to assess how output volatility affects

growth as financial sectors develop.

3 Empirical Model, Methodology and Data

3.1 Generalized Methods of Moments

Arcand et al. (2012) propose the following linear model to analyze the non-linear relationship between financial development and economic growth:

$$\Delta y_{it} = \alpha_i + \beta_0 f_{i,t-1} + \beta_1 f^2_{i,t-1} + \Gamma X_{i,t-1} + \varepsilon_{i,t} \tag{1}$$

Where α_i is the individual fixed effect, Δy_{it} is the economic growth rate, $f_{i,t-1}$ and $f^2_{i,t-1}$ are the lags of the level of credit to the private sector and its square. $X_{i,t-1}$ is the vector of control variables (initial income, human capital, trade openness, government expenditure and inflation) and $\varepsilon_{i,t}$ is the error term. However this methodology suffers from some drawbacks as we mentioned above, consequently, the PSTR model is the most suitable methodology to assess the nonlinear effects of financial development on economic growth.

3.2 Panel Smooth Transition Regression: model specification

The panel smoothing transition regression (hereafter PSTR) model considers the following two equations:

$$\Delta y_{it} = \alpha_i + \beta_0 f_{i,t-1} + \beta_1 f_{i,t-1}\Gamma(q_{it};\gamma,c) + \delta z_{it} + \varepsilon_{it} \tag{2}$$

where Δy_{it} is the GDP growth rate of country i at time t, $f_{i,t-1}$ is the first lag of the level of income per capita and financial development, α_i denotes a country fixed effect, z_{it} includes output volatility and control variables. The residual ε_{it} is assumed to be $\sim i.i.d(0,\sigma^2_\varepsilon)$. The transition function $\Gamma(q_{it};\gamma,c)$ is a continuous and bounded function of the threshold observable variable q_{it}. Following the work of Granger and Terasvirta (1993) for the time series STAR models, Gonzalez et al. (2005) consider the following transition function:

$$\Gamma(q_{it};\gamma,c) = \left[1 + exp\left(-\gamma\prod_{z=1}^{m}(q_{it}-c_z)\right)\right]^{-1}, \gamma > 0, c_1 < ... < c_m \tag{3}$$

where $c = (c_1 ..., c_m)'$ denotes a m-dimensional vector of location parameters (threshold) and where the slope of the transition function γ determines the smoothness of the transition from one regime to another. Indeed, the properties of the transition function and of the PSTR model, crucially depend upon the (non-negative) transition parameter. When $m = 1$ and $\gamma \rightarrow \infty$, the transition function approaches an indicator function $\Gamma(q_{it}; c)$ that is $\Gamma(q_{it}; c) \rightarrow 1$: the model collapse into the simple PTR model with $r + 1$ regimes. As a result, the change from the first to the second regime becomes instantaneous or abrupt. Conversely, as $\gamma \rightarrow 0$, the transition function becomes a homogeneous or linear panel regression model with fixed effects. For $m > 1$ and $\gamma \rightarrow \infty$, the number of distinct regimes remains two with the transition function switching between 0 and 1 at c_1,..., c_m. In the case $m = 2$, the transition function has its minmum at $\frac{(c_1+c_2)}{2}$. Finally, for any value of m, the transition function (2) becomes constant when $\gamma \rightarrow 0$, in which case the model collapses into a homogeneous or linear panel regression model with fixed effects. The PSTR model can be interpret in two distinct ways. On the one hand, the PSTR can be thought of as a regime switching model, that allows for a small number of extreme regimes associated with the extreme value of a transition function ($\Gamma(q_{it}; \gamma, c) = 0$ and $\Gamma(q_{it}; \gamma, c) = 1$ respectively) and where the transition from one regime to the other is smooth. On the other hand, the PSTR model allows for a "continuum" of regimes, each one characterized by a different value of the transition function. In our context, the PSTR presents different advantages. First, it allows the elasticities to vary across countries and with time. It allows for nonlinearity in the parametric approach. More specifically, this model allows the coefficients of the GDP growth to change smoothly as a function of the threshold variable (in our case financial development and the level of income per capita).

3.3 Estimations and Specification Test

The estimation is carried out in two steps. The first involves eliminating the individual fixed effects α_i, by removing individual-specific means to the variables of the model. The second step consists in applying nonlinear least squares to the transformed model. However, the threshold model deals with two specification issues: the linearity test and the test of the number of regimes.

The specification is the initial stage of the modeling. It consists in testing linearity against the PSTR alternative, that is, H_0: $\gamma = 0$ or $H_0^{'}$: $\beta_1 = 0$. A homogeneity allows to avoid the estimation of unidentified models. These tests are nonstandard since under the null, the PSTR contains unidentified nuisance parameters. To solve this issue, Gonzalez et al. (2005) replace the transition function $\Gamma(q_{it}; \gamma, c)$ by its first-order Taylor expansion around $\gamma = 0$, then they test an equivalent hypothesis in an auxiliary regression. In our context we obtain the following regression:

$$\Delta y_{it} = \alpha_i + \beta_0 f_{i,t-1} + \beta_1 q_{it} f_{i,t-1} + \delta z_{it} + \varepsilon_{it}^* \tag{4}$$

Colletaz and Hurlin (2006), proposed a generalization of the previous equation and assumed the existence of m thresholds for each transition function. Thus the previous equation becomes:

$$\Delta y_{it} = \alpha_i + \beta_0 f_{i,t-1} + \beta_1 q_{it} f_{i,t-1} + \beta_2 q_{it}^2 f_{i,t-1} + ... + \beta_m q_{it}^m f_{i,t-1} \delta z_{it} + \varepsilon_{it}^* \tag{5}$$

Testing the linearity against the PSTR model consists in testing H_0:$\beta_1 = ... = \beta_m = 0$. Let us denote SSR_0 the panel sum squared residuals under the null (linear panel with fixed individual effects) and SSR_1 the panel sum of squared residuals under the alternative H_1, the PSTR model with m regimes. Then the Wald (LM) test can be written as follows:

$$LM = NT(SSR_0 - SSR_1)/SSR_0 \sim \chi^2(mK) \tag{6}$$

The Fisher test is computed as follows:

$$LM_F = \left[\left(SSR_0 - SSR_1\right)/Km\right] / \left[SSR_0 / \left(NT - N - mK\right)\right] \sim F\left(mK, NT - N - mK\right) \tag{7}$$

where T is the number of years, N the number of countries, and K the number of explanatory variables. Finally, the likelihood ratio test is defined as:

$$LRT = -2\left[log\left(SSR_1\right) - log\left(SSR_0\right)\right] \sim \chi^2(mK) \tag{8}$$

Once the linearity test is computed, the next step is to identify the number of transition functions. The procedure is the following: the sequential approach is used to test the null hypothesis of no remaining non-linearity in the transition function. For example, let us suppose that the linearity hypothesis is rejected. The next step is to test whether there is one transition function ($H_0 : r = 1$) against the existence of at least two transition functions ($H_1 : r = 2$). Let us assume that we have two transition functions, thus we obtain the following model:

$$\Delta y_{it} = \alpha_i + \beta_0 f_{i,t-1} + \beta_1 f_{i,t-1}\Gamma_1(q_{it};\gamma_1, c_1) + \beta_2 f_{i,t-1}\Gamma_2(q_{it};\gamma_2, c_2) + \delta z_{it} + \varepsilon^*_{it} \tag{9}$$

The null hypothesis of no remaining non-linearity can be formulated as $H_0 : \gamma_2 = 0$. It consists in replacing the second transition function by its first order Taylor expansion around $\gamma_2 = 0$. The model becomes:

$$\Delta y_{it} = \alpha_i + \beta_0 f_{i,t-1} + \beta_1 f_{i,t-1}\Gamma_1(q_{it};\gamma_1, c_1) + \theta q_{it} f_{i,t-1} + \delta z_{it} + \varepsilon^*_{it} \tag{10}$$

The test is defined by: $H_0 : \theta = 0$. The different statistic tests are computed as before. Given a PSTR model with r^* transition functions , we test the null hypothesis that the model is linear that is $H_0 : r = r^*$ versus $H_1 : r = r^* + 1$. If the null is not rejected, the procedure ends and we estimate a two-regime PSTR model. Otherwise, we estimate a three regime model. The testing procedure continues until the first acceptance of the null hypothesis of no remaining heterogeneity. At each step of the sequential procedure, the significance level must be reduced by a constant factor τ is assumed to be equal to 0.5 in order to avoid excessively large models.

3.4 Data

Our analysis is based on a sample of 64 developed and developing countries over 1980-2010. The selection of countries was motivated by the requirement of having continuous data records from 1980 to 2010. Following Levine and Renelt (1992), the baseline growth equations included a standard set of explanatory variables that are widely accepted proxies for growth determinants. The dependent variable is output growth of real GDP per capita. Our regression included the following explanatory variables:

1. real GDP per capita as a measure of economic development,
2. inflation rate,
3. government size measured by the government expenditure to GDP ,
4. trade openness as the sum of export and export in percentage of GDP,
5. Output volatility is measured by three years rolling window standard deviation of GDP per capita growth and
6. the variable education which is the average years of secondary schooling.

We employ the most common measure of financial development, namely credit by deposit money banks and other financial institutions to the non-financial private sector as a percentage of GDP. This measure excludes credit to public institutions and credit issued by central bank. As a result, it measures the activity of financial intermediaries in channeling savings to investors.

Data on financial development are obtained from the update November 2013 update of the financial development dataset of Beck et al. (2010). The GDP per capita growth rates, inflation, trade openness and government expenditure are from the World development indicator database. The data on education are extracted from Barro and Lee (2010) database. We test the nonlinear effects of finance on growth through different thresholds: financial development and the level of income.

3.5 Summary statistics

Table 1: summary statistics

	Wholesample			OECD			Africa			Other countries		
Variables	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min
LRGDP	8.5	11.36	4.96	10.23	11.36	8.90	6.81	9	4.96	7.77	10.45	5.22
Growth	1.71	18.62	-19.38	1.93	18.62	-8.71	0.948	16.95	-19.37	1.84	13.88	-15.22
Volatility	2.27	15.77	0.02	1.58	9.52	0.025	2.85	15.77	0.059	2.51	31.09	1.03
LGC	2.68	3.99	1.17	2.94	3.72	2.24	2.62	3.99	1.57	2.46	3.15	1.17
LINF	3.005	10.05	1.31	2.72	1.87	6.62	3.05	5.58	1.31	3.25	10.06	2.16
LEDUC	2.38	3.30	0.237	2.90	3.27	1.74	1.70	3.03	0.23	2.29	3.21	0.59
PC	55.39	272.92	1.38	95.66	272.91	17.27	20.79	82.78	1.38	16.85	41.19	1.39
LOPEN	4.17	6.08	1.84	4.22	5.86	2.77	4.15	5.31	1.84	4.13	6.08	2.48

LRGDP is the logarithm of real GDP, Growth is real GDP growth, LGC is the logarithm of government expenditure, LINF is the logarithm of the inflation rate, LEDUC is the logarithm of education, PC is private credit and LOPEN is the logarithm of trade openness.

Table 1 provides the descriptive statistics for the dependent variable, that is, output growth, the variables of output volatility and private credit, and the control variables. The real GDP per capita and the economic growth of advanced countries are on average greater than those of African countries and the rest of countries, which is in consistent with the existing literature. However, the government size seems to be more important in developed countries, whereas African countries and the other developing countries have the highest rates of inflation. Advanced countries are slightly more open than developing countries. We also observe from the data that the financial sector is barely 21% of GDP in African countries. So, the financial sector remains underdeveloped in developing countries, while it seems to be overdeveloped in high income countries.

Comparing advanced and developing countries

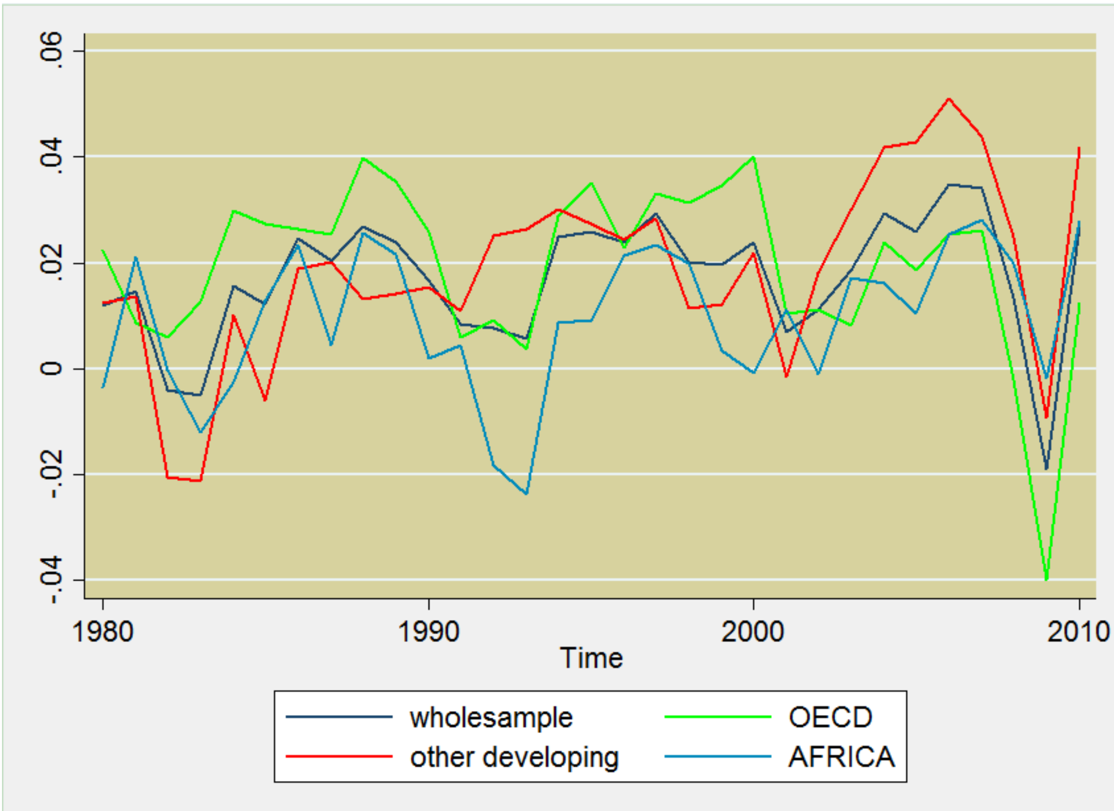

Figure 1: Evolution of output growth

Figure 1 shows the evolution of GDP growth for each subgroup over time. We observe that, before 2001, the growth rate of advanced countries was the greatest, however in the last decade developing countries grew more than the developed one. We also observe from the figures that the economies are quite synchronized. But while in 2008 all the sub-samples register a drop in GDP growth rate, the drop is deeper in the case of advanced countries and GDP growth rate continues to be higher in developing countries.

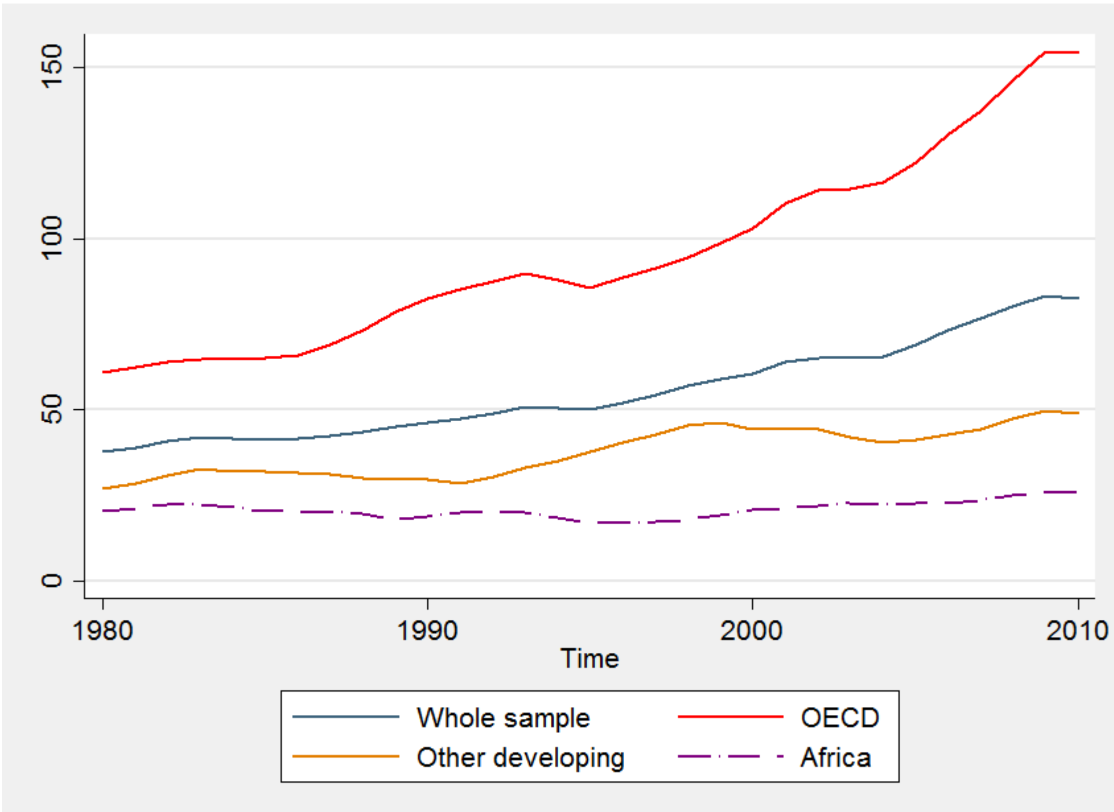

Figure 2: Evolution of the level of financial development

Figure 2 displays the evolution of the level of private credit by sub-sample. It is relatively constant over time in African countries, while it increases in other developing countries though remaining far below the level registered by developed countries.

The figures suggest that, developing countries continue to be dramatically financially underdeveloped, and that, financial development does not always foster economic growth. Indeed between 2000 and 2008 the level of private credit continued to grow but the growth rate of OECD countries remained below the rate recorded before 2000.

4 Empirical Results

4.1 Financial development, macroeconomic stability and economic growth

This section investigates the non-linear relationship between finance and economic growth. First, using generalized methods of moments proposed by Arellano and Bover (1995) and Blundell and Bond (1998). The dataset is averaged over five-year periods, the lagged values of the independent variables are used as instruments. Next, the same regression is implemented with PSTR in order to compare the thresholds obtained with each methodology. Finally, we estimate this relation using output volatility.

Table 2 reports the results of the estimates with GMM systems. The first column displays the reults of the estimates with output volatility whereas the latter is omitted in column 2. The variable of financial development is positive and significant in both cases, while its square term is negative suggesting an inverted U-shape curve. To obtain the turning point, we compute the partial derivative of economic growth relative to the variable of financial development. We observe that the thresholds are not the same. When we control for output volatility, financial deepening promotes growth only when the level of private credit is below 75.4% (which is quite close to the turning point of 74% obtained by Arcand et al. (2012). The threshold tends to be higher when we exclude the variable of volatility from our regression around 87.1% of GDP (Arcand et al. (2012) found a threshold of 89%). We also find that output volatility reduces growth significantly, confirming the findings of Ramey and Ramey (1995). Finally, with the exception of the variable initial income, all control variables have the expected signs and are significant: whereas higher level of inflation and government spending lowers growth, a more open economy with a high level of education tends to experience faster growth.

Table 2: GMM methodology

Variables	(1)	(2)
f_{it-1}	0.809**	1.224***
f^2_{it-1}	-0.536***	-0.702***
$LOPEN_{t-1}$	2.758***	3.332***
VOL	-1.124***	—–
LGC_{t-1}	-1.590***	-2.216***
$LINF_{t-1}$	-1.590***	-2.216***
$LEDUC_{t-1}$	0.374**	0.0495
$LGDP_{t-1}$	-0.378	0.113
$\frac{dGR}{dPC}=0$	0.754	0.871

Output growth is regressed over the log of private credit (f) and its square term, the log of trade openness (LOPEN), the variable of volatility (VOL), the log of inflation (LINF), the log of average years of schooling (LEDUC) and the log of real GDP(LGDP). All the control variables are lagged.**,*** stand for 5% and 1% significant level.

Table 3: PSTR estimates when the threshold depends on financial development

	Wholesample		OECD	Africa	Other countries
Opt. number of thresholds	2	2	1	1	1
Variables					
Government	-0.0217***	-0.0247***	-0.106**	-0.008 **	-0.025***
Inflation	-0.0126 ***	-0.0127***	0.017	-0.002**	-0.017 ***
Initial income	-0.0007	-0.0001	0.075***	-0.008	0.005
Education	0.0040	0.0032	0.008	0.004	0.006
Trade	0.0343 ***	0.035***	0.04**	0.038***	0.020**
Financial development					
Regime 1	-0.0135 ***	0.0345***	0.243***	-0.016***	-0.017***
Regime 2	0.022 ***	-0.0239*	0.02	0.031*	0.017*
Regime 3	-0.0295 ***	-0.0121 ***	-	-	-
Output volatility					
Regime 1($c_j < 3.8644$)	-0.0018	–	0.017**	0.0024	-0.007 ***
Regime 2($c_j > 4.3746$)	-0.0029	-	-0.047***	-0.003	-0.006
Regime 3($c_j > 4.3746$)	-0.0058*	-	-	-	-
Location parameters c_j					
first transition function	3.8644	3.8841	4.6154	3.0652	3.7092
second transition function	4.3746	4.4297		-	

Notes: *,**,*** stand for 10%, 5% and 1% significant level.

Table 3 presents the results of the PSTR methodology. The results suggest that there are two thresholds (three regimes) for the whole sample and one threshold for each sub-group. Table 3 column 2 and 3 display the results of the estimates for the wholesample. There are two thresholds, implying that financial development spurs growth between 48% (exp(3.8644)) and 80% (exp(4.3746)) of GDP when output volatility is considered, suggesting an inverted S-shaped curve which is in accordance with the findings of Favara (2003). In the case without output volatility, financial development seems to have first order positive effects on economic growth, but only up to around 48% (3.8841) which confirms the findings of Sahay et al. (2015). However, the effects become negative and statistically significant when the level of private credit reaches around 84% of GDP, suggesting an inverted U-shaped curve. Given that, the level of financial development is not the same between developed and developing countries, let us split our sample into OECD, Africa and other developing countries. We only consider the case with output volatility because we are mostly interested in the effects of financial development and macroeconomic stability on economic growth. The results are reported in columns 4-6 of Table 3. We observe that, the thresholds are quite different across the subsamples, however the highest is registered by OECD countries. Column 4 reveals that, in OECD countries, financial development increases growth up to the threshold of 4.6154 or around 101% of GDP which is quite close to the threshold of 100% found by (Arcand et al. (2012)) or Easterly et al. (2000) and Dabla-Norris and Srivisal (2013). Above this threshold the effect of financial development on growth is no longer significant. Conversely, in the case of developing countries the results are quite different, financial development starts having weak effects on growth, only when the threshold exceeds 3.06 or 21% and 3.7092 or 40% of GDP, which is in contrast with the results of (Law and Singh (2014)).

The other variable of interest is output volatility. In the case of OECD countries output volatility seems to impact positively on growth, when the level of financial developement is below 101% of GDP, then, it turns negative and significant which is in accordance with the findings of Easterly et al. (2000) and Dabla-Norris and Srivisal (2013). In the case of developing countries, the effects are quite ambiguous, it seems that, when the level of private credit is below 21% of GDP, output volatility does not affect growth in the group Africa, whereas in the case of the other developing countries, below the thresholds of 40%, output volatility reduces growth. However when this critical value is achieved, a further expansion of the financial sector tends to stabilize the economy. Which seems to confirm the hypothesis that, the level of financial development determines the stability of an economy. Our results also suggest that, the effect of financial development on growth may depend on the level of economic development. In the next sub-section, we are going to estimate the relation between financial development and economic growth using the PSTR methodology and the level of income per capita as threshold variable.

4.2 The level of income and financial development

In Table 3, we found an inverted S-shaped curve of the effects of financial development on economic growth for the whole sample and heterogeneous threshold effects across the sub-group of countries, suggesting that pooling countries in large panels may conduct to misleading results. Indeed, splitting the sample into OECD and developing countries suggests that, the relationship between finance and growth depends non-linearly on the level of income per capita.

Specifically, we follow Deidda and Fattouh (2001) and Yilmazkuday (2011) by using the level of income per capita as the threshold variable. The null of linearity is rejected at 1% level, implying that the relationship between the level of income and finance is nonlinear. The parameter's estimates of the final PSTR model are reported in Table 4.

Table 4: Financial development and growth using income per capita as threhold variable.

	Wholesample		OECD	Africa	Other countries
Opt. number of thresholds	2	2	2	1	1
Variables					
Government	-0.0170 **	-0.0170 **	-0.557***	-0.0042	-0.0119
Inflation	-0.0131 ***	-0.0149 ***	0.005	-0.05	-0.017 ***
Education	0.0018	-0.0003	0.0697**	0.046***	0.0057
Trade	0.0246 ***	0.0246 ***	0.251***	0.028*	0.023**
Financial development					
Regime 1	-0.0183**	-0.0196***	0.0132	-0.056***	-0.0248***
Regime 2	0.0123 **	0.0139**	-0.0294	0.037*	-0.0142
Regime 3	-0.0167***	-0.0158***	-0.0324*	-	-
Output volatility					
Regime 1	-0.0076**	–	0.0243 **	0.095	-0.0107 ***
Regime 2	0.0015	–	-0.0269 ***	-0.018	0.004
Regime 3	-0.0001**	–	-0.0182**	-	-
Location parameters c_j					
first transition function	6.9516	7.0077	9.2843	5.9644	8.2827
second transition function	8.1985	8.1985	10.9079	-	

Notes: *,**,*** stand for 10%, 5% and 1% significant level.

Table 4 displays the results of the estimates when the level of income is used as threshold. The empirical results confirm that, financial development impacts on growth differently, depending on the level of development. Our study identifies two thresholds (three regimes) of income for the wholesample and the sub-sample of OECD countries and one threshold for the sub-samples of African and other developing countries. The results of the first two columns indicate that, financial development enhances growth only in countries at intermediate levels of economic development, that is, when the level of income lies between 1096$ (exp(7)) and 3640.95$ (exp(8.1985)). Additionnally, the effects of output volatility seem to change with the level of economic development. In particular, low-income economies seem to be the most affected by the negative effects of output volatility on economic growth, which is in accordance with the existing literature. Moreover, the results also evidence positive effects of output volatility on economic growth for economies at intermediate level of income, and negative effects for high-income countries.

The subdivision of the sample into sub-groups leads to more interesting results. In the case of OECD countries, we notice that below a threshold of 10768 $(exp(9.2843)), financial development impacts positively but not significantly on growth, whereas the effect becomes negative but not significant in the middle regime and weakly significant when the level of income is greater than 54606$ (exp(10.9079)). On the other hand, output volatility seems to promote growth when the level of income is below 10768, above this threshold, the effects become negative and significant. The last two columns show that below a threshold of 403 $ (exp(6))and 3955$ (exp(8.2827)) financial development is harmful to growth, however the effects become positive and weakly significant for African countries and becomes not significantly different from zero for other developing countries. Our findings suggest that, in low-income economies financial liberalization is more harmful than beneficial for growth. which is in contrast with the findings of Yilmazkuday (2011) and Calderón and Liu (2003) who found the effects of financial development to be larger in low-income economies than in the high-income ones. It is worth noting that, except for OECD countries, the results are quite similar to those found in Table 4. This result may be explained by the fact that the level of financial development and income per capita are so strongly correlated that, the nonlinear effect of financial development on growth is almost the same for Africa and other developing countries.

Concerning the non financial variables, the impact of government size is negative and significant only for the wholesample and sub-group of OECD countries. Inflation tends to deter growth for the wholesample and the sub-group of other developing countries. Also the variable trade shows that greater openness to trade promotes growth significantly whatever the level of income. Finally, concerning the variable education, it seems to have positive and significant effects on economic growth for the sub-groups of developed and African countries.

Overall our analysis is consistent with the hypothesis of vanishing effects of financial development on economic growth but not with the hypothesis that the positive effects of financial development are higher in low-income economies. The analysis also confirms that differential effects of financial development on growth depend on the level of economic and financial development. We show that the critical thresholds are heterogeneous across subgroups: the threshold is higher in developed countries. Beside, the effect of financial development are weak in developing countries and decreasing in the developed ones. On the other hand, the beneficial role of financial development in dampening output volatility tends to vanish when the level of financial development exceeds the critical level of around 101% which is in line with Dabla-Norris and Srivisal (2013). The analysis is also consistent with the argument that low-income countries are the most affected by the detrimental effects of output volatility on economic growth. Finally, our findings support the inverted U-shaped effect of financial development on growth only when macroeconomic stability is omitted. Nonetheless, the curve becomes S-shaped once output volatility is accounted for.

5 Conclusion

The article reexamines the relationship between finance and economic growth and between finance and the level of economic development. The analysis is on a sample of 64 developed and developing countries covering 1980 through 2010. One of the contribution of the paper is to capture nonlinearities between financial deepening and economic growth through panel smoothing transition regression model. The empirical findings reveal that financial development promotes growth only in countries which are ongoing a middle phase of industrialization. In particular, financial deepening lowers growth in low and high income economies, while it tends to promote it in middle ones. Deidda (2006) explains that the negative effects of finance on growth in low income countries is due to their premature financial development. Thus, he suggests to delay the financial intermediation until a sufficiently high level of income is achieved. The second contribution is based on the nonlinear relationship between finance and output volatility. Output volatility increases growth only in advanced countries provided the level of private credit does not exceed 101% of GDP. On the other hand, there is not a single threshold in the finance-growth nexus, but two thresholds. To promote growth, the level of private credit may lie between 48% and 84%, implying that an increase of private credit in underdeveloped and overdeveloped financial markets is harmful to growth. It also emerges from the analysis that macroeconomic instability is linked to financial under/over-development. Finally, it seems that the model with financial development as threshold variable leads to results that are more consistent with the existing literature.

Our findings suggest that too much finance is definitely bad for growth, but neither too low finance is desirable. Moreover, for finance to be effective, a minimum level of income is needed. The empirical results also highlight that financial development does not spur growth in developing countries when either income or financial development is low. In terms of policy implications, before liberalizing their financial markets, developing countries need to improve their policy in order to create an environment suitable for volatility reduction and sustainable growth. We also find that the sensitivity to macroeconomic volatility increases as the financial sector expands, suggesting that there is a wide range of financial development levels that promotes growth and macroeconomic stability (Sahay et al. (2015)). Moreover, financial over-development also means that too many resources are dedicated to unproductive financial activity, to offset the negative effects of finance in advanced countries, financial markets must be regulated so that they may continue to enjoy the beneficial effects of finance at lower risks.

Chapter 3

Output Volatility and Growth: A meta-analysis

1 Introduction

For two decades advanced economies enjoyed dramatically low levels of output volatility and steady growth, the so-called "Great Moderation" phenomenon. Bernanke (2004) attributes this phenomenon to good luck in the form of low crisis frequency, better macroeconomic policies and structural changes (such as innovations). As a result, agents believed that this period of economic tranquility was permanent, thus, they engaged in riskier activities in order to grasp dividend from reduced macroeconomic volatility (Bean (2010)). This in turn, expose economies to the current financial crisis and contribute to increase macroeconomic instability, reviving the old debate on the relationship between output volatility and economic growth.

On the one hand, the Shumpeterian theory claims that output volatility favors growth. For instance, Black (1987) points out that investment in riskier technologies are made if and only if the expected return is large enough to offset the extra risk. Moreover, the positive relationship could also arise from lower opportunity costs during recessions (Howitt and Aghion (1998)), and from cleansing effects on inefficient firms (Schumpeter (1939), Caballero and Hammour (1994)). The thesis of a positive effect of output volatility on growth assumes the existence of the following trade-off: high volatility- high growth. Which implies that stabilization polices are costly rather than beneficial.

On the other hand, Pindyck (1991) presents a theory of detrimental effects of output volatility on economic growth. This point of view is based on the theory of irreversibility of investments under uncertainty. It is also argued that irreversibilities of investments, which make capital reallocation inefficiently expensive once installed, lead to higher volatility and much more uncertainty about long-term inflation, implying lower investment and consequently lower growth. Moreover, it is stressed that macroeconomic fluctuations negatively impact on future productivity because losses in the long-run are far more significant than any temporary gains. This thesis has been strongly supported by authors as (Stiglitz (1993), Bernanke (1980), Martin and Rogers (1995)).

Since the global financial crisis, macroeconomic instability has increased, but the positive effects on growth never materialized, only the cleansing effects has been observed, further supporting the thesis of a negative relationship between output volatility and economic growth, and contradicting theories suggesting a trade-off between output volatility and economic growth.
Given the inconclusiveness of the theoretical literature, there is no way to determine the direction of the relationship between output volatility and economic growth. Many studies attempt to resolve this issue empirically. However, the empirical analysis differ according to the sample, the measure of volatility, the period, the econometric methodologies leading to a further heterogeneity in studies' outcomes.

The purpose of the present study is to uncover the main empirical works on the relationship between output volatility and economic growth, in order to bridge the evidence gap by conducting a systematic review of the literature based on meta-analysis methods. Meta-analysis is a quantitative research synthesis extensively employed in medicine and education research, and from two decades, applied in economics. Contrary to the narrative literature, the meta-analysis provides a more formal and objective process of reviewing the empirical literature (Stanley and Jarrell (1989)). Moreover, by controlling for variations in study characteristics, meta-analysis provides quantitative insight into which factors really matter in explaining study-to-study variations in the empirical literature (Koetse et al. (2009)).
The remainder of the paper is structured as follows. Section 2 presents the measures of volatility in the literature. Section 3 provides an overview of the data collection procedure, descriptive statistics and the methodology. Section 4 discusses the meta-regression results. Section 5 summarizes the main findings and concludes.

2 Measuring economic volatility

The volatility-growth relationship may depend on the definition of output volatility. For example, the conventional view defines output volatility as temporary deviations from the trend. In other words, output fluctuations usually refer to short-run deviations of output growth from its natural rate (steady growth rate state). However, it is important to distinguish between variability and uncertainty. On the one hand, the uncertainty is measured by the conditional variance of shocks to output growth from volatility forecasting models as GARCH/ARCH, i.e uncertainty measures the unpredicted component of growth. On the other hand, variability, i.e temporary deviation from trend, encompasses the predicted and unpredicted components. In the literature different statistical methodologies are used to calculate the variability indicator. The first approach measures volatility as the standard deviation of output growth. The second method considers the standard deviation of the cyclical component as volatility. This second approach isolates cycles by the means of filters as band-pass of Baxter and King (1999) and Hodrick and Prescott (1997).

To sum up, there are two main approaches to measure output volatility: the first approach consists in measuring uncertainty or risk and the second approach measures output variability that is the overall volatility. However, each approach presents specific shortcomings. The approach based on uncertainty generally uses forecasting error models and does not consider explanatory variables. For instance, Launov et al. (2014) point out that, since the volatility term appears among explanatory variables in the growth equation, omitted variables in the conditional variance equation potentially lead to correlation between explanatory variables and the error term, hence, to biased estimates. On the other hand, the approach based on variability encompasses the overall volatility that is, the predictable variability and the pure risk (uncertainty). According to Aizenman and Pinto (2005), this measure tends to overestimate macroeconomic volatility. Thus, based on the previous arguments which approach is suitable to measure output volatility? answering to this question is difficult without the help of meta-analysis.

3 Data collection and model specification

3.1 Data collection

The empirical literature investigating the volatility-growth link includes t-statistics (the effect size) from academic journals as well as working papers. Our decision to use t-statistic as the effect size measure is motivated by the fact that, the measure of volatility is not homogeneous in the empirical literature. We construct our data set searching on the most relevant databases such as RePec, Google Scholar, and EconLit. In addition to the search engines, we also searched references from identified studies. The keywords used was business cycles fluctuations, uncertainty, macroeconomic fluctuations, output volatility and economic growth. To be included in our systematic review, a study must report t-statistics and standard errors. This process identified 39 relevant studies which provide 324 estimates.
Table 1-2 and Figure 1-4 present descriptive statistics of the studies employed in our meta-analysis. We observe from Table 1 that most of the studies report more than one t-statistic, and that there is a large heterogeneity across and within studies on whether output volatility has a positive or negative effect on economic growth. Figure 1 illustrates the frequency distribution of the t-statistic. The important feature emerging from the graph is that the number of t-statistics lying inside the not significance region (i.e inside the red lines) is almost identical to the number lying outside; 164 t-statistics are significant and 160 are not significant. However, Table 2 shows that, the number of negative t-statistics is almost twice the number of positive t-statistics. Furthermore, according to Figure 2, standard deviation and conditional variance are the most used measures of output volatility. Finally, Figure 3 and figure 4 show that studies mainly focus on OECD countries, panel and aggregate data.

Table 1: Summary statistics from each study

	Authors	Number of coefficents	Min	Max	Standard deviation	Mean
1	**Aghion et al. (2010)**	6	−3.15	-1.27	0.709892	-2.167
2	**Andreou et al. (2008)**	7	-0.3	2.78	1.1716	1.3814
3	**Badinger (2010)**	4	-4.821	-3.14425	0.7879	-4.0664
4	**Badinger (2012)**	8	-27.757	-1.734	9.419	-6.882
5	**Berument et al. (2012)**	5	-10.1	-0.90869	3.7361	-6.794
6	**Bredin and Fountas (2009)**	24	-55	12.422	-3.5699	-0.9425
7	**Bredin et al. (2009)**	14	-13.5	10.25	5.6251	-0.9425
8	**Caporale and McKiernan (1996)**	1	3.52	3.52	–	3.52
9	**Dabušinskas et al. (2013)**	3	-0.2526	0.009	0.0600	-0.1834
10	**Dawson and Stephenson (1997)**	2	-1.71	0.17	1.3294	-0.77
11	**Dejuan and Gurr (2004)**	3	0.7056	2.5493	0.9370	1.5305
12	**Döpke (2004)**	16	-0.72	4.59	1.6161	1.3937
13	**Fang and Miller (2008)**	22	-2.184	1.4249	0.78998	0.1829
14	**Fountas et al. (2004)**	9	1	1.5468	0.197	1.339
15	**Fountas and Karanasos (2006)**	3	1.218	2.5338	0.7225	2.048
16	**Furceri (2010)**	8	-6.3	-2	1.3891	-3.3862
17	**Grier and Perry (2000)**	3	0.78	0.98	0.1126	3.4366
18	**Grier and Tullock (1989)**	14	-3.35	2.48	1.795	0.3914
19	**Hnatkovska and Loayza (2003)**	20	-4.25	-1.32	0.8836	-2.793
20	**Imbs (2002)**	6	-2.28	1.48	1.3934	-0.8767
21	**Imbs (2007)**	4	2.74	3.16	0.2017	2.955
22	**Jetter (2014)**	12	-0.0165	5.028	1.785	1.974
23	**Kneller and Young (2001)**	9	-7.24	1.98	3.1987	-2.0844
24	**Kormendi and Meguire (1985)**	6	1.9	3.1	0.574	2.617
25	**Ayhan Kose et al. (2005)**	9	-0.149	0.21	0.2240	-0.0574
26	**Lee (2010)**	1	20	20	–	20
27	**Macri and Sinha (2000)**	1	-2.19	-2.19	–	-2.19
28	**Macri and Sinha (2007)**	3	-1.1412	-0.1924	0.2667	-0.834
29	**Mobarak (2005)**	4	-3.33	3.03	2.837	-1.0625
30	**Norrbin and Yigit (2005)**	22	-5.54	2.04	1.770	-0.8714
31	**Posch and Wälde (2011)**	2	-3.1569	-2.9638	0.1365	-3.060
32	**Rafferty (2005)**	4	-2.986	-1.823	0.486	-2.450
33	**Ramey and Ramey (1995)**	4	-2.61	0.67	1.500	-1.54
34	**Lin and Kim (2014)**	39	-62.859	-1.373	17.62946258	-18.8321
35	**Siegler (2005)**	6	-4.4468	-0.3928	1.51998	-2.7682
36	**Speight (1999)**	4	0.0799	1.34	0.5149	0.71245
37	**Stastny and Zagler (2007)**	1	3.6	3.6	–	3.6
38	**Tochkov and Tochkov (2010)**	14	-6.75	0.68	2.4465	-2.489
39	**Turnovsky and Chattopadhyay (2003)**	1	-1.67	-1.67	–	-1.67

Table 2: Descriptive Statistics

		count	percentage	count	percentage
Negative	significant	122	37%	215	67%
	insignificant	93	29%		
Positve	significant	42	13%	109	33%
	insignificant	67	21%		
Total		324	100%	324	100%

Figure 1: Frequency distribution of the t-statistics

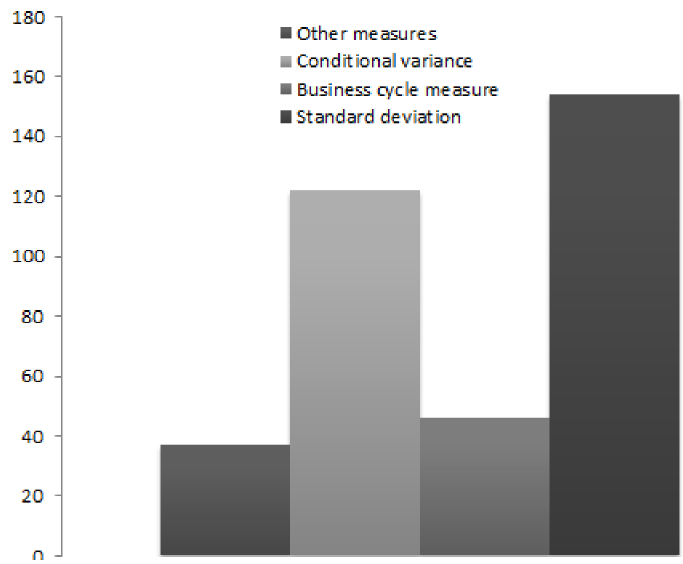

Figure 2: Distribution of studies by volatility measures

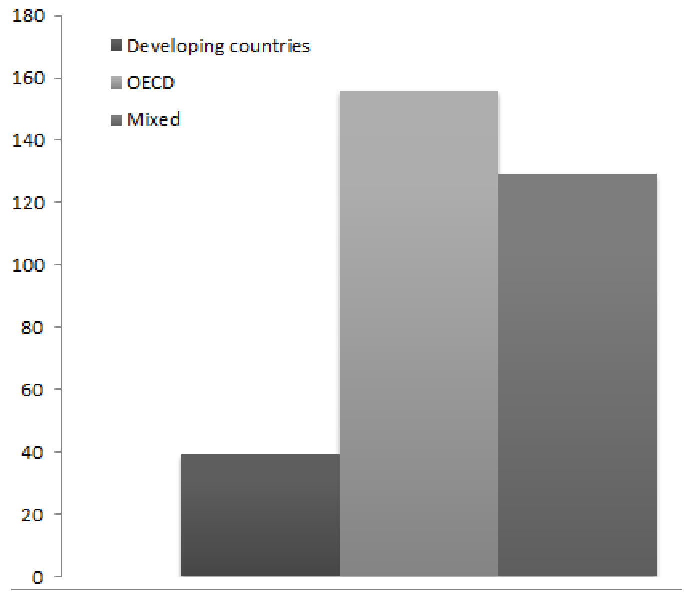

Figure 3: Distribution of studies by sample size

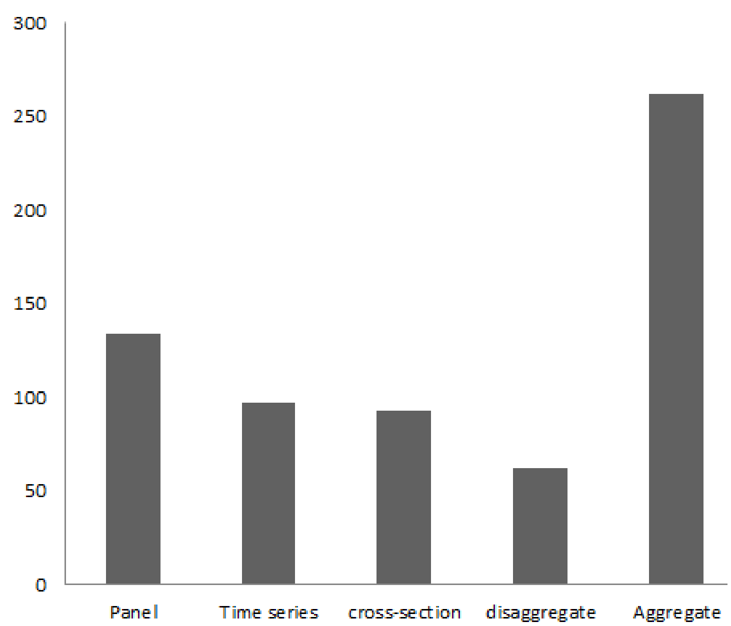

Figure 4: Distribution of studies by data type

3.2 Model specification

The second step of the research focuses on meta-analysis to characterize empirical findings and subsequently identify the heterogeneity across and within studies. When collecting data, we observe that, the t-statistics diverge between and within studies, thus our dataset can be considered as a two-level structure. The between differences correspond to level 1 whereas the within information are located at level two. As Bumann et al. (2013) and De Dominicis et al. (2008), we rely on the following two-level mixed effect model:

$$\begin{aligned} \text{Level1 :} \quad & T_{ij} = \beta_{0j} + \beta_1 X_{ij}^1 + ... + \beta_k X_{ij}^k + e_{ij} \\ \text{Level2 :} \quad & \beta_{0j} = \beta_0 + U_{0j} \end{aligned} \tag{1}$$

where the dependent variable T_{ij} is the reported individual t-statistic (i) within a given study (jth) , X_{ij}^k is a vector of meta-independent variables reflecting differences across studies including K elements (moderator variables). Our decision to use t-statistic as the effect size measure is motivated by the fact that, the measure of volatility is not homogeneous in the empirical literature. On the other hand, t-statistics are presumed to influence the study outcome (Mookerjee (2006)). β_{0j} is the intercept that varies between studies as indicated by j and is a function of an average intercept (β_0) and a random effect (U_{0j}) with $U_{0j} \sim iid(0, \sigma_u^2)$. Finally $e_{ij} \sim N(0, \sigma_e^2)$ is the error term and σ_e^2 indicates the within-variance. This model specification corresponds to the mixed effects models, which account for fixed effects and random effects.

3.3 Moderator variables

In this section, we consider moderator variables that may potentially impact on the reported effect of output volatility on economic growth. Table 3 presents the definition of the explanatory variables used in the meta-regression analysis.

The first set of the explanatory variables are related to the measures of output volatility. So, we consider the most used measures of volatility: business cycle (BC), output growth volatility (SD) which are the standard deviation of detrended data and GDP growth respectively, and conditional variance(CV). Since, the effect of output volatility could depend on the level of economic development, we distinguish between OECD and developing countries. We also create a dummy variable which takes one if a study considers other types of volatility as inflation or trade volatility. In addition, we control for data characteristics as the number of countries. Moreover, we introduce dummies for studies considering aggregate or disaggregate data. Our analysis further controls for data types used across studies: dummy variables are employed for panel, cross-section and time series data. To investigate whether the econometric methodology matters on the growth-volatility relationship we include a dummy variable which equals one if a study addresses the endogeneity issue and zero otherwise. Our choice is based on the idea that, in macroeconomics every variable is virtually endogenous (Kocherlakota et al. (2010)), thus, it is important to control for endogeneity. Since differences among the regression results may be partly explained by the data sources, we construct a dummy variable for data sources taking one if the data source is Penn world Table, zero otherwise. Finally, we consider commonly used control variables in the empirical growth literature, so we created eight dummies for trade, investment, government, demographics, human capital, financial development, institution and inflation. The last set of the explanatory variables are related to differences in publication: we assign a dummy variable reflecting that a study is published in an academic journal or is a working paper.

Table 3: Moderator Variables

Variables	Description	Mean	Standard deviation
	Variables related to the measure of volatility		
BC	= 1 if the standard deviation of detrended variables is used to measure volatility, 0 otherwise.	0.35	0.14
sdvol	= 1 if standard deviation of output growth is used to measure volatility, 0 otherwise.	0.47	0.5
CV	= 1 if conditional variance is used to measure volatility, 0 otherwise.	0.37	0.48
	Variables related to the sample		
Developed	= 1 if the study employs OECD countries, 0 otherwise.	0.48	0.5

Continued on next page

Table 3: Moderator Variables

Variables	Description	Mean	Standard deviation
Developing	= 1 if the study focuses on developing countries, 0 otherwise.	0.12	0.325
N of countries	number of countries in the study.	48.38	53.16
PWT	= 1 if the study employs data from penn world table, 0 otherwise.	0.26	0.44
Panel	= 1 if the study uses panel data, 0 otherwise.	0.42	0.49
Cross-section	= 1 if the study uses cross-section, 0 otherwise.	0.28	0.45
Time series	= 1 if the study uses time series data, 0 otherwise.	0.3	0.46
aggregate	= 1 if the study employs macro data.	0.8	0.39

Continued on next page

Table 3: Moderator Variables

Variables	Description	Mean	Standard deviation
Endogeneity	= 1 if the estimation method address endogeneity, 0 otherwise.	0.21	0.41
	Variables related to economic conditions		
Trade	= 1 if a trade variable is included.	0.09	0.29
Human capital	= 1 if a human capital variable is included.	0.14	0.35
Institution	if a variable of institution is used.	0.1	0.3
FD	= 1 if a variable of financial development is included .	0.07	0.25
investment	= 1 if investment is used.	0.22	0.42
Demographics	= 1 if population growth is included.	0.35	0.48

Continued on next page

Table 3: Moderator Variables

Variables	Description	Mean	Standard deviation
Government	= 1 if government spending is used.	0.08	0.28
Additional volatility	= 1 if the study employs other type of volatility as inflation or trade volatility	0.11	0.32
	Variables related to differences in publication		
Working papers	= 1 if the study is a working paper and was not published, 0 otherwise.	0.16	0.36
Journal	= 1 if the study was published in a journal, 0 otherwise.	0.84	0.36

Notes: all variables, except N of countries take values 0 or 1.

4 Meta-regression Results

Table 4 presents the results of the meta-regression from the hierarchical linear model. Column 1 through 5 report the results of the analysis when decomposing the variability measure into two components: standard deviation of output growth rate and standard deviation of detrended data. Column 1 shows that, studies that use variability measures based on either standard deviation of deterended data or output growth rates, tend to report higher effects of output volatility on growth than those that use the uncertainty measure. Which implies that, the measure of volatility based on the total variability tends to overestimate the effect of output volatility on economic growth because it encompasses predictable and unpredictable volatility (Aizenman and Pinto (2005)). Column 2 considers the heterogeneity based on countries group. We find that, the negative effects of volatility on growth tend to be exacerbated in developing countries, confirming the findings of Hnatkovska and Loayza (2004). The results in column 3 suggest that while cross-sectional data studies are not statistically different from panel data, times series studies tend to report strongly positive effects than studies using panel data. Also the econometric methodology matters. Studies using IV/GMM inference find on average, significantly negative effects than studies using OLS or GARCH estimator. This is not surprising because, models such as GARCH models are mostly bivariate regressions and do not include the explanatory variables commonly used in the growth literature. This suggests that GARCH models may suffer from omitted variable bias and endogeneity, which is in accordance with Klomp and Valckx (2014). Moreover Lamoureux and Lastrapes (1990) shows that misspecifications in GARCH models lead to upward biases in estimates which is in accrodance with our findings. The results from column 4 confirm that the link between output volatility and growth is significantly negative in developing countries. The results also suggest that the number of countries as well as the type of data used (aggregate or disaggregate) influence the reported results. Finally, we add conditioning variables commonly used in the growth literature. The results are displayed in column 5. Only two conditioning variables are found to be significant. Studies using government expenditure tend to report higher t-statistics, whereas those studies that incorporate demographics report, on average negative effects of output volatility on economic growth.

However, estimates based on equation (1) may suffer from publication bias, since smaller studies tend to search for larger effects in order to compensate for their larger standard errors Doucouliagos (2005).

Table 4: Meta-Regression Analysis

Dependent variable t-statistics	(1)	(2)	(3)	(4)	(5)
BC	5.263***	5.218***	17.86***	15.15***	14.91***
	(3.26)	(3.21)	(8.88)	(7.23)	(6.65)
sdvol	3.581***	3.608***	16.71***	13.89***	14.15***
	(3.17)	(3.18)	(9.27)	(7.15)	(7.08)
Developing		-0.424	-3.194**	-3.852***	-4.551***
		(-0.26)	(-2.44)	(-2.96)	(-3.34)
cross-section			0.222	0.495	1.435
			(0.20)	(0.44)	(1.09)
time-series			16.53***	11.50***	11.91***
			(8.28)	(4.73)	(4.78)
Endogeneity			-5.387***	-2.212	-2.868 *
			(-4.18)	(-1.43)	(-1.73)
Aggregate				-0.396	-0.550
				(-0.26)	(-0.38)
N of countries				-0.0534***	-0.0396**
				(-3.78)	(-2.38)
PWT				0.285	-0.298
				(0.25)	(-0.23)
Additional volatility					-1.854
					(-0.86)
Trade					1.156
					(0.54)
Investment					0.0557
					(0.03)
Government					4.013**
					(2.23)
Human capital					0.464
					(0.28)
Demographics					-2.943*
					(-1.95)
FD					0.0629
					(0.03)
institution					1.078
					(0.62)
Inflation					2.060
					(1.15)
Constant	-5.586***	-5.542***	-17.10***	-11.36***	-12.08***
	(-6.64)	(-6.46)	(-9.19)	(-4.27)	(-4.55)
Observations	324	324	324	324	324

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.1 publication bias

Publication bias occurs when editors, reviewers or researchers have a preference for statistically significant results (Stanley (2008)). In other words, papers reporting insignificant results are either not submitted or are rejected by the editors (Bom and Ligthart (2014)). Thus, studies that find relatively small and insignificant effects are much less likely to be published, because they may be thought to say little about the phenomenon in question (Stanley et al. (2008)). Publication bias is particularly strong in fields that show little disagreement about the correct sign of the parameter. Whereas research area where there is widely accepted theoretical support for both positive and negative effects, are likely to be free of significant publication bias because all empirical outcomes are consistent with theory. Consequently, we expect publication bias to be no significant in the volatility-growth literature.

The simplest way to detect publication bias is the funnel graph, which is a scatter diagram of an empirical precision (i.e. the inverse of the standard error, or 1/SE) and the t-statistics (the effect size). The funnel plot is based on the idea that studies with a smaller sample size should have larger sampling error than those with a larger sample size Doucouliagos (2005). Consequently, the volatility-growth relationship in smaller studies should have a larger spread around the mean effect, which itself could be positive, negative or zero. In the absence of publication selection and regardless of which measure of precision one uses, a funnel graph should be symmetric and shaped approximately as an inverted funnel (Stanley and Doucouliagos (2010)).

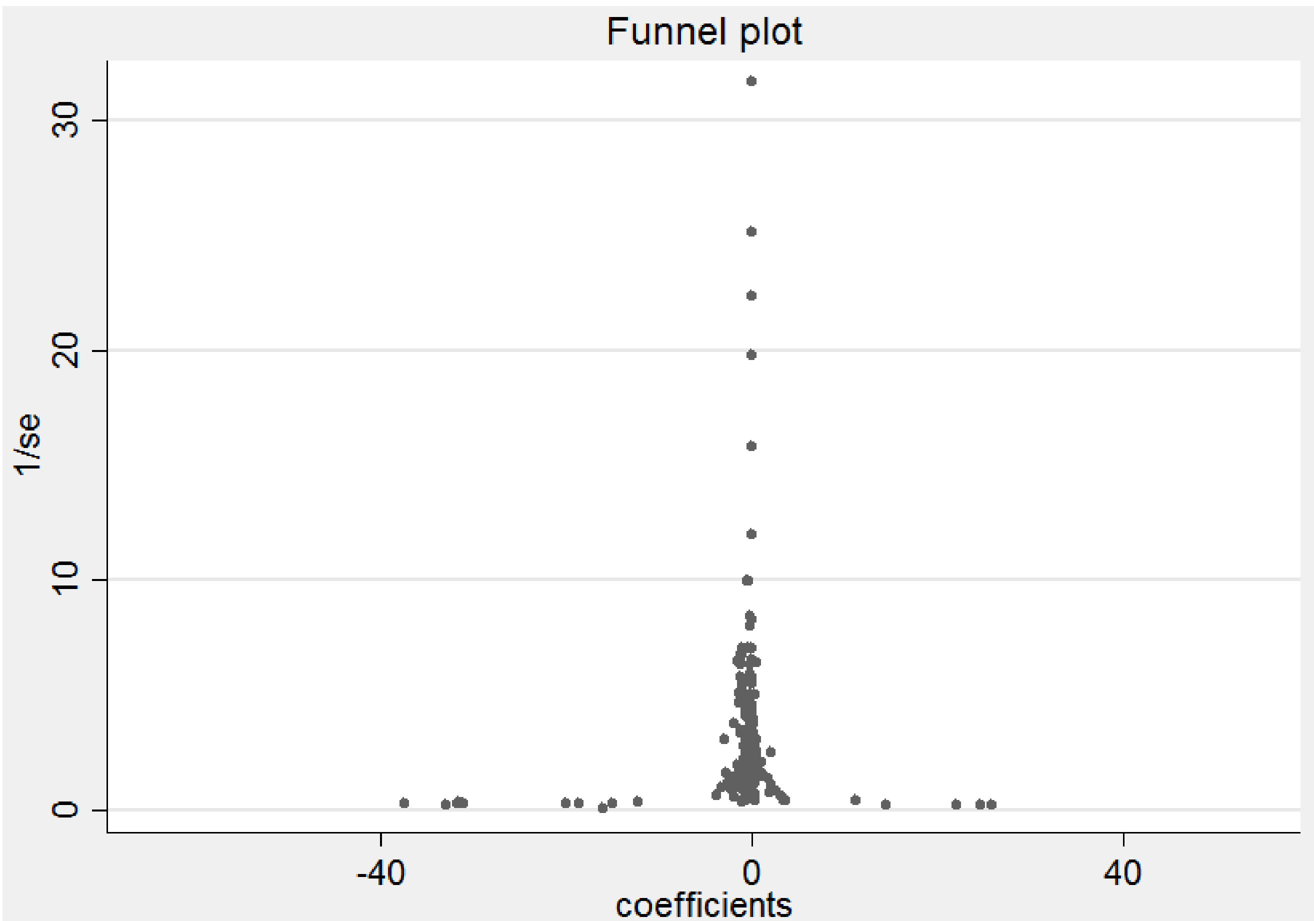

Figure 5: Funnel plot of the effects of output volatility on economic growth

The funnel plot in Figure 4 looks lightly skewed to the left as the plot is over-weighted at the left hand side. Thus, the visual inspection suggests a weak publication bias toward negative effects of output volatility on economic growth.

Even if funnel plots help in tracing publication bias, or in general small study effects in the data, visual assessment of funnel plot is essentially subjective. Furthermore, funnel plot asymmetry is not necessarily due to publication bias. It may arise from heterogeneity in underlying effects and/or low methodology quality of smaller study. So, funnel plots may be considered as generic means for investigating small study effects, not as a tool to diagnose a specific type of bias Mekasha and Tarp (2013). Hence the importance of running an objective statistical test for publication selection. The most documented formal analysis for publication bias (the "Funnel Asymmetry Test" (FAT)) was developed by Egger et al. (1997). The test is based on the following model:

$$\text{effect}_i = \beta_0 + \beta_1 SE_i + \varepsilon_i \tag{2}$$

where effect_i is the focus of the analysis (output volatility on economic growth) or the t-statistics, SE_i the corresponding standard errors and ε_i is the error term. In the absence of publication selection, the estimated empirical effect should be independent of its standard error, that is, β_1 should be equal to zero. Similarly, estimated effects will vary randomly around the "true" effect, β_0. However, studies attempt to explain the same relationship through different econometric methodologies and sample sizes, which leads to heteroschedastic standard errors in equation 2. Thus, Stanley (2008) suggests to solve this issue by weighting equation 2 by standard errors. So equation 2 can be rewritten in the following way:

$$t_i = {}^{\text{effect}_i}/_{\text{SE}_i} \;= \beta_1 + \beta_0({}^1/_{\text{SE}_i}) + e_i \tag{3}$$

Which in the hierarchical model corresponds to the following equation:

$$\begin{aligned} \text{Level1}: \quad & t_{ij} = \beta_{0j} + \beta_{00}({}^1/_{\text{SE}_i}) + \beta_1(X^1_{ij}/SE_i) + \beta_k(X^K_{ij}/SE_i) + e_{ij} \\ \text{Level2}: \quad & \beta_{0j} = \beta_0 + U_{0j} \end{aligned} \tag{4}$$

where t_{ij} is the i^{th} t-statistic of study j. X are the meta-independent variables. e_{ij} and U_{0j} are respectively the error terms at the observational level (level 1) and at the study level. The results of the FAT (funnel asymmetry test) are reported in Table 5. In the first column the constant term is negative and weakly significant, indicating the presence of a weak publication bias, however the coefficient of the inverse standard error, i.e. the true effect, is negative and statistically insignificant. The simple FAT alone is not enough to determine the genuine effect of output volatility on economic growth, because of differences across important research dimensions such as the level of economic development, time periods, econometric methodologies. Thus, the researcher needs to account for those factors in his/her meta-analysis. The results of the test with moderator variables are reported in column 2. The constant is no longer significant suggesting an absence of publication bias. However, we note that the coefficient of the inverse standard deviation becomes highly significant, implying negative and significant effect of output volatility on economic growth which is at odd with the literature suggesting the inverse relationship. Moreover, while variables as the number of countries and demographics become insignificant, variables such as Penn World table and institution quality become significant. Therefore, we identify several variables that significantly influence the reported effect of output volatility on economic growth. The measure of output volatility continues to be an important determinant of the volatility-growth relationship. On average, studies that measure variability rather than uncertainty tend to report larger effects of output volatility on economic growth. We also note from column 2 that the effect is almost the same whatever the measure of variability confirming the findings of Blanchard and Simon (2001). Also the level of economic development matters. Studies that focus on developing countries report on average, significantly lower t-statistics, confirming that the negative effects of output volatility are larger in developing countries (Loayza et al. (2007)). Column 2 suggest that, time series data analysis tend to find significantly positive effects of output volatility than does the panel data. On the other hand, cross-section data are not significantly different from panel data. It seems that, the number of observations is not an important determinant of a study's outcome. Studies that take into account endogeneity report strongly negative effects compared to studies that ignore the endogeneity issue. Controlling for inflation, seems to be without any effect, whereas controlling for government size leads to higher t-statistics. The sign of the relationship seems to be related to the sources of data employed in the studies. Indeed, data from Penn world table seem to provide lower estimates than other data sources. The inclusion of other type of volatility (such as nominal volatility), as well as the variable of trade, the level of education and financial development do not significantly impact on the study's outcome. However, the quality of institutions plays an important role in the volatility-growth link. The meta-regression results show that studies that control for the quality of institutions, report significantly negative effects of volatility and economic growth.

In column 3 we control for publication differences. The results are quite similar to those of column 2 with some differences. Human capital and investment variables become significant. The first show that countries controlling for investment report, on average higher t-statistics, whereas considering the level of education conducts to negative effects of output volatility on economic growth. The analysis shows that working papers tend to report strongly positive estimates than published papers. Finally, the constant term turns to be negative and weakly significant implying a downward publication bias.

Table 5: Publication selection bias

Dependent variable t-statistics	(1)	(2)	(3)
1/se	-0.00961 **	-0.231*	-0.381***
	(-2.57)	(-4.16)	(-4.04)
BC/se		0.390***	0.445***
		(3.32)	(3.91)
sdvol/se		0.393***	0.467***
		(5.13)	(6.19)
Developing/se		-0.0254***	-0.0258***
		(-3.02)	(-3.18)
Cross-section/se		-0.0758	-0.0857
		(-0.88)	(-1.03)
Time-series/se		0.205**	0.351***
		(2.23)	(3.75)
Endogeneity/se		-0.847***	-0.841***
		(-4.01)	(-4.12)
Aggregate/se		0.0345*	0.0402**
		(2.38)	(2.86)
N of countires/se		0.000339	-0.000276
		(0.21)	(-0.18)
PWT/se		-0.236*	-0.0858
		(-2.05)	(-0.74)
Additional volatility/se		-0.0125	0.0804
		(-0.07)	(0.48)
Trade/se		-0.0110	0.0759
		(-0.06)	(0.41)
Investment/se		0.184	0.347**
		(1.16)	(2.22)
Government/se		0.637***	0.359*
		(4.51)	(2.43)
Human capital/se		-0.177	-0.306*
		(-1.46)	(-2.54)
Demographics/se		-0.187	-0.152
		(-1.61)	(-1.35)
FD/se		0.178	0.0842
		(0.91)	(0.45)
institution/se		-0.324**	-0.350**
		(-2.03)	(-2.27)
Inflation/se		0.0701	0.121
		(0.87)	(1.55)
Working paper/se			0.431***
			(4.90)
Constant	-2.205 *	-0.414	-0.721*
	(-1.95)	(-1.02)	(-1.82)
Observations	324	324	324

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.2 Robustness check escluding 5% extreme values

To test the robustness of the results in Table 5, we proceed to the exclusion of the 5% of the most extreme values. The results are displayed in Table 6 and are quite similar to that of the previous analysis. In particular, the genuine negative effect of output volatility on economic growth still holds, whereas the publication bias disappears completely. We find that the t-statistics tend to be higher when investment, time series and government spending are considered. Nevertheless, the relationship becomes negative, when the study considers the endogeneity issue, the quality of institutions and the level of economic development. Controlling for investment makes t-values significantly positive only when we control for publication differences. The negative effect continues to hold in developing countries. The results from working papers are positive and statistically different from that of journal published papers.

Overall, our findings point to the absence of publication bias in the volatility-growth literature, and to the existence of a genuine detrimental effect of output volatility and economic growth. Moreover, many variables influence the volatility-growth link. More specifically, studies using the variability measures as the volatility indicator tend to report larger estimates than those using the measure of uncertainty. However, it is hard to identify an appropriate measure of volatility: commonly used measures embody arbitrary assumptions (Malik and Temple (2009)). The positive effect holds also when the variables of government spending, investment and aggregate data are considered in the analysis. Which is not really surprising, since macroeconomic variables such as government spending and investment are strongly correlated with output growth, hence the need to correct for endogeneity. On the other hand, controlling for institution quality, the level of economic development and human capital implies strong negative effects of volatility and growth. Finally, time series tend to report strong positive results relative to panel data.

Table 6: Robustness Check

Dependent variable t-statistics	(1)	(2)	(3)
1/se	-0.00937	-0.233**	-0.382***
	(-1.46)	(-2.47)	(-3.96)
BC/se		0.390**	0.445***
		(3.25)	(3.82)
sdvol/se		0.391***	0.466***
		(4.99)	(6.03)
developing/se		-0.0253***	-0.0258**
		(-2.95)	(-3.11)
Cross-section/se		-0.0754	-0.0853
		(-0.86)	(-1.01)
Time-series/se		0.207**	0.351***
		(2.20)	(3.68)
Endogeneity/se		-0.849***	-0.842***
		(-3.93)	(-4.04)
Aggregate/se		0.0348**	0.0403***
		(2.34)	(2.80)
N of countries/se		0.000360	-0.000262
		(0.22)	(-0.17)
PWT/se		-0.235**	-0.0862
		(-2.00)	(-0.73)
Additional volatility/se		-0.0129	0.0799
		(-0.07)	(0.46)
Trade/se		-0.0124	0.0747
		(-0.06)	(0.40)
Investment/se		0.183	0.346**
		(1.13)	(2.17)
Government/se		0.638***	0.360**
		(4.42)	(2.39)
Human capital/se		-0.178	-0.305**
		(-1.43)	(-2.48)
Demographics/se		-0.188	-0.152
		(-1.58)	(-1.33)
FD/se		0.179	0.0852
		(0.90)	(0.44)
Institutions/se		-0.328**	-0.352**
		(-2.01)	(-2.23)
Inflation/se		0.0705	0.121
		(0.86)	(1.51)
Working paper/se			0.430***
			(4.78)
Constant	-2.265 *	-0.346	-0.678
	(-1.92)	(-0.80)	(-1.61)
Observations	308	308	308

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5 Conclusion

The empirical literature on the relationship between volatility and growth is ambiguous. Some studies advocate a positive relationship, whereas others suggest a negative one. The present paper investigates the reason of the inconclusiveness existing in the literature, as well as, the true impact of output volatility on economic growth. Specifically, we run meta-regression analysis using 324 t-statistics from 39 studies. Moreover, we examine whether the differences within and between studies may be explained by the volatility measure, country samples and the estimation method.

Our main findings can be summarized as follows. First, we do not find evidence of publication selection bias in the volatility-growth literature suggesting an efficient selection of papers by the reviewers. In addition, we show that the volatility-growth link is negative and significant. In particular, developing countries are the most affected by the detrimental effects of volatility on economic growth. The heterogeneity across studies also depends on the measure of output volatility. Moreover, we show which control variables really matter for the volatility-growth link. Studies that control for human capital, institution quality and endogeneity tend to report strong negative effects of output volatility on economic growth. While studies controlling for investment, time series and government spending report positive effects.

Our analysis suggests that, output volatility decreases growth. Moreover, these detrimental effects are aggravated by poor institutions, low level of education and poor growth. Furthermore, the thesis of strong positive effects of output volatility on economic growth, may be biased because of omitted variables and endogeneity based estimations. A significant number of studies suggesting that output volatility fosters growth focuses on unpredictable volatility that is, on uncertainty. However, this literature mainly employs disaggregate data, time series and econometric methodologies that ignore potential simultaneity between output volatility and economic growth: the endogeneity issue. On the other hand, the relationship becomes negative when panel data are used and the endogeneity issue is addressed. For instance, Ramey and Ramey (1995) and Rafferty (2005) confirm that unpredictable volatility is detrimental to growth and the consequences of the recent financial crisis strengthens this thesis. Moreover, Ramey and Ramey (1995) suggest that, because most movements are unpredictable, measures of combined volatility have a "net negative effect". In other words, uncertainty as well as variability are harmful to growth.

Our results have also important policy implications. Assuming output volatility increases growth implies the existence of a kind of trade-off between output volatility and economic growth and costs from stabilization policies. However, we learned from the recent global crisis that, output volatility is a concern since it induces welfare costs, thus, policymakers should intervene in order to stabilize the economy and avoid the disastrous effects of output volatility that tend to propagate rapidly due to cross-country dependence. Finally, given the limits of econometrics to make predictions about economic activity, basic theory, shrewd observation, and common sense are surely more reliable guides for policy (Mankiw et al. (1995)).

Conclusion

This dissertation presented three independent essays that focus on the relationship between output volatility and economic growth. Special attention is given to cross-section dependence, heterogeneity, endogeneity and non-linearity.

The first chapter addressed cross-section dependence and heterogeneity issues in the relationship between output volatility and economic growth. The study focuses on a sample of 85 countries from 1975-2006. Then, the sample is split into OECD and developing countries. The results confirm the detrimental effects of output volatility on economic growth, however, the most affected by these detrimental effects are developing countries. Additionally, OECD countries become more vulnerable to shocks due to high economic integration and to the persistence of common shocks implying a propagation mechanism through international trade and financial co-movements.

The higher sensitivity to macroeconomic fluctuations in developing countries is often attributed to low level of financial deepening. More specifically, it has been shown that low degree of financial development predicts higher sensitivity of economic growth to exogenous shocks (Aghion and Banerjee (2005)).The existing literature recognizes the detrimental effects of output volatility on economic growth, but has not explored potential nonlinearities between volatility and growth in panel smoothing regression models. Additionally, no study except Law and Singh (2014) attempt to estimate the optimal level of private credit at which financial development promotes growth. The second essay tries to contribute to the literature by assessing how output volatility affects growth when we consider the level of economic and financial development. The study is based on a sample of 64 countries from 1980 to 2010 and the estimates are run with panel smoothing transition regression models. Our analysis suggests that poorly or excessively developed financial markets tend to increase vulnerability to shocks. Moreover, the study further confirms that, low-income economies are the most affected by the negative effects of output volatility, and that financial development tend to be harmful in low and high income economies. Hence, financial development promotes growth and stability only at intermediate level of financial and economic development. Finally, under a given level of private credit, output volatility tends to have no significant effects on growth. Implying that under some circumstances financial development may dampen the detrimental effects of output volatility on growth, but it never leads to positive and significant effects of volatility on economic growth.

Looking back at the previous literature on the relationship between output volatility and economic growth, the main conclusions are quite ambiguous. Indeed, the first strand advocate a positive relationship (Caporale and McKiernan (1996), Kormendi and Meguire (1985)). The second strand shows negative results (Ramey and Ramey (1995), Henry & Olekans (2002), Tochkov and Tochkov (2009), Aghion and Banerjee (2005) and Badinger (2010)). The third and last chapter attempts to explain the reasons of this ambiguity through meta-analysis. The aim of this analysis is to find the true effect of output volatility on economic growth and to explain why the empirical results change from one study to another.

The results confirm that output volatility adversely affects economic growth. The positive effects found in the literature depend mostly on the measure of volatility, the sample and econometric methodology. A significant number of studies suggesting that output volatility fosters growth focuses on unpredictable, volatility that is, on uncertainty. However, this literature mainly employs disaggregate data, time series and econometric methodologies that ignore potential simultaneity between output volatility and economic growth: the endogeneity issue. However, endogeneity could raise a issue of weak or too many instruments leading to overidentification. Even though, some research in this area suggest various tools to handle

these issues, macroeconomic variables are so interrelated that it is really difficult to come up with good instruments.
The broader conclusions drawn from this dissertation are in line with other studies and are the following. We confirm the findings of Ramey and Ramey (1995) on detrimental effects of output volatility on economic growth and of the "vanishing effects" of finance reported in the recent finance-growth literature. In particular, we find a limit beyond which financial development looses its effectiveness in mitigating shocks and enhancing growth. Moreover, we show that poorly or excessively developed financial markets tend to increase macroeconomic instability and adversely affect growth. The other conclusion of this thesis is that under some circumstances, financial development may contribute to higher resilience to shocks, but it does not lead to positive and significant effects of macroeconomic fluctuations on economic growth. Therefore, studies suggesting an existence of a trade-off between volatility and growth may be biased due to endogeneity.

Our analysis may have important policy implications for financial liberalization in developing countries. Financial intermediation in countries at early stages of economic development is costly, since it increases volatility and the likelihood of crises. Thus, they need to delay financial intermediation until a sufficiently high level of income is achieved. We learned from the global crisis that financially developed economies are not self-stabilizing and that large financial systems tend to expose economies to shocks that tend to spread rapidly due to cross-country dependence. Hence, the need to implement robust micro and macroprudential regulation in order to reap the benefits of deep financial markets without increasing economic instability.

6 Further research areas

Our research can be extended in a number of directions. While the study in the second chapter spanning over 1975-2006, allows us to improve our understanding about the volatility-growth relationship, we can further enhance this understanding by considering structural breaks in the context of cross-section dependence. Our future agenda, also includes updating the data set to introduce the effects of the global crisis in our analysis. Second, in the third chapter, we investigate how the volatility-growth link is influenced by the level of economic and financial development. However, we do not estimate the threshold of output volatility under which financial development fosters growth. A possible extension of this study might be to assess whether there exists an optimal level of volatility that favors growth. Another area of research, may be to exploit the PSTR models to estimate the optimal level of exchange rate that may fasten growth in the CFA zone countries.

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