THE RIMINI CENTRE FOR ECONOMIC ANALYSIS

WP 17-12

Dimitrios Bakas
Nottingham Trent University, UK
The Rimini Centre for Economic Analysis

Georgios Chortareas
King's College London, UK
University of Athens, Greece

Georgios Magkonis
University of Bradford, UK

VOLATILITY AND GROWTH: A NOT SO STRAIGHTFORWARD RELATIONSHIP

The Rimini Centre for Economic Analysis
75 University Ave W., LH3079, Waterloo, Ontario, Canada, N2L3C5
www.rcfea.org

Volatility and Growth: A not so straightforward relationship

Dimitrios Bakas[a,e], Georgios Chortareas[b,c], Georgios Magkonis[d]

[a]*Nottingham Business School, Nottingham Trent University, UK*
[b]*School of Management and Business, King's College London, UK*
[c]*Department of Economics, University of Athens, Greece*
[d]*School of Management, University of Bradford, UK*
[e]*Rimini Centre for Economic Analysis (RCEA), Italy*

E-mail: dimitrios.bakas@ntu.ac.uk, georgios.chortareas@kcl.ac.uk and g.magkonis@bradford.ac.uk

Abstract

This paper is motivated by the conflicting theories and empirical evidence regarding the relationship between business cycle volatility and economic growth. The average reported effect of volatility on growth is negative, but the empirical estimates vary substantially across studies. We identify the factors that explain the heterogeneity of the estimates by conducting a meta-analysis. Our evidence suggests that researchers' choices regarding the measure of volatility, the control set of the estimated equation, the estimation methods, and the data characteristics play a significant role in the total outcome. Finally, the literature is found to be free of publication bias.

Keywords: *Economic Growth, Volatility, Business Cycles, Meta-Analysis, Bayesian Model Averaging*

JEL Classification: *C83, E32, O40*

1. Introduction

The connection between the business cycle and economic growth has been extensively explored in modern macroeconomics. The direction of the effect of business cycle volatility on economic growth, however, is still ambiguous and no consensus exists either in the theoretical or in the empirical literature. A number of theoretical models attempt to identify the impact of volatility on growth with divergent conclusions.[1] Several theoretical rationales exist suggesting either a positive relationship (Schumpeter, 1939, 1942; Black, 1987; Aghion and Saint-Paul, 1998) or a negative relationship (Arrow, 1962; Stadler, 1990; Martin and Rogers, 2000), or even no association at all (Friedman, 1968) between business cycles volatility and growth. Motivated by the absence of a clear theoretical consensus, several studies attempt to resolve this issue empirically, overcoming the existing ambiguity. Nevertheless, the extensive empirical literature on the link between volatility and growth has also been proven inconclusive.

The extant empirical literature investigating the relationship between volatility and growth, builds on the work of Ramey and Ramey (1995). In general, the empirical contributions follow two different paths. On the one hand, most studies on the volatility-growth link follow the empirical literature on growth determinants employing growth regressions. On the other hand, several empirical contributions utilise the generalised auto-regressive conditional heteroskedasticity (GARCH) model to analyse the relationship between output fluctuations and growth.

Most of the existing empirical evidence supports a negative association exists between business cycles and growth (Ramey and Ramey, 1995; Martin and Rogers, 2000; Kneller and Young, 2001), while several others (Kormendi and Meguire, 1985; Caporale and McKiernan, 1996; Fountas and Karanasos, 2006) point to a positive link. Finally, a few studies report a lack of association between the two variables (Speight,

[1] See Priesmeier and Stahler (2011) for a review of the literature.

1999; Grier and Perry, 2000; Fang and Miller, 2008). In summary, the literature is far from reaching a consensus on the sign of the relationship between growth and cyclical fluctuations on either theoretical or empirical grounds.

According to more than one thousand econometric estimates collected from 84 empirical studies on the effect of output volatility on growth, 41% of the point estimates indicate a statistically significant negative effect, 17% find a statistically significant positive effect, and 42% are not significant. The empirical studies report, on average, a negative impact of volatility on growth equals to -0.05, however, the individual estimates vary heavily both within and across studies. The absence of conclusive empirical evidence regarding the relationship between output volatility and growth motivates the need for a quantitative synthesis of research to explain the diverse empirical findings. Thus, we conduct a systematic meta-analysis to explore the sources of the heterogeneity in the empirical literature (Stanley and Jarrell, 1989; Stanley, 2001). Over the past three decades, meta-analytic studies have been applied to interpret the diverse, and often conflicting, empirical findings across many areas of economics (Card and Krueger, 1995; Disdier and Head, 2008; Card *et al.*, 2010; Doucouliagos *et al*. 2012; Havranek, 2015).

To the best of our knowledge, this is the first meta-analytic study on the literature of volatility and growth, and, thus, we aim to fill this gap. We collect and analyse 1010 estimates on the impact of volatility on economic growth, as reported in 84 empirical studies over the period 1985-2015. Our meta-analysis relies on two alternative methodological approaches to explore the sources of the empirical heterogeneity: a Bayesian Model Averaging (BMA) method and an ordered probit model, both controlling for several aspects of the empirical research. The BMA method allows to address modelling uncertainty stemming from the large number of potential explanatory variables in the meta-regression specification. The ordered probit model allows to overcome the potential erroneous inference due to the incomparability of alternative volatility measures. The empirical literature uses alternative measures for output volatility; e.g., standard deviation (SD) vs. GARCH. This diverse set of volatility measures may rise concerns regarding the direct comparison of the estimated effect across empirical studies. In total, we take into account for five groups of potential factors: i) differences in variables used, ii) modelling specifications, iii) dataset characteristics, iv) differences in estimation strategies and v) publication characteristics.

Our results show that certain aspects of the empirical research design are crucial in explaining the heterogeneity of the estimates. Specifically, the choice of volatility measure matters; the use of an SD instead of a GARCH measure appears to be a key determinant of the observed heterogeneity of the collected coefficients. Additionally, certain aspects of the volatility-growth equation specification can explain the heterogeneous estimates. The presence of proxies for human capital, government size, and the inflation rate are significant sources of the observed empirical heterogeneity. The results show that studies accounting for the impact of human capital and the inflation rate in the empirical modelling increases the probability of obtaining a negative effect, while the inclusion of government size results in a higher probability of a positive effect. In contrast, the inclusion of proxies for financial development, financial integration, and trade openness does not seem to influence the results in a systematic way. Furthermore, several aspects of data characteristics emerge as decisive in explaining the heterogeneity of the literature estimates. These include the number of observations, the short-span of datasets and the presence of developing countries in the dataset. Interestingly, the negative relationship is more prominent in developing countries rather than in developed ones. In contrast, controlling for the period of great moderation does not affect the empirical estimates. Furthermore, controlling for endogeneity is an important determinant of the results that reveal a negative relationship. Finally, none of the publication-related variables is significant, indicating that the empirical literature is free from publication bias.

The remainder of the paper is structured as follows. **Section 2** discusses the theoretical and empirical literature on business cycle volatility and economic growth. **Section 3** describes the data selection process and the data characteristics. **Section 4** analyses the potential factors that explain the observed heterogeneity of the estimates. **Section 5** presents the results from our meta-regression analysis and, **Section 6** performs several robustness checks and provides further evidence. Finally, **Section 7** concludes.

2. Volatility and Growth: Theory and Empirics

2.1. The Theory of Volatility and Growth

Until the early 1980's, business cycles and economic growth have been typically treated as separated areas of macroeconomics (Ramey and Ramey, 1995). The real business cycle approach (Kydland and Prescott, 1982; Long and Plosser, 1987, among others) changed this perspective, suggesting that business cycle fluctuations constitute an integral part of the growth process (Aghion and Banerjee, 2005). Subsequently, several theoretical contributions have focused on the relationship between volatility and growth, providing alternative rationales for either positive or negative link.

Within the literature, two broad categories on the link between business cycles and economic growth exist, based on their prediction regarding the sign of the relationship. The route of the first group of studies traces its origins to Schumpeter's (1939, 1942) theory of 'creative destruction' corroborating the view that volatility and growth tend to correlate positively. The opposite view builds on Arrow's (1962) contribution on human capital formation with 'learning by doing'. Several growth models incorporating this hypothesis show that higher variability of economic fluctuations can have a negative impact on output.

According to the Schumpeterian view of economic development, recessions have a positive effect on an economy ('creative destruction'). Schumpeter interprets the process of capitalist development as a succession of expansionary and recessionary phases, emphasising the role of innovation in production. Over economic slowdowns the new technology replaces the old one, causing a rise in average productivity and, thus, higher economic growth. In a similar fashion, Black (1987) argues that a positive relationship exists between output volatility and growth. The implication is that economies face a trade-off between risk and return in their choice of technology, as economic agents choose to invest in riskier technologies only if they expect to yield a higher rate of return as compensation for the extra risk. Therefore, technologies with higher output volatility will be adopted by economic agents only if they offer a higher growth rate of output. More recent theoretical models incorporate the mechanism of 'creative destruction' and provide alternative explanations for the positive relationship including the 'disciplining' effect (Aghion and Saint-Paul, 1998), the 'cleaning-up' effect (Caballero and Hammour, 1994) and the 'opportunity costs' effect (Hall, 1991).

On the contrary, several approaches that model growth as an endogenous process give rise to a negative relation between business cycles and economic growth (see Aghion and Howitt, 1997, for a review). King *et al.* (1988) are the first to integrate endogenous growth theory with real business cycles. They show that temporary production disturbances can lead to permanent effects on output growth. Models that incorporate the 'learning by doing' mechanism of Arrow (1962), produce a negative effect of business cycle volatility on growth. Stadler (1990) uses the 'learning by doing' assumption to incorporate technical change and shows that volatility can negatively impact long-term growth. Similarly, Martin and Rogers (2000) show that the long-run growth rate is negatively related to business cycle volatility. The results of Blackburn's (1999) contribution constitute an exception. Blackburn (1999) uses a stochastic endogenous growth model with 'learning by doing' technology and suggests that there is a positive relationship between business cycle volatility and growth when technological improvements are complementary to production.

A series of papers exists, providing alternative explanations for a negative relationship between volatility and growth. Bernanke (1983) and Pindyck (1991) among others, suggest that the negative link between volatility and output growth emerges from investment irreversibility. Therefore, a higher level of business cycle volatility leads to a reduced level of investment and, consequently, to a lower level of capital accumulation and lower output growth. Finally, Aghion and Banerjee (2005) explore the interactions between volatility and growth using a Schumpeterian model with credit constraints and show that the level of financial development affects the negative relationship between volatility and growth. In particular, long-run growth is more sensitive to business cycles volatility in economies where the degree of financial development is lower.

2.2. The Empirics of Volatility and Growth

The empirical branch of the examined literature does not differentiate itself from the theoretical one as the evidence remains ambiguous.[2] A considerable number of empirical studies point to the presence of a negative link (Ramey and Ramey, 1995; Martin and Rogers, 2000; Kneller and Young, 2001; Badinger, 2010), while several others (Kormendi and Meguire, 1985; Caporale and McKiernan, 1996; 1998; Fountas and Karanasos, 2006) report a positive link. Finally, some studies suggest the absence of any association between the two variables (Speight, 1999; Grier and Perry, 2000; Fang and Miller, 2008).

The empirical literature can be divided into two sets of studies. The bulk of the empirical studies on the volatility-growth nexus follow the empirical work on growth

[2] See Dopke (2004) and Norrbin and Yigit (2005) for an extensive summary of the empirical literature.

determinants. According to this view, the specification of the link between business cycle volatility and economic growth is part of the growth regression modelling literature, where volatility is one of the explanatory variables for growth (e.g., Kormendi and Meguire, 1985; Grier and Tullock, 1989; and Ramey and Ramey, 1995; among others).

The second set of studies relies on generalised auto-regressive conditional heteroskedacity (GARCH) models to investigate the relationship between output fluctuations and growth (e.g., Caporale and McKiernan, 1998; Grier and Perry, 2000; Fountas and Karanasos, 2006; among others). Using the GARCH-in-mean model specification (Engle *et al.*, 1987) for output growth, these studies allow for the simultaneous estimation of both equations for the conditional mean and the conditional variance of output growth.

2.2.1. Volatility and Growth: Empirical Specifications

Kormendi and Meguire (1985) and subsequently Grier and Tullock (1989) are the first papers that investigate the relationship between growth and volatility as a part of an exploratory cross-country study on the macroeconomic determinants of economic growth. Ramey and Ramey (1995), however, set the benchmark in the empirical literature on volatility and growth. They calculate the mean and standard deviation of per capita annual growth rates over time for each country and examine the cross-country relationship between growth and volatility. Specifically, they estimate the following cross-country regression equation:

$$\Delta y_i = \alpha + \beta\sigma_i + u_i, \tag{1}$$

where Δy_i is the average growth rate of output and σ_i is the standard deviation of output growth in country i. In addition, they extend their analysis into a panel context and estimate:

$$\Delta y_{i,t} = \alpha_i + \beta\sigma_{i,t} + X'_{i,t}\,\theta + \varepsilon_{i,t}\,, \tag{2}$$

where $\Delta y_{i,t}$ is the growth rate of output for country i in year t, expressed as a log difference; α_i is the cross-section fixed effects; $\sigma_{i,t}$ is the standard deviation of the residuals that account for both the cross-section and time series dimensions; $X'_{i,t}$ is a vector of control variables; and θ is a vector of coefficients, which is assumed to be common across countries, while $\varepsilon_{i,t}$ is the error term. In both specifications, a significantly positive β estimate indicates that higher volatility is associated with higher economic growth, while a negative and significant β coefficient suggests that volatility and growth are inversely related.

Most of the above model specifications rely on the growth determinants literature and measure growth volatility with the standard deviation of the output growth rate, i.e., $\sigma = SD(\Delta y)$. Several authors employ GARCH models to obtain estimates of the time varying conditional variance measure of output growth variability. A common specification in this literature is the GARCH-in-mean model for output growth (see for example, Caporale and McKiernan, 1996; Fountas and Karanasos, 2006; Fang and Miller, 2008), which allows to simultaneously estimate equations for the conditional mean and variance of output growth. The empirical model can be summarised as follows:

$$\Delta y_t = \gamma_0 + \beta\sigma_t + e_t; \qquad e_t \sim N\,(0, \sigma_t^2) \tag{3}$$

with

$$\sigma^2_t = \delta_0 + \delta_1\, e^2_{t-1} + \delta_2\, \sigma^2_{t-1}, \tag{4}$$

where σ_t^2 denotes the conditional variance of output growth. The presence of the square root of the conditional variance, σ_t, as a regressor in the mean equation of the growth rate makes **Equation (3)** a GARCH-in-mean specification (Engle *et al.*, 1987). Clearly, again, a positive (negative) value of β implies that higher growth volatility leads to higher (lower) growth rates.

2.2.2. Volatility and Growth: Empirical Evidence

Early studies that employ cross sectional data provide some evidence for a positive link. Specifically, Kormendi and Meguire (1985) using a cross-section of 47 countries find a positive relationship between the mean growth rate and volatility of output (measured by the standard deviation of the growth rate). Grier and Tullock (1989), considering a broader sample of countries and employing pooled cross-section data analysis, provide evidence that uphold the positive relationship.

In contrast to these early findings, Ramey and Ramey (1995), using panel data and a sample of 92 countries, document a significant negative relationship between volatility and growth, which remains robust to the inclusion of country specific control variables. These findings question the Schumpeterian hypothesis of a positive nexus between volatility and growth. Several works confirm the results of Ramey and Ramey (1995), including Martin and Rogers (2000), Kneller and Young (2001), Aghion and Banerjee (2005) and Aghion *et al*. (2010), among others. For example, Martin and Rogers (2000) consider the impact of the 'learning by doing' hypothesis on the relation between growth and short-term instability at the aggregate level. Their evidence supports a statistically significant negative relation between growth and the amplitude of the business cycle, where the last is measured by the standard deviation of growth or the standard deviation of unemployment. Similarly, Kneller and Young (2001) estimate separately the long-run and short-run effects of volatility on growth, and provide evidence of a negative association between the two variables. More recent analyses by Dopke (2004), Norrbin and Yigit (2005), and Chatterjee and Shukayev (2006) put the Ramey and Ramey (1995) results through various robustness tests. Such checks employ several variations regarding the choice of countries, the time periods considered, the estimation methodologies, and the measurement of key variables. Norrbin and Yigit (2005) provide evidence of a robust negative relationship between the volatility and growth of output when the full sample of countries is used in their analysis. They show that the results of cross-country analyses are highly sensitive to the choice of time periods, the group of countries in the sample, and the estimation method employed.

Chatterjee and Shukayev (2006) show that the results of Ramey and Ramey (1995) are not robust to either the definition of the growth rate or the composition of the sample. They conclude that the relationship between the two variables in question is not significant. Dopke's (2004) results challenge further the presence of a negative relationship between volatility and growth. Furthermore, Aghion and Banerjee (2005) show that that the negative impact of volatility on growth depends on the degree of financial development in an economy. Therefore, they reconcile the finding of a strong negative effect of volatility on growth in the full sample of countries with that of a nonsignificant effect for the OECD countries. Adding further to the controversy, Imbs (2007) shows that the link between volatility and growth can be either positive or negative depending on the level of aggregation. Specifically, Imbs (2007) documents the existence of a negative link at the aggregate level (i.e., across countries), but when the analysis focuses on the sectoral level, the correlation among growth and volatility becomes positive.

The second strand in the literature consists of studies employing time series techniques (the GARCH-in-mean model) to measure output variability and allowing for a simultaneous estimation of the conditional mean and variance equations for output growth. A variety of studies that use this approach arrive at conflicting results. Caporale and McKiernan (1996) find a positive relationship for the UK and the US, whereas Fountas and Karanasos (2006) find a positive relationship for Germany and Japan. In contrast, Grier and Perry (2000) and Fountas and Karanasos (2006) conclude that no relationship exists for the US. Similarly, Fang and Miller (2008), accounting for possible structural changes in the volatility process, report a non-significant relationship between the output growth rate and its volatility for the US. Finally, Lee (2010) extends the GARCH-in-mean methodology into a dynamic panel context and provide evidence for the G7 countries, showing that while higher output growth is associated with higher volatility, higher growth does not lead to more economic uncertainty.

Finally, several papers explore the link of business cycles volatility on economic growth by introducing alternative channels, which can affect this relationship. Aghion and Banerjee (2005) stress the channel of financial development as an important determinant for the negative association between the two variables. Aghion *et al*. (2010) extend this view exploring the effects of financial frictions on the composition of investment over the business cycle, and the impact on economic growth. They find that financially underdeveloped countries have higher volatility, and exhibit a pronounced negative correlation between volatility and growth. Also, Furceri (2009) shows that business cycle volatility affects negatively output growth through higher levels of fiscal convergence across countries. Finally, Jetter (2014) suggests that volatility has not only a positive direct effect on growth, but also a negative indirect effect which operates through the insurance mechanism of government size. These findings provide some explanations for the ambiguity of the growth effect of volatility, which permeates the empirical literature.

3. Data Selection Process and Data Characteristics

We pursue the data collection process following the methodological steps suggested in Stanley *et al*. (2013). We initiate the paper selection process by searching in *Google Scholar*, which is regarded as the most inclusive database. To eliminate the possibility of overlooking any relevant study, we repeat the same process in *Econlit* and *Scopus*. The search includes several combinations of the keywords 'growth', 'economic growth' or 'output growth', with 'volatility', 'variability' or 'uncertainty'. This process produces 166 papers in total. We characterise each study as appropriate for inclusion to our meta-dataset when it reports at least one estimated coefficient of the effect of volatility on output growth. We exclude 82 of these studies either because they develop a theoretical argument or they do not provide sufficient information regarding the estimation results. This process leaves us with 84 studies.

Figure 1 portrays how the volatility-growth empirical literature has evolved over time. After the two initial publications in mid-1980s, there is a gap of almost one decade. The interest in business cycle volatility and its effects on growth resurges in the economic literature after the study of Romer and Romer (1995) and a clearly increasing trend appears after mid-1990s. A further surge of papers on the volatility-growth relationship coincides with the end of Great Moderation period. The financial turbulence of 2008-9 and the subsequent European sovereign crisis, both associated with higher levels of economic variability, motivate interest in the growth process in the context of a volatile environment. Since 2010, 31 relevant empirical studies have been published in peer-reviewed journals. This renewed interest and the volume of recent empirical contributions partly reflects the absence of an empirical consensus.

Figure 1 here – Number of Publications over Time

To obtain an overview of the meta-analytic data set we report the boxplot in **Figure 2**. We show the degree of dispersion of the estimates across and within studies, using the partial correlation coefficients from the 84 collected papers. We choose to base our analysis on partial correlation coefficients, and not on the direct estimated effects reported by the studies or the corresponding t-statistics. The reason is that the reported estimates are not comparable across studies due to different measures of volatility used. Following Doucouliagos *et al*. (2012) and Stanley and Doucouliagos (2012), we calculate the partial correlation coefficient, r_{ij}, from the t-statistics as; $r_{ij} = t_{ij}/\sqrt{t_{ij}^2 + df_{ij}}$ where t and df are the t-statistics and the degrees of freedom, respectively, while i and j refer to the i observation from the j study. The corresponding standard errors are equal to $\sqrt{(1 - r_{ij}^2)/df_{ij}}$. This approach renders all the estimates comparable regardless of the different volatility proxies used. The full sample of 84 studies consists of 70 published papers in peer-reviewed journals and the remaining 14 are working papers. Following the current consensus in meta-analytic literature, we include the working papers in our analysis (Stanley, 2001).[3] The wide range of variation, displayed by the partial correlation coefficient in the boxplot, suggests that a high degree of heterogeneity exists over the estimates, both within and across the empirical studies reported in the literature. We model explicitly this feature in the next section.

Figure 2 here – Boxplot

A first step in analysing the meta-analytic data on the volatility-growth nexus consists in examining the relationship of the estimated effects with their corresponding precision. We report in **Figure 3** the funnel plot; that is, the scatter plot of the partial correlation coefficients along with their inverse standard errors.

Figure 3 here - Funnel Plot

The funnel plot appears quite symmetric around the average effect. Not surprisingly, this feature is consistent with the fact that the empirical literature is inconclusive as outlined in **Section 2**. This is an indication that publication bias is quite unlikely to occur. In other words, editors and referees do not tend to prefer a specific empirical outcome over the other. In **Section 4**, we explicitly investigate publication bias controlling for several publication characteristics of the sample. As it becomes evident from both the boxplot and the funnel plot, the values of partial correlation coefficient cover the full range, from the maximum value of 0.976 to the minimum value of -0.999. Finally, **Table 1** reports the computed (unweighted and weighted)

[3] Considering only published papers does not alter our results (see Section 6).

average of the partial correlation coefficients. The unweighted mean of the reported estimates equals -0.049, which suggests that on average the effect of volatility on growth is negative. Following the guidelines of Doucouliagos (2011), this average partial correlation can be considered as a small effect in economics. This result should be cautiously interpreted. As we discuss in more details in **Section 4** and **6**, the dispersion of estimates is vast. However, the number of negative estimates is greater than the positive ones, resulting in a negative average effect. Moreover, the mean effect remains very close to zero. Further to this, the interval between the 5th and 95th percentile (-0.492 to 0.361) implies that there is substantial uncertainty about the average effect. The negative effect holds even when we calculate the weighted mean of the reported estimates that allows for each study to have the same weight irrespectively of the number of the estimates that are included in each study (i.e., the mean is weighted by the inverse of the number of observations that are reported in each study). However, the average effect that is reported here could be a biased estimate of the true effect due to publication bias (Doucouliagos and Stanley, 2013). Finally, based on both plots in **Figures 2** and **3** as well as on the mean estimates in **Table 1,** it is apparent existence of a substantial heterogeneity of the estimates both within and across studies. Thus, the emerging challenge is to model this observed heterogeneity. This is the topic of the next section.

Table 1 here - Mean Estimate of the Partial Correlation Coefficient

4. Modelling Heterogeneity

In the absence of a priori theory regarding the types of moderators, we should take into account as many aspects of the literature as possible. **Table 2** lists the all the potential moderator variables collected from the collected 84 empirical studies along with a short description and their summary statistics. We group the moderators into five broad categories, which capture the following features: 1) variable factors, 2) specification, 3) data features, 4) estimation methods and 5) publication characteristics.

Table 2 here - List of Moderators

The first group accounts for the researchers' choices regarding the two main variables of the estimated model; that is, the growth rate and the proxy of volatility. We call them variable factors. Although the majority of studies use the GDP growth (or GDP per capita growth) as dependent variable, some researchers use the industrial production index instead. Therefore, the first moderator controls whether the measurement of growth plays a role. Considering as base category the estimates that use either GDP growth or GDP per capita growth, we introduce the dummy 'industrial index', which takes the value 1 when the measure of growth is constructed using the industrial production index and the value 0 otherwise.

The next important designing issue is the measurement of volatility. As we mentioned above, there are different ways of modelling volatility. In the first set of studies, the usage of standard deviation of growth rates was the norm. Even though, GARCH modelling became quite popular, especially in 2000s, some authors continued to prefer using standard deviations. We create two dummies considering as base the estimates that use GARCH modelling approach. The first dummy ('SD volatility') takes the value of 1 when a standard deviation is used and 0 in all the remaining cases. The second dummy ('other measure of volatility') takes 1 when other measures (apart from GARCH and SD) are used.[4]

Regarding the issues associated with the specification of the estimated model, a quick examination of the empirical papers can confirm the use of a large number of conditional variables. Trying to be as inclusive as possible, we construct eleven moderator variables. The first one is the number of total regressors. This moderator is

[4] See for instance Turnovsky and Chattopadhyay (2003).

a proxy of how parsimonious a model is. The next nine variables are dummies related to whether the estimated equations include proxies that measure one of the following variables; 1) agricultural production or primary sector of the economy, 2) population, 3) government size, 4) inflation rate, 5) measure of investments, 6) measure of human capital, 7) financial development, 8) financial liberalization and 9) trade openness. Finally, the eleventh variable takes the value of 0 when the models includes only growth rate volatility and 1 when it includes the volatility of another macroeconomic variable (apart from the growth rate volatility). For instance, some of the GARCH studies are examining at the same time the role of inflation volatility. Other researchers (e.g., Fatás and Mihov, 2013) have used proxies of policy volatility.

The third category focuses on several aspects of the datasets that have been used so far. Since our pool of primary papers is fairly large, covering almost two decades, we are capable of identifying several potential factors of heterogeneity. We start by the variable that measures the number of observations. Consequently, we distinguish between those that use panel data (almost half of studies) and those that use time series and cross-sectional data. Considering studies that use panel data as base category, we construct two dummies; one for time series and one for cross-section data. Furthermore, an important aspect is the country sample. Since the number of country groups examined in the literature is large, the only plausible way to discover any potential geographical differentiations is to separate developed (base category) from developing economies. So, we use the dummy 'developing' that takes only for the cases of developing countries. For the cases where the group of countries contains both developed and developing countries, we include an additional dummy ('mixed').

As the above categorisation is not sufficient enough, we also take into account an additional country-group feature. Due to the fact that most of the studies use a huge amount of different combinations of countries, we investigate another related feature; that is, whether our meta-dataset consists of homogeneous sets of countries or not. A dataset is considered as homogeneous when it contains countries that are members of OECD or members of the same geographical region (for instance, Euro area, Latin American or sub-Saharan economies). We create a dummy ('homogeneous') that takes 1 when the paper focuses on a homogeneous set of countries. Another closely related aspect regarding the country characteristics is whether a paper examines a single country or a multiple set of countries. This is captured by the dummy 'single' that takes 1 when a single country is examined. Another feature of datasets is the time span. We are able to distinguish two cases; studies that use very long periods and papers with relatively short ones.[5] Assuming as a large time span datasets that covers at least 40 years, we create a dummy ('Short span') that takes 1 when a short span is used and 0 when a study uses a long one. Lastly, we examine whether the dataset covers the period of Great Moderation. Following the consensus (Bernanke, 2004; Davis and Kahn, 2008), we assume that this period includes the years between 1985 and 2007. So, we put 1 when at least ten years of this period are covered.

The forth group consists of one dummy that captures differences in the econometric methodology. In the literature under examination, the differences in the econometric techniques are mostly captured by the differences in volatility measures, and the proxy that distinguished between panel data, time series or cross-section dataset. For example, GARCH methodology constitutes one way to calculate a volatility proxy and, at the same time, is a distinct econometric method. If we introduce additional dummies for these econometric techniques, then our estimation may suffer from multicollinearity. To avoid this problem, we construct one moderator variable that deals with the issue of endogeneity. This moderator takes the value of 1 when the results come from estimation methods that account for endogeneity and 0 for the cases that they do not.

The last group deals with publication features that are captured by three variables. The first is the most typical variable in meta-analysis; i.e., a dummy

[5] For instance, Caporale and McKiernan (1998) and Shields *et al*. (2005) use data since 1870 and 1947, respectively.

('Published') taking 1 when the study has been published in peered-review journal and 0 when it is in a working-paper form. Additionally, we include a trend variable ('Publication date') starting from 1985 (which is the date of the oldest paper we found) until 2015 (most recent paper found). Finally, we include the RePEc recursive impact factor of the journals to test whether the quality of the journal plays a role.

5. Meta-Regression Analysis

The purpose of our analysis is to look into the factors that affect the estimated coefficients collected from the empirical studies. In the previous section, 27 moderator variables were defined. In this section, we try to identify which of these factors systematically affect the estimated outcomes using the following linear model;

$$r_{ij} = c + \sum_{k=1}^{27} \gamma_k Z_{k,ij} + e_{ij}, \tag{5}$$

where r is the partial correlation, the Z matrix contains the moderator variables, γ the corresponding coefficients, while i is an index for a regression estimate from the j^{th} study. Due to the large number of moderators, the model uncertainty becomes quite significant as the 'general-to-specific' approach may lead to erroneous results. The seriousness of this problem becomes even clearer given the need of applied researchers for reporting robust results (Lu and White, 2014). One way to deal with model uncertainty is the Bayesian Model Averaging (BMA). Originally applied in growth econometrics (Fernandez *et al*. 2001), this method has recently become popular in meta-analysis studies (Havranek and Rusnak, 2013; Havranek *et al*., 2015). Starting from Bayes rule, the posterior probability density is given by the following:

$$p(\gamma \mid r, Z) = \frac{p(r, Z \mid \gamma)\, p(\gamma)}{p(r, Z)}, \tag{6}$$

where $p(r,Z|\gamma)$ is the marginal likelihood, $p(\gamma)$ is the prior probability density and $p(r,Z)$ is the probability of the data. The main advantage of BMA is that the statistical inference does not rely on individual regressions. On contrary, as its name suggests, it gives weighted average of individual regressions. Assuming that N is the number of regressors, the maximum number of alternative models, M, is 2^N across which the researcher must choose the best ones. So overall there are $M_1,\ldots,M_\mu$, where $\mu \in [1, 2^N]$. Assuming a likelihood function and a prior probability density we result to the posterior probability density for each model M_μ that is written as;

$$p(\gamma_\mu \mid M_\mu, r, Z) = \frac{p(r \mid \gamma_\mu, M_\mu, Z)\, p(\gamma_\mu \mid M_\mu)}{p(r \mid M_\mu, Z)}, \tag{7}$$

with each model M_μ depending on the parameters γ_μ. The criterion of choosing among this large number of models is the posterior model probability, $p(M_\mu|r)$. More precisely, the best models are the ones with higher posterior model probability (PMP). According to Bayes' rule the PMP of model M_μ is equal to:

$$p(M_\mu \mid r, Z) = \frac{p(r \mid M_\mu, Z)\, p(M_\mu)}{\sum_{\mu=1}^{2^N} p(Z \mid M_\mu)\, p(M_\mu)}, \tag{8}$$

where $p(r|M_\mu,Z)$ is the likelihood function of model M_μ, $p(M_\mu)$ is the model prior, and the denominator is the integrated likelihood. In this way, BMA provides a useful summary of alternative models. The next step is to identify which regressors seem to play a significant role across the estimated models. The answer is given by the posterior inclusion probability (PIP) which is defined as:

$$PIP_n = \sum_{\mu=1}^{2^N} p(M_\mu \mid r), \tag{9}$$

where $n \in [1,\ldots N]$ denotes each individual regressor. As the above equation shows, each moderator variable has a specific PIP which is the sum of posterior model probabilities of all models where this variable is included. The higher the PIP of a variable, the more explanatory power it has.

As mentioned above, the maximum number of models that can be estimated using *N* explanatory variables is 2^N. In our case of 27 explanatory variables, this means that the number of all models is more than 134 million. Due to the limited computational capacity of conventional computers, only a subset is estimated using a Markov chain Monte Carlo (MCMC) algorithms. In this way, the MCMC provides an approximation of the posterior distribution by simulating a sample from it. Following Zeugner (2011), we use the Metropolis-Hastings algorithm. We begin our analysis by assuming the unit information prior as parameters' prior. This is a suitable start as it provides the same piece of information as one observation in the data set. Regarding the model prior, we assume the uniform model prior that gives to each model the same prior probability.[6] In the next section, we assume an alternative set of priors in order to test the robustness of our results.

Figure 4 depicts a map which is a useful visualisation of our results. In this map, the 5000 models with the highest posterior inclusion probabilities are summarised. The horizontal axis measures the cumulative model probabilities with the best models depicted on the left. As we move to the right, each model's posterior probability is reduced. In the vertical axis, the moderators are sorted by descending order according to their PIP. In other words, variables in top of the axis play a more significant role in explaining heterogeneity compared to the ones in the bottom. The red colour (lighter grey) signifies that the variable is included and its estimated sign is negative, while the blue colour (darker grey) indicates a positive sign.

Figure 4 here - Bayesian Map I

According to the best model, 9 variables seem to play a significant role in explaining the heterogeneity of the estimated coefficients. Clearly, these variables appear to the majority of the estimated model as the red/blue colour intensity shows.

[6] See Eicher *et al*. (2011) for more details.

The numerical results are shown in **Table 3**, where each variable's PIP as well as the posterior mean and its standard deviation are reported. We follow Kass and Raftery's (1995) rule as a guide to the level of significance. Specifically, the effect of a variable is considered as weak, positive, strong and decisive if its PIP lies between *0.5-0.75*, *0.75-0.95*, *0.95-0.99* and *0.99-1*, respectively. Regarding the variable factors, our outcome suggests that the way of measuring volatility is significant. Studies that use the standard deviation as proxy for volatility tend to report less negative estimates than the studies using GARCH-based measures. The usage of other methods used by a small number of researchers does not have any systematic influence in the estimates; the variable 'other measure of volatility' appears only in a small sample of models and its PIP is rather low. Also, the choice of the dependent variable does not seem to play any role in the reported estimate.

Table 3 here - Bayesian Model Averaging Estimates

Another message from **Figure 4** and **Table 3** is that model specification matters. In other words, the choice of variables that the researcher adds in **Equation (2)** seems to be an important aspect that affects the reported estimates. The variables that have a significant influence are the proxies of human capital, inflation rate, and government size. Inclusion of measures of human capital tends to give more negative estimates. This result is in accordance to the evidence provided by Aghion and Banerjee (2005). In the specifications that they take into account secondary school enrollment, the reported coefficients of volatility are proved to be more negative. In other words, human capital appears to be a key factor that explains the relationship between growth and volatility, supporting the negative one. The same conclusion holds for the inclusion of the inflation rate in the estimated equation. This output brings support to the arguments developed by Bruno and Easterly (1998) and Barro (2013) regarding the negative effects of inflation on growth. Interestingly, a distinctive part of the literature, besides the primary focus on growth volatility, has also examined the interactions of growth volatility and inflation volatility on growth and inflation rates (Grier and Perry, 2000; Grier *et al*. 2004; Bredin and Fountas, 2009; Neanidis and Savva, 2013). Contrary to the case of inflation uncertainty, the inclusion of inflation levels as an explanatory variable was never of interest as it was only included to capture the broader macroeconomic environment.

On the contrary, when the government size is considered, more positive estimates are reported. The role of the government has attracted a quite significant interest in the examined literature. In theoretical grounds, Martin and Rogers (1997) and Blackburn (1999) discuss the usefulness of stabilization policies in reducing volatility. More recently, Furceri (2009) examines whether the existence fiscal convergence (i.e., similar government budget positions) alleviates the business cycle variability. Our evidence that proxies of government size are a significant factor is in accordance to Jetter (2014) who emphasizes the importance of including government size. In line with the above-mentioned research, he supports the view that government expanses can act as an insurance mechanism in volatile times. Thus, not accounting this channel may lead to erroneous results.

Regarding the recent issue of how the credit growth can affect the examined relationship (Aghion *et al*. 2010), our evidence suggests that there is no systematic pattern in the meta-data set. This probably is because only a small group of studies take into account this channel by including corresponding proxies to the estimated model. Furthermore, there is no evidence for any significant effects of trade openness. In this way, our results confirm previous evidence regarding the limited role of trade (e.g., Fatás; 2002 and Hnatkovska and Loayza; 2005).

Turning to data characteristics, several aspects are found to explain the magnitude of the estimated effects. Firstly, the more observations used in a study, the more positive the estimated coefficient is. In a similar fashion, studies using shorter time spans tend to report more negative evidence. An interesting finding related to datasets is the sample country. When the study focuses on developing countries tend to report a more negative relationship between growth and volatility. This implies that volatility can be more damaging for growth rate in developing countries, while developed ones are more robust. To the best of our knowledge, there are not studies that compare the effects of volatility in alternative groups of countries, like developed vs. developing economies. In contrast, there are studies that examine specific groups of countries, such as Bredin *et al*. (2009) who restrict their focus only on Asian economies. This gap of the literature may bring new research in the area. Finding additional empirical evidence and trying to explain the differences between country groups seems a new potential direction for the growth-volatility literature. Finally, the choice among cross-sectional data, time series and panels data does not seem to systematically affect the reported estimates. The researcher's decision to examine the relationship over time or across time cannot explain the reported heterogeneity.

The last evidence regarding the data characteristics refers to the homogeneous data sets. It seems that when more homogeneous country-sets are used, more positive estimates tend to be reported. Even though its marginally positive significance, this outcome suggests that the arguments of a negative relation are valid when the dataset consists of heterogeneous sets. When the examined countries have shared the same broad set of characteristics, the negative relation seems to become weaker. This result is in accordance with Norrbin and Yigit (2005) who find there is a strong negative relationship for a set of 76 economies. When they restrict to OECD countries the relationship becomes less strong. Finally, the moderator related to the econometric methods appears to be significant to almost all estimated models; studies that consider endogeneity issues report more negative estimates. This implies that neglecting endogeneity may cause an upward bias. As far as the publication characteristics are concerned, neither variable appears to have any systematic influence on partial correlation. This confirms the initial visual indication given by the funnel plot; the literature on volatility-growth is free from publication bias. Thus, the empirical results so far are not driven by any preferential reporting. Interestingly, Ioannidis *et al*. (2017) report that many fields in economics research suffer from this bias. Consequently, growth-volatility relationship seems to be the one of the few empirical topics that are free of such a bias.

6. Robustness and Further Evidence

6.1. Alternative Specifications

The first robustness test assumes alternative priors. We use Zellner's *g* and beta-binomial as parameters and model priors, respectively. This set of priors is the most appropriate choice for cases where there is not any real knowledge about the parameters and the model's size (Ley and Steel, 2009). As an easy way to compare these results with the previous ones we show the map of 5000 models in **Figure 5**. The factors that seem to have a significant influence remain the same, irrespective of priors. The numerical results are reported in **Table 4**. Also, we test the robustness of BMA results using a frequentist approach (OLS). The right panel of **Table 3** display the OLS meta-regression using all explanatory variables with a PIP value higher than 0.3 (Havranek *et al*. 2015). The results show that all variables with a high posterior inclusion probability in the BMA method continue to have the same sign and magnitude and remain statistical significant in the OLS method. Among others, both sets of results confirm the absence of publication bias. Even though the distinction between published and unpublished studies was found not to play any role, we repeat the same analysis using only published papers. As a further additional moderator related to publication characteristics, we also include the RePEc recursive impact factor. As **Figure 6** shows, the BMA exercise continues to distinguish the same variables as the most influential. The right-hand panel of **Table 4** reports the estimates obtained using only the 70 published studies.

Figure 5 here - Bayesian Map II (Robustness: Alternative Priors)

Figure 6 here - Bayesian Map III (Robustness: Only Published Papers)

Table 4 here - Bayesian Model Averaging (Robustness: Alternative Models)

6.2 Further Evidence

One basic feature of the literature examined in this paper is that the very notion of volatility is treated by different methodologies. In the previous sections, we account for this difference through the moderator variables that capture the alternative methods of measuring volatility (see the moderators 'SD volatility' and 'other measures of volatility' in **Table 2**) as well as for differences on the variables used for measuring the growth rates (GDP or industrial index). Additionally, in order to make the reported effects comparable, we chose to use partial correlation coefficients. Even though the partial correlation can prevent us from 'comparing apples with oranges', one serious concern is whether so many different studies can be mixed up. With the aim of excluding this possibility and reassuring that our previous results are robust, we follow an alternative way of analysis. Given the ambiguity of the exact definition of volatility, we stress our attention only to the sign and the statistical significance of the collected estimates, neglecting their value. This leads to the usage of a probit meta-analysis (see Koetse *et al.*, 2009; Card *et al.*, 2010; Groot *et al.*, 2015, for recent examples in this setting). Specifically, the model assumes the presence of a latent variable y_{ij}^{*}, that is explained by the moderators used in the previous analysis. The model is now written as:

$$y_{ij}^{*} = \sum_{k=1}^{27} \beta_k Z_{k,ij} + \varepsilon_{ij}, \tag{10}$$

where y_{ij}^{*} is unobservable and ε_{ij} is the error term that is normally and *iid* distributed. The proxy for y_{ij}^{*} is the latent variable y_{ij} that constructed as follows:

Category A: y=0 if estimate is statistically significant negative

Category B: y=1 if estimate is insignificant (either negative or positive)

Category C: y=2 if estimate is statistically significant positive

Using as threshold the 10% level of significance, **Table 5** gives a quantitative overview of the collected meta-dataset. Interestingly, less than half, but not much lower than 50%, of the empirical estimates are positive. However, most of these positive estimates (62%) are insignificant. On contrary, the 75% of negative coefficients is statistical significant.

Table 5 here - Descriptive Statistics of the Sign and the Statistical Significance of the Growth-Volatility Estimates

Since the estimated coefficients from an ordered probit model are not straightforward and should not be used for inference, we also calculate the marginal effects. Under this framework, the marginal effects show the change in the probability of finding a specific outcome. Regarding the dummy variables, the marginal effects provide information about the change in the probability of an outcome in one of the three categories of the dependent variable (i.e., of finding a significant negative, an insignificant or significant positive estimate) when the dummy is changing from 0 to 1. For the case of continuous moderator variables, the marginal effects show the probability change from an increase of the dependent variable by one.

Table 6 shows the results. Overall, the probit analysis confirms the results found by the Bayesian model averaging. Apart from the measure of volatility and the span of the data used, all the other variables found in **Section 5** continue to be significant. Beginning with the specification characteristics, the inclusion of specific variables seems to affect the reported estimates. The inclusion of proxies of human capital and inflation rate increase the probability of finding a negative effect, while the opposite is true for the government size. Furthermore, the evidence regarding homogeneous subsets of countries is also confirmed as the probability of a positive estimate is increased. Also, studies using data from developing countries and studies that account for endogeneity tend to give higher probability for negative coefficients. As far as the publication bias is concerned, none of the publication-related variables are found to be significant. This evidence reinforces our previous results supporting the view that the literature is bias free. As a final robustness test, we estimate a panel ordered probit. In this way, we control for the fact each study used in this meta-analysis contains different numbers of estimates. The results, reported in **Table 7**, remain qualitatively and quantitatively the same to the pooled estimates.

Table 6 here - Pooled Ordered Probit Model

Table 7 here - Panel Ordered Probit Model

7. Conclusion

The impact of business cycles volatility on economic growth has gained considerable attention over the last decades. Despite the plethora of empirical estimations, there is no conclusive evidence. Motivated by a number of divergent theoretical models and empirical results, this paper analyses the existing empirical literature to identify the factors that affect the reported results. We find that the effect of volatility on growth is negative, on average, but the estimates vary considerably across the empirical studies. We, thus, conduct a meta-analysis exploring a wide range of potential factors that explain the sources of this heterogeneity of the estimates. In total, we use 27 explanatory variables, grouped into 5 categories. To this end, we employ two distinct approaches, a Bayesian model averaging method and an ordered probit model, to deal with two critical empirical challenges. The former method captures model uncertainty, while the latter addresses the issue of incomparability of the estimated coefficients across studies.

Our results identify three main sources of the observed heterogeneity of the estimates. The choice of the measure of volatility matters in explaining the variation of the empirical results; the frequently used measure of volatility based on the GARCH family models tend to give more negative results compared to more traditional measures. Moreover, certain aspects of the empirical design can explain the observed heterogeneity of the estimated coefficients. Specifically, the choice of the specification characteristics, such as the inclusion of human capital and inflation rate proxies, result to more negative estimates whereas other aspects, such as data and estimation characteristics tend to support a positive relationship. Interestingly, the negative relationship is found to be stronger for samples of developing countries. This evidence may signal a potential research avenue. Finally, our analysis shows that the empirical literature on volatility and growth is free from publication bias. This is a reflexion of the fact that both positive and negative outcomes have theoretical and empirical support. In this way, the growth-volatility literature seems to be one field in the economics research that is publication-bias free.

References

Aghion, P. & Banerjee, A. (2005). *'Volatility and Growth: Clarendon Lectures in Economics'*, Oxford: Oxford University Press.

Aghion, P. & Howitt, P. (1997). *'Endogenous Growth Theory'*, Cambridge, MA: MIT Press.

Aghion, P. & Saint-Paul, G. (1998). 'Virtues of Bad Times: Interaction between Productivity Growth and Economic Fluctuations ', *Macroeconomic Dynamics*, 2, 322-344.

Aghion, P., Angeletos, G.M., Banerjee, A., & Manova, K. (2010). 'Volatility and Growth: Credit Constraints and the Composition of Investment', *Journal of Monetary Economics*, 57, 246-265.

Arrow, K.J. (1962). 'The Economic Implications of Learning by Doing', *Review of Economic Studies*, 29, 155-173.

Badinger, H. (2010). 'Output Volatility and Economic Growth', *Economics Letters*, 106, 15-18.

Barro, R.J. (2013). 'Inflation and Economic Growth', *Annals of Economics and Finance*, 14, 85-109.

Bernanke, B. (1983). 'Irreversibility, Uncertainty, and Cyclical Investment', *Quarterly Journal of Economics*, 98, 85-106.

Bernanke, B. (2004). '*The Great Moderation'*, In the Taylor Rule and the Transformation of Monetary Policy, Institutions Press Publication Hoover.

Black, F. (1987). '*Business Cycles and Equilibrium*', Cambridge, MA: Basil Blackwell.

Blackburn, K. (1999). 'Can Stabilisation Policy Reduce Long-Run Growth?', *The Economic Journal*, 109, 67-77.

Bredin, D., Elder, J. & Fountas, S. (2009). ‘Macroeconomic Uncertainty and Performance in Asian Countries’, *Review of Development Economics*, 13, 215-229.

Bredin, D., & Fountas, S. (2009). ‘Macroeconomic Uncertainty and Performance in the European Union’, *Journal of International Money and Finance*, 28, 972-986.

Bruno, M & Easterly, W. (1998). ‘Inflation Crises and Long-run Growth’, *Journal of Monetary Economics*, 41, 3-26.

Caballero, R. & Hammour, M. (1994). ‘The Cleansing Effect of Recessions’, *American Economic Review*, 84, 1350-1368.

Caporale, T. & McKiernan, B. (1996). ‘The Relationship between Output Variability and Growth: Evidence from Post-War UK Data‘, *Scottish Journal of Political Economy*, 43, 229-236.

Caporale, T. & McKiernan, B. (1998). ‘The Fischer Black Hypothesis: Some Time-Series Evidence‘, *Southern Economic Journal*, 765-771.

Card, D. & Krueger, A. (1995). ‘Time-Series Minimum-Wage Studies: A Meta-Analysis‘, *American Economic Review*, 85, 238-243.

Card, D., Kluve, J. & Weber, A. (2010). ‘Active Labour Market Policy Evaluations: A Meta-Analysis‘, *The Economic Journal*, 120, F452-F77.

Chatterjee, P., & Shukayev, M. (2006). ‘Are Average Growth Rate and Volatility Related?’, Bank of Canada working paper 2006-24.

Davis, S.J. & Kahn, J.A. (2008). ‘Interpreting the Great Moderation: Changes in the Volatility of Economic Activity at the Macro and Micro Levels’, *Journal of Economic Perspectives*, 22, 155-180.

Disdier, A.C., & Head, K. (2008). ‘The Puzzling Persistence of the Distance Effect on Bilateral Trade‘, *Review of Economics and Statistics*, 90, 37-48.

Dopke, J. (2004). 'How Robust is the Empirical Link between Business-Cycle Volatility and Long-Run Growth in OECD Countries?', *International Review of Applied Economics*, 18, 103-121.

Doucouliagos, H. (2011). 'How Large is Large? Preliminary and Relative Guidelines for Interpreting Partial Correlations in Economics', Economics Series Working Paper 05/2011, Deakin University.

Doucouliagos, H., Haman, J. & Stanley, T.D. (2012). 'Pay for Performance and Corporate Governance Reform', *Industrial Relations: A Journal of Economy and Society*, 51, 670-703.

Doucouliagos, H. & Stanley, T.D. (2013). 'Are all Economic Facts Greatly Exaggerated? Theory Competition and Selectivity', *Journal of Economic Surveys*, 27, 316-339.

Eicher, T.S., Papageorgiou, C. & Raftery, A.E. (2011). 'Default Priors and Predictive Performance in Bayesian Model Averaging, with Application to Growth Determinants', *Journal of Applied Econometrics*, 26, 30-55.

Engle, R.F., Lilien, D.M. & Robins, R.P. (1987). 'Estimating Time Varying Risk Premia in the Term Structure: The ARCH-M Model', *Econometrica*, 55, 391-407.

Fang, W.S. & Miller, S.M. (2008). 'The Great Moderation and the Relationship between Output Growth and Its Volatility', *Southern Economic Journal*, 74, 819-838.

Fatás, A., (2002). 'The Effects of Business Cycles on Growth'. In: Loayza, N., Soto, R. (Eds.), Economic Growth: Sources, Trends and Cycles. Central Bank of Chile, Santiago.

Fatás, A., & Mihov, I. (2013). 'Policy Volatility, Institutions, and Economic Growth', *The Review of Economics and Statistics*, 95, 362-376.

Fernandez, C., Ley, E. & Steel, M.F. (2001). 'Model Uncertainty in Cross-Country Growth Regressions', *Journal of Applied Econometrics*, 16, 563-576.

Fountas, S. & Karanasos, M. (2006). 'The Relationship between Economic Growth and Real Uncertainty in the G3', *Economic Modelling*, 23, 638-647.

Friedman, M. (1968). 'The Role of Monetary Policy', *American Economic Review*, 58, 1-17.

Furceri, D. (2009). 'Fiscal Convergence, Business Cycle Volatility, and Growth', *Review of International Economics*, 17, 615-630.

Grier, K. & Perry, M. (2000). 'The Effects of Real and Nominal Uncertainty on Inflation and Output Growth: Some GARCH-M Evidence', *Journal of Applied Econometrics*, 15, 45-58.

Grier, K. & Tullock, G. (1989). 'An Empirical Analysis of Cross-National Economic Growth 1951-1980', *Journal of Monetary Economics*, 24, 259-276.

Grier, K.B., Henry, Ó.T., Olekalns, N. & Shields, K. (2004). 'The Asymmetric Effects of Uncertainty on Inflation and Output Growth', *Journal of Applied Econometrics*, 19, 551-565.

Groot, H.L., Poot, J. & Smit, M.J. (2015). 'Which Agglomeration Externalities Matter Most and Why? ', *Journal of Economic Surveys*, 30, 756-782.

Hall, R.E. (1991). 'Labor Demand, Labor Supply, and Employment Volatility', *NBER Macroeconomics Annual*, 6, 17-47.

Havranek, T. (2015). 'Measuring Intertemporal Substitution: The Importance of Method Choices And Selective Reporting', *Journal of the European Economic Association, European Economic Association*, 13, 1180-1204.

Havranek, T. & Rusnak, M. (2013). 'Transmission Lags of Monetary Policy: A Meta-Analysis', *International Journal of Central Banking*, 9, 39-76.

Havranek, T., Horvath, R., Irsova, Z. & Rusnak, M. (2015). 'Cross-Country Heterogeneity in Intertemporal Substitution', *Journal of International Economics*, 96, 100-118.

Hnatkovska, V. & Loayza, N., (2005). 'Volatility and Growth', In: Aizenman, J., Pinto, B. (Eds.), Managing Economic Volatility and Crises: A Practitioner's Guide. Cambridge University Press.

Imbs, J. (2007). 'Growth and Volatility', *Journal of Monetary Economics*, 54, 1848-1862.

Ioannidis, J.P.A., Stanley, T.D. & Doucouliagos, C., (2017). 'The Power of Bias in Economics Research', *The Economic Journal* (forthcoming).

Jetter, M. (2014). 'Volatility and Growth: Governments are Key', *European Journal of Political Economy*, 36, 71-88.

Kass, R.E. & Raftery, A.E. (1995). 'Bayes Factors', *Journal of the American Statistical Association*, 90, 773-795.

King, R.G., Plosser, C.I., & Rebelo, S.T. (1988). 'Production, Growth and Business Cycles: II. New Directions', *Journal of Monetary Economics*, 21, 309-341.

Kneller, R. & Young, G. (2001). 'Business Cycle Volatility, Uncertainty and Long-Run Growth', *The Manchester School*, 69, 534-552.

Koetse, M.J., De Groot, H.L. & Florax, R.J. (2009). 'A Meta-Analysis of the Investment-Uncertainty Relationship', *Southern Economic Journal*, 76, 283-306.

Kormendi, R.C. & Meguire, P.G. (1985). 'Macroeconomic Determinants of Growth: Cross-Country Evidence', *Journal of Monetary Economics*, 16, 141-163.

Kydland, F.E. & Prescott, E.C. (1982). 'Time to Build and Aggregate Fluctuations', *Econometrica*, 50, 1345-1370.

Lee, J. (2010). 'The Link between Output Growth and Volatility: Evidence from a GARCH Model with Panel Data', *Economics Letters*, 106, 143-145.

Ley, E. & Steel, M.F. (2009). 'On the Effect of Prior Assumptions in Bayesian Model Averaging with Applications to Growth Regression', *Journal of Applied Econometrics*, 24, 651-674.

Long, J.B. & Plosser, C.I. (1987). 'Sectoral vs. Aggregate Shocks in the Business Cycle', *American Economic Review*, 77, 333-336.

Lu, X. & White, H. (2014). 'Robustness Checks and Robustness Tests in Applied Economics', *Journal of Econometrics*, 178, 194-206.

Martin, P. & Rogers, C.A. (1997). 'Stabilization Policy, Learning-by-Doing, and Economic Growth', *Oxford Economic Papers*, 49, 152-166.

Martin, P. & Rogers C.A. (2000). 'Long-Term Growth and Short-Term Economic Instability', *European Economic Review*, 44, 359-381.

Neanidis, K.C. & Savva, C.S. (2013). 'Macroeconomic Uncertainty, Inflation and Growth: Regime-Dependent Effects in the G7', *Journal of Macroeconomics*, 35, 81-92.

Norrbin, S.C. & Yigit, F. P. (2005). 'The Robustness of the Link between Volatility and Growth of Output', *Review of World Economics*, 141, 343-356.

Pindyck, R. (1991). 'Irreversibility, Uncertainty, and Investment', *Journal of Economic Literature*, 29, 1110-1148.

Priesmeier, C. & Stahler, N. (2011). 'Long Dark Shadows or Innovative Spirits? The Effects of (Smoothing) Business Cycles on Economic Growth: A Survey of the Literature', *Journal of Economics Surveys*, 25, 898-912.

Ramey, G. & Ramey, V.A. (1995). 'Cross-Country Evidence on the Link between Volatility and Growth', *American Economic Review*, 85, 1138-1151.

Schumpeter, J.A. (1939). '*Business Cycles: A Theoretical, Historical and Statistical Analysis of the Capitalist Process*', New York: McGraw-Hill.

Schumpeter, J.A. (1942). '*Capitalism, Socialism and Democracy*', New York: Harper and Brothers.

Shields, K., Olekalns, N., Henry, Ó.T. & Brooks, C. (2005). 'Measuring the Response of Macroeconomic Uncertainty to Shocks', *Review of Economics and Statistics*, 87, 362-370.

Speight, A.E.H. (1999). 'UK Output Variability and Growth: Some Further Evidence', *Scottish Journal of Political Economy*, 46, 175-184.

Stadler, G. (1990). 'Business Cycle Models with Endogenous Technology', *American Economic Review*, 80, 763-778.

Stanley, T.D. (2001). 'Wheat from Chaff: Meta-Analysis as Quantitative Literature Review', *Journal of Economic Perspectives*, 15, 131-150.

Stanley, T.D. & Doucouliagos, H. (2012). '*Meta-Regression Analysis in Economics and Business*, Oxford: Routledge.

Stanley, T.D., Doucouliagos, H., Giles, M., Heckemeyer, J.H., Johnston, R.J., Laroche, P., Pugh, G., Nelson, J., Paldam, M., Poot, J., Rosenberger, R. & Rost, K., (2013). 'Meta-Analysis of Economics Research Reporting Guidelines', *Journal of Economic Surveys*, 27, 390-394.

Stanley, T.D. and Jarrell, S.B. (1989). 'Meta-Regression Analysis: A Quantitative Method of Literature Surveys', *Journal of Economic Surveys*, 3, 161-170.

Turnovsky, S.J. & Chattopadhyay, P. (2003). 'Volatility and Growth in Developing Economies: Some Numerical Results and Empirical Evidence', *Journal of International Economics*, 59, 267-95.

Zeugner, S. (2011). 'Bayesian Model Averaging with BMS', Tutorial to the R-package.

Tables

Table 1:

Mean Estimate of the Partial Correlation Coefficient

	Unweighted			*Weighted*		
	Mean	*5%*	*95%*	*Mean*	*5%*	*95%*
r	-0.049	-0.492	0.361	-0.044	-0.446	0.458

Notes: The table reports the mean values of the effect of volatility on growth. 5% and 95% denotes the 5th and 95th percentile, respectively. *Weighted* denotes the mean estimate that is weighted by the inverse of the number of observations that are reported in each study.

Table 2:

List of Moderators

Variable Name	Variable Description	*Mean*	*SD*
Partial Correlation	*r*	-0.049	0.254
Variable Characteristics			
Industrial index	D=1, if growth rate is based on industrial production index	0.112	0.315
SD volatility	D=1, if standard deviation (SD) is used as proxy of volatility	0.607	0.489
Other measures of volatility	D=1, if other measure (apart from SD or GARCH) is used as proxy of volati	0.058	0.235
GARCH volatility	Base category		
Specification Characteristics			
Regressors	Number of regressors included	5.081	3.412
Agriculture	D=1, if a proxy of agricaltural (primary) sector is included	0.019	0.139
Population	D=1, if population is included	0.238	0.426
Government	D=1, if a proxy of government size is included	0.098	0.297
Inflation	D=1, if a measure of inflation is included	0.041	0.197
Investment	D=1, if a proxy of investments is included	0.273	0.446
Human capital	D=1, if a proxy of human capital is included	0.231	0.421
Financial development	D=1, if a proxy of financial development is included	0.075	0.264
Financial liberalization	D=1, if a proxy of financial liberalisation is included	0.059	0.237
Trade openness	D=1, if a proxy of trade openness is included	0.098	0.297
Other volatility	D=1, if volatility of other variables is included	0.173	0.379
Data Characteristics			
Observations	Number of observations	525.963	775.225
Countries	Number of countries/units	68.890	185.970
Time series	D=1, if time-series data are used	0.287	0.453
Cross section	D=1, if cross sectional data are used	0.303	0.460
Panel	Base category		
Developing	D=1, if developing countries are included in the sample	0.052	0.223
Mixed	D=1, if a mixed set of countries are included in the sample	0.393	0.489
Developed	Base category		
Homogeneous	D=1, if the group of countries are homogeneous	0.642	0.480
Great moderation	D=1, if the period covers the Great Moderation period (1 until 1995)	0.741	0.439
Short span	D=1, if short span data are used (less than 40 years period)	0.832	0.374
Single	D=1, if single country is examined	0.309	0.462
Endogeneity-Econometric Method			
Endogeneity	D=1, if the econometric method takes into account the endogeneity	0.205	0.404
Publication Characteristics			
Published	D=1, if the study is published	0.792	0.406
Publication date	A trend variable putting 1 for the year of 1st publication (1985)	3.513 (2007)	5.106
Impact Factor	The recursive RePEc impact factor	1.508	1.529

Notes: The total number of observations is 1010 collected from 84 studies examining the effect of volatility on growth.

Table 3:

Bayesian Model Averaging and OLS Estimates

Categories	Variable	Bayesian Model Averaging PIP	post Mean	post SD	Frequentist check (OLS) Coeff.	SD	p-value
Variable Characteristics							
	Industrial index	0.028	-0.00005	0.005			
	SD volatility	0.958[b]	0.08400	0.036	0.085***	0.019	0.000
	Other measures of volatility	0.140	0.01802	0.053			
Specification Characteristics							
	Regressors	0.215	0.00127	0.003			
	Agriculture	0.024	0.00005	0.008			
	Population	0.151	0.00782	0.021			
	Government	0.959[b]	0.15842	0.049	0.177***	0.032	0.000
	Inflation	0.935[b]	-0.16571	0.065	-0.177***	0.046	0.000
	Investment	0.274	0.01656	0.031			
	Human capital	0.999[a]	-0.10514	0.030	-0.089***	0.019	0.000
	Financial development	0.025	-0.00015	0.005			
	Financial liberalization	0.031	0.00078	0.007			
	Trade openness	0.036	0.00101	0.008			
	Other volatility	0.378	0.01863	0.027	0.048**	0.019	0.014
Data Characteristics							
	Observations	1.000[a]	0.00007	0.000	0.00007***	0.000	0.000
	Countries	0.106	0.00001	0.000			
	Time series	0.138	0.01167	0.035			
	Cross section	0.039	-0.00085	0.006			
	Developing	0.998[a]	-0.14282	0.034	-0.148***	0.033	0.000
	Mixed	0.547	-0.07811	0.082	-0.096**	0.039	0.014
	Homogeneous	0.721	0.11379	0.083	0.101**	0.039	0.011
	Great moderation	0.036	-0.00057	0.005			
	Short span	0.995[a]	-0.10207	0.025	-0.103***	0.022	0.000
	Single	0.034	-0.00040	0.009			
Econometric Method Characteristics							
	Endogeneity	1.000[a]	-0.11478	0.022	-0.119***	0.019	0.000
Publication Characteristics							
	Published	0.030	-0.00004	0.004			
	Publication date	0.187	-0.00072	0.002			

Notes: We assume unit information prior as parameters' prior and uniform model prior. *PIP* stands for posterior inclusion probability; *post Mean* is the posterior mean and *post SD* is the posterior standard deviation. *a*/*b*/*c* denotes decisive/strong/positive evidence of a regressor having an effect respectively, according to Kass and Raftery (1995). For the frequentist check, the variables with *PIP>0.3* are included. Statistical significance is indicated with stars: ***, ** and * denotes statistically significance at the 1%, 5% and 10% significance levels, respectively. Clustered standard errors are used based on study level.

Table 4:

Bayesian Model Averaging Estimates (Robustness: Alternative Models)

Categories	Variable	Alternative priors			Only published papers		
		PIP	*post Mean*	*post SD*	*PIP*	*post Mean*	*post SD*
Variable Characteristics							
	Industrial index	0.019	0.00002	0.004	0.032	-0.00036	0.006
	SD volatility	0.931[b]	0.07911	0.036	1.000[a]	0.12116	0.034
	Other measures of volatility	0.126	0.01780	0.054	0.110	0.01227	0.042
Specification Characteristics							
	Regressors	0.167	0.00101	0.003	0.156	0.00094	0.003
	Agriculture	0.016	0.00006	0.007	0.031	-0.00130	0.015
	Population	0.113	0.00596	0.019	0.220	0.01376	0.030
	Government	0.929[b]	0.15065	0.056	0.995[a]	0.20531	0.045
	Inflation	0.863[c]	-0.14884	0.075	0.992[a]	-0.20701	0.056
	Investment	0.199	0.01207	0.027	0.181	0.01013	0.025
	Human capital	0.989[b]	-0.09823	0.031	1.000[a]	-0.12784	0.032
	Financial development	0.016	-0.00010	0.004	0.027	-0.00013	0.006
	Financial liberalization	0.022	0.00053	0.006	0.155	0.01142	0.031
	Trade openness	0.024	0.00067	0.007	0.035	0.00067	0.009
	Other volatility	0.282	0.01385	0.025	0.422	0.02266	0.030
Data Characteristics							
	Observations	0.999[a]	0.00007	0.000	1.000[a]	0.00009	0.000
	Countries	0.069	0.00001	0.000	0.496	-0.00029	0.000
	Time series	0.099	0.00825	0.030	0.135	0.01158	0.035
	Cross section	0.029	-0.00068	0.006	0.027	-0.00027	0.004
	Developing	0.995[a]	-0.14259	0.035	1.000[a]	-0.16875	0.037
	Mixed	0.533	-0.08242	0.086	0.458	-0.08137	0.093
	Homogeneous	0.667	0.11003	0.087	0.563	0.10196	0.094
	Great moderation	0.024	-0.00039	0.004	0.030	0.00038	0.004
	Short span	0.983[b]	-0.10021	0.028	0.994[a]	-0.10572	0.027
	Single	0.025	-0.00033	0.008	0.108	0.00733	0.025
Econometric Method Characteristics							
	Endogeneity	1.000[a]	-0.11378	0.022	1.000[a]	-0.13956	0.022
Publication Characteristics							
	Published	0.020	-0.00002	0.003	0.102	-0.02707	0.096
	Publication date	0.133	-0.00052	0.002	0.048	-0.00009	0.001
	Impact Factor				0.034	0.00013	0.001

Notes: We assume Zellner's *g* prior as parameters' prior and beta-binomial model prior. *PIP* stands for posterior inclusion probability; *post Mean* is the posterior mean and *post SD* is the posterior standard deviation. *a*/*b*/*c* denotes decisive/strong/positive evidence of a regressor having an effect respectively, according to Kass and Raftery (1995).

Table 5:

Descriptive Statistics of the Sign and the Statistical Significance of the Growth-Volatility Estimates

Sign	Significance	*Number*	*Percentage*	*Number*	*Percentage*
Negative	significant	410	40.59%	545	**53.96%**
	insignificant	135	13.37%		
Positive	significant	175	17.33%	465	**46.04%**
	insignificant	290	28.71%		
Total		1010	100.00%	1010	100.00%

Notes: The total 1010 observations are separated into two main categories (negative and positive) and four subcategories (negative significant, negative insignificant, positive insignificant and positive significant).

Table 6:

Pooled Ordinal Probit Model

Categories	Variable	Estimated Coefficient	*Marginal Effects* Singificantly negative	Insignificant	Singificantly positive
Variable Characteristics					
	Industrial index	-0.167	0.064	-0.017	-0.047
		(-0.61)	(0.61)	(-0.63)	(-0.61)
	SD volatility	0.443	-0.170	0.044	0.125
		(1.37)	(-1.37)	(1.46)	(1.30)
	Other measures of volatility	0.183	-0.070	0.018	0.052
		(0.44)	(-0.44)	(0.45)	(0.44)
Specification Characteristics					
	Regressors	-0.012	0.005	-0.001	-0.003
		(-0.56)	(0.56)	(-0.55)	(-0.56)
	Agriculture	1.041**	-0.399**	0.104	0.295**
		(2.10)	(-2.10)	(1.63)	(2.19)
	Population	0.132	-0.051	0.013	0.037
		(0.35)	(-0.35)	(0.35)	(0.35)
	Government	1.964***	-0.753***	0.197**	0.556***
		(4.42)	(-4.43)	(2.47)	(4.65)
	Inflation	-1.187**	0.455**	-0.119**	-0.336**
		(-2.40)	(2.42)	(-1.99)	(-2.37)
	Investment	0.471	-0.181	0.047	0.133
		(1.40)	(-1.40)	(1.33)	(1.38)
	Human capital	-1.096***	0.420***	-0.110***	-0.310***
		(-3.22)	(3.25)	(-2.71)	(-2.94)
	Financial development	-0.468	0.180	-0.047	-0.133
		(-1.21)	(1.21)	(-1.12)	(-1.21)
	Financial liberalization	0.173	-0.067	0.017	0.049
		(0.66)	(-0.65)	(0.59)	(0.68)
	Trade openness	-0.586	0.225	-0.059	-0.166
		(-1.57)	(1.56)	(-1.32)	(-1.61)
	Other volatility	0.295	-0.113	0.030	0.084
		(1.36)	(-1.35)	(1.24)	(1.35)
Data Characteristics					
	Observations	0.000***	-0.000***	0.000**	0.000***
		(3.32)	(-3.28)	(2.29)	(3.27)
	Countries	0.001**	-0.000**	0.000*	0.000**
		(2.45)	(-2.41)	(1.91)	(2.42)
	Time series	0.871	-0.334	0.087	0.247
		(1.27)	(-1.29)	(1.23)	(1.27)
	Cross section	0.152	-0.058	0.015	0.043
		(0.46)	(-0.46)	(0.44)	(0.46)
	Developing	-1.032***	0.396***	-0.103**	-0.292***
		(-2.81)	(2.85)	(-2.34)	(-2.70)
	Mixed	-0.460**	0.176**	-0.046*	-0.130**
		(-2.06)	(2.09)	(-1.73)	(-2.10)
	Homogeneous	0.851***	-0.326***	0.085**	0.241***
		(3.48)	(-3.36)	(2.10)	(3.64)
	Great moderation	-0.170	0.065	-0.017	-0.048
		(-0.89)	(0.89)	(-0.86)	(-0.89)
	Short span	-0.248	0.095	-0.025	-0.070
		(-1.13)	(1.13)	(-1.03)	(-1.14)
	Single	-0.436	0.167	-0.044	-0.124
		(-0.67)	(0.68)	(-0.66)	(-0.68)
Econometric Method Characteristics					
	Endogeneity	-0.595**	0.228**	-0.060*	-0.169**
		(-2.31)	(2.30)	(-1.89)	(-2.28)
Publication Characteristics					
	Published	0.133	-0.051	0.013	0.038
		(0.72)	(-0.72)	(0.74)	(0.71)
	Publication date	0.004	-0.001	0.000	0.001
		(0.16)	(-0.16)	(0.16)	(0.16)
Obs		1010	1010	1010	1010
N		84			
McFadden R^2		0.225			
Log Likelihood		-850.467			
X^2 Test		489.615			
X^2 Prob		0.000			

Notes: *t*-statistics are in parentheses. Statistical significance is indicated with stars: ***, ** and * denotes statistically significance at the 1%, 5% and 10% significance levels, respectively. Marginal effects are calculated as average for all covariates.

Table 7:

Panel Ordinal Probit Model

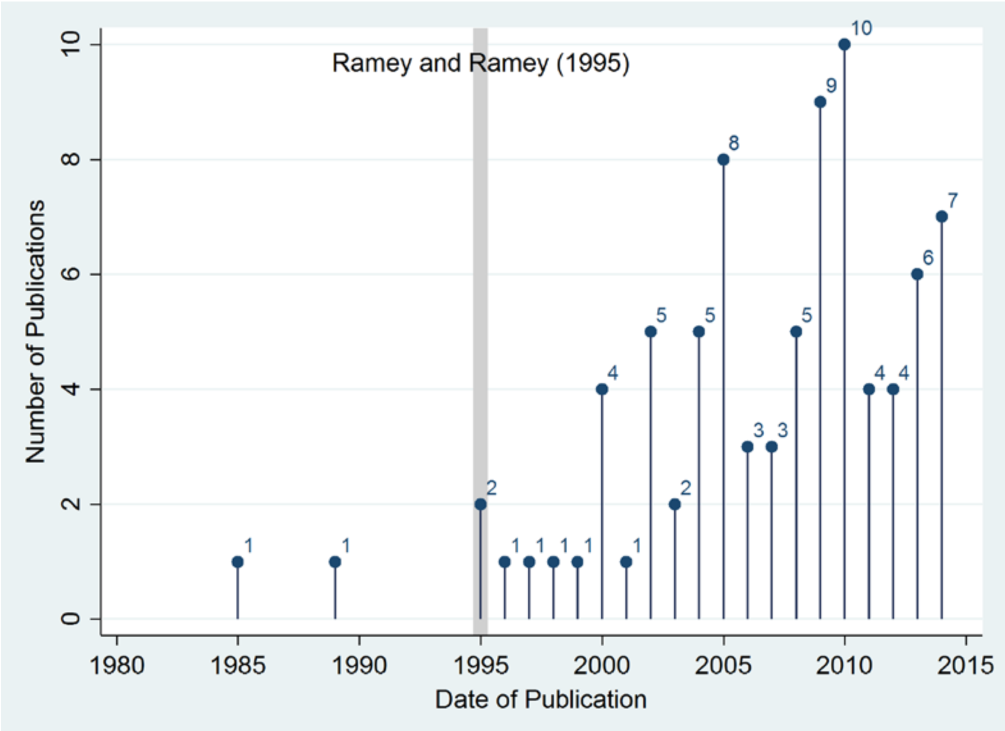
Categories	Variable	Estimated Coefficient	Marginal Effects: Singificantly negative	Marginal Effects: Insignificant	Marginal Effects: Singificantly positive
Variable Characteristics					
	Industrial index	0.448	-0.173	0.081	0.092
		(1.11)	(-1.11)	(1.03)	(1.12)
	SD volatility	-0.132	0.051	-0.024	-0.027
		(-0.38)	(0.38)	(-0.37)	(-0.38)
	Other measures of volatility	-0.337	0.130	-0.061	-0.069
		(-0.63)	(0.63)	(-0.61)	(-0.64)
Specification Characteristics					
	Regressors	0.036	-0.014	0.006	0.007
		(1.15)	(-1.15)	(1.12)	(1.10)
	Agriculture	1.230	-0.474	0.221	0.253
		(1.24)	(-1.25)	(1.14)	(1.25)
	Population	0.255	-0.098	0.046	0.053
		(0.59)	(-0.59)	(0.58)	(0.59)
	Government	1.740***	-0.671***	0.313**	0.358***
		(3.02)	(-3.02)	(2.10)	(3.00)
	Inflation	-0.791*	0.305*	-0.142*	-0.163*
		(-1.91)	(1.93)	(-1.67)	(-1.84)
	Investment	0.176	-0.068	0.032	0.036
		(0.57)	(-0.57)	(0.58)	(0.56)
	Human capital	-1.115***	0.430***	-0.201***	-0.229***
		(-3.36)	(3.45)	(-2.68)	(-2.68)
	Financial development	-0.412	0.159	-0.074	-0.085
		(-0.96)	(0.96)	(-0.91)	(-0.96)
	Financial liberalization	-0.053	0.020	-0.010	-0.011
		(-0.14)	(0.14)	(-0.14)	(-0.13)
	Trade openness	-0.597*	0.230*	-0.107	-0.123*
		(-1.72)	(1.69)	(-1.40)	(-1.78)
	Other volatility	0.231	-0.089	0.042	0.048
		(0.90)	(-0.90)	(0.85)	(0.90)
Data Characteristics					
	Observations	0.000***	-0.000***	0.000**	0.000***
		(2.83)	(-2.77)	(1.97)	(2.86)
	Countries	0.001**	-0.000**	0.000*	0.000**
		(2.44)	(-2.42)	(1.96)	(2.25)
	Time series	1.289	-0.497	0.232	0.265
		(1.54)	(-1.56)	(1.34)	(1.60)
	Cross section	0.637**	-0.246**	0.115*	0.131**
		(2.18)	(-2.18)	(1.78)	(2.12)
	Developing	-1.010	0.390	-0.182	-0.208
		(-1.58)	(1.60)	(-1.49)	(-1.50)
	Mixed	-0.853***	0.329***	-0.154**	-0.176***
		(-3.56)	(3.73)	(-2.47)	(-3.24)
	Homogeneous	0.387**	-0.149*	0.070	0.080**
		(1.99)	(-1.95)	(1.57)	(2.02)
	Great moderation	-0.279	0.108	-0.050	-0.057
		(-1.30)	(1.31)	(-1.16)	(-1.35)
	Short span	-0.055	0.021	-0.010	-0.011
		(-0.24)	(0.24)	(-0.24)	(-0.24)
	Single	-1.282	0.495	-0.231	-0.264
		(-1.49)	(1.51)	(-1.32)	(-1.53)
Econometric Method Characteristics					
	Endogeneity	-0.597*	0.230*	-0.107	-0.123*
		(-1.74)	(1.73)	(-1.50)	(-1.72)
Publication Characteristics					
	Published	0.090	-0.035	0.016	0.018
		(0.28)	(-0.28)	(0.29)	(0.28)
	Publication date	0.010	-0.004	0.002	0.002
		(0.29)	(-0.29)	(0.29)	(0.29)
Obs		1010	1010	1010	1010
N		84			
Log Likelihood		-773.597			
X^2 Test		121.568			
X^2 Prob		0.000			
LR Test		153.740			
LR Prob		0.000			

Notes: *t*-statistics are in parentheses. Statistical significance is indicated with stars: ***, ** and * denotes statistically significance at the 1%, 5% and 10% significance levels, respectively. Marginal effects are calculated as average for all covariates.

Figures

Figure 1:

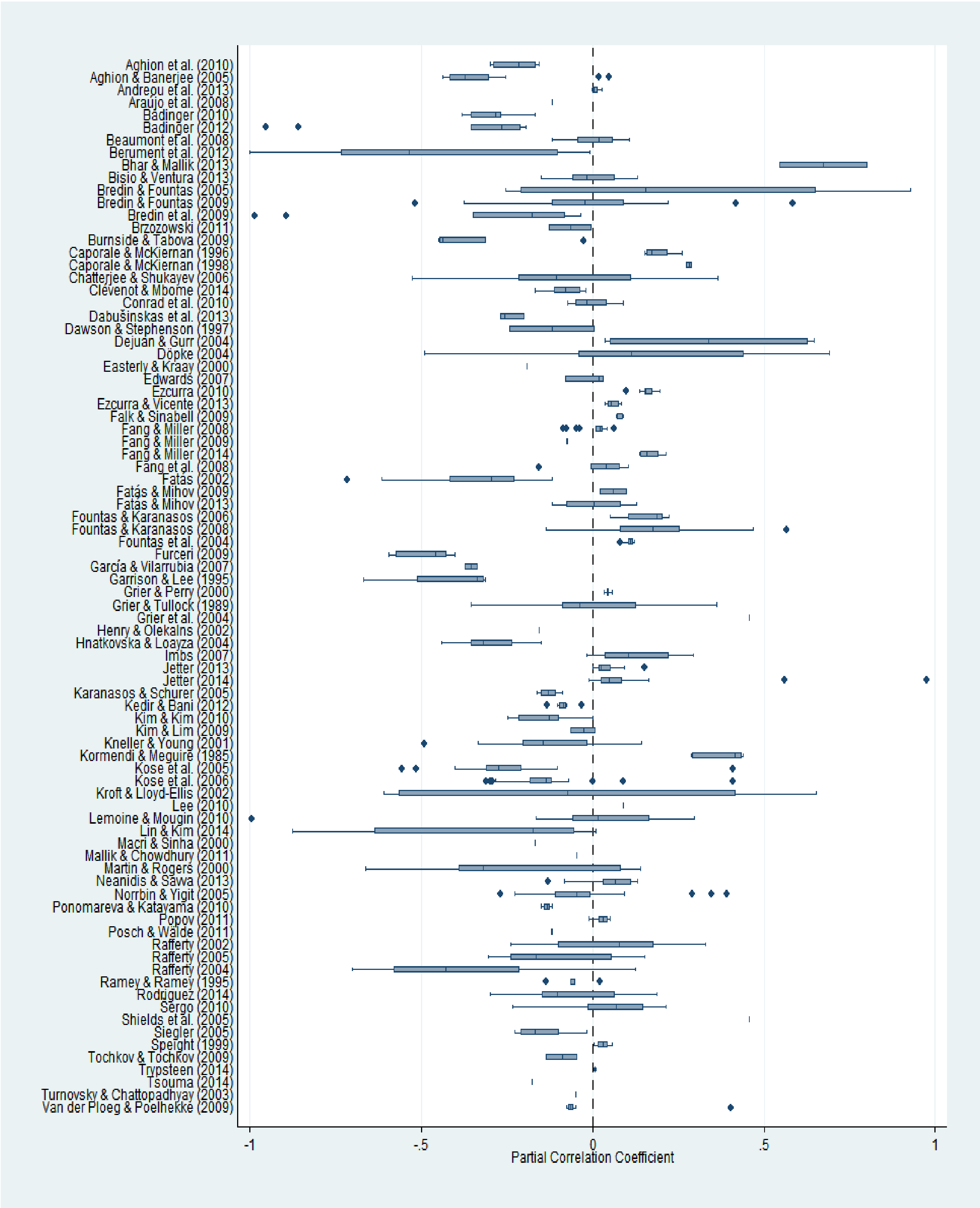
Number of Publications over Time



Notes: The figure shows the evolution of the empirical literature over time. Numbers indicate the number of published studies for each year. The shade line shows the year when the most influential study (Ramey and Ramey, 1995) was published. Even though the paper is not the first empirical study, it is considered as the seminal one due to the significant amount of citations (approximately, 2192 citations according to google scholar).

Figure 2:

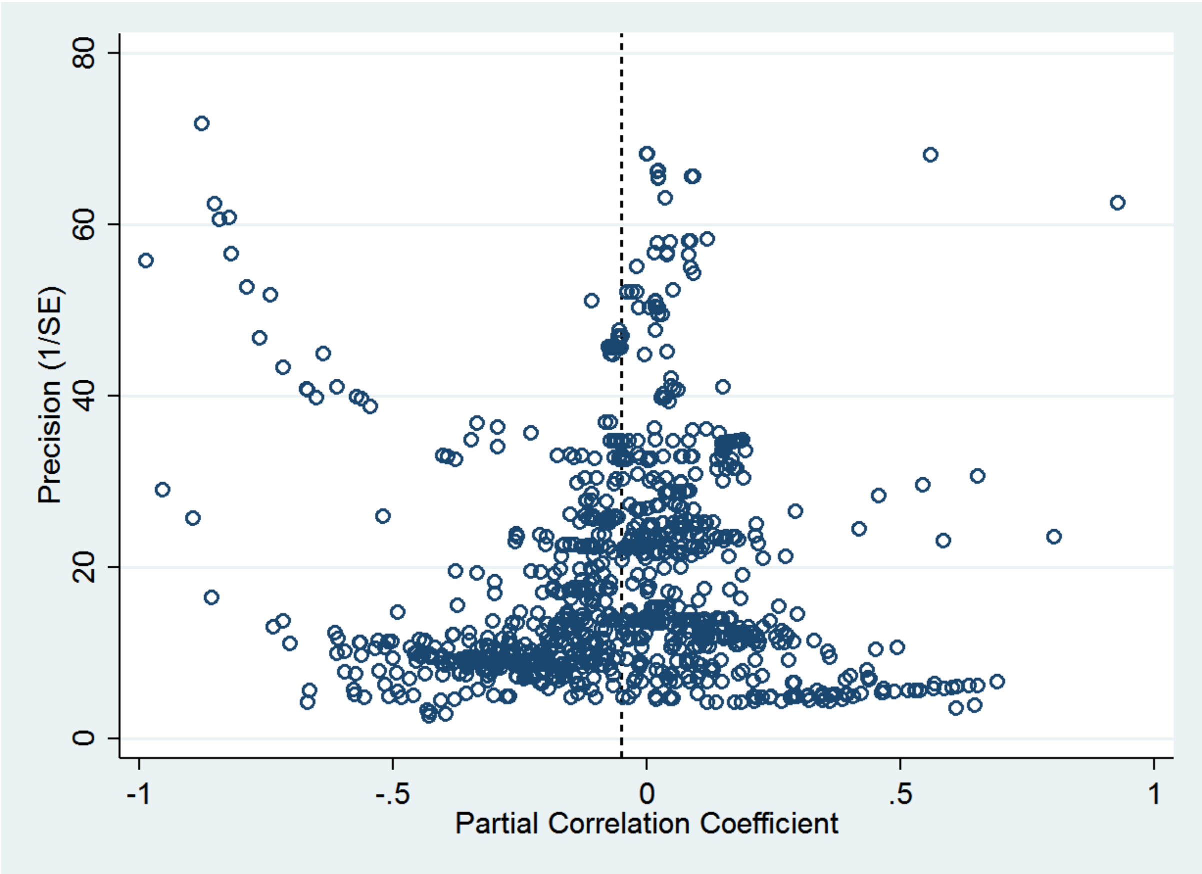
Boxplot



Notes: The figure depicts the boxplot of the collected estimates from the 84 empirical studies. For better exposition of the observed heterogeneity across studies, we have used partial correlation coefficients. Studies are sorted alphabetically. The full list of papers is provided in the Appendix.

Figure 3:

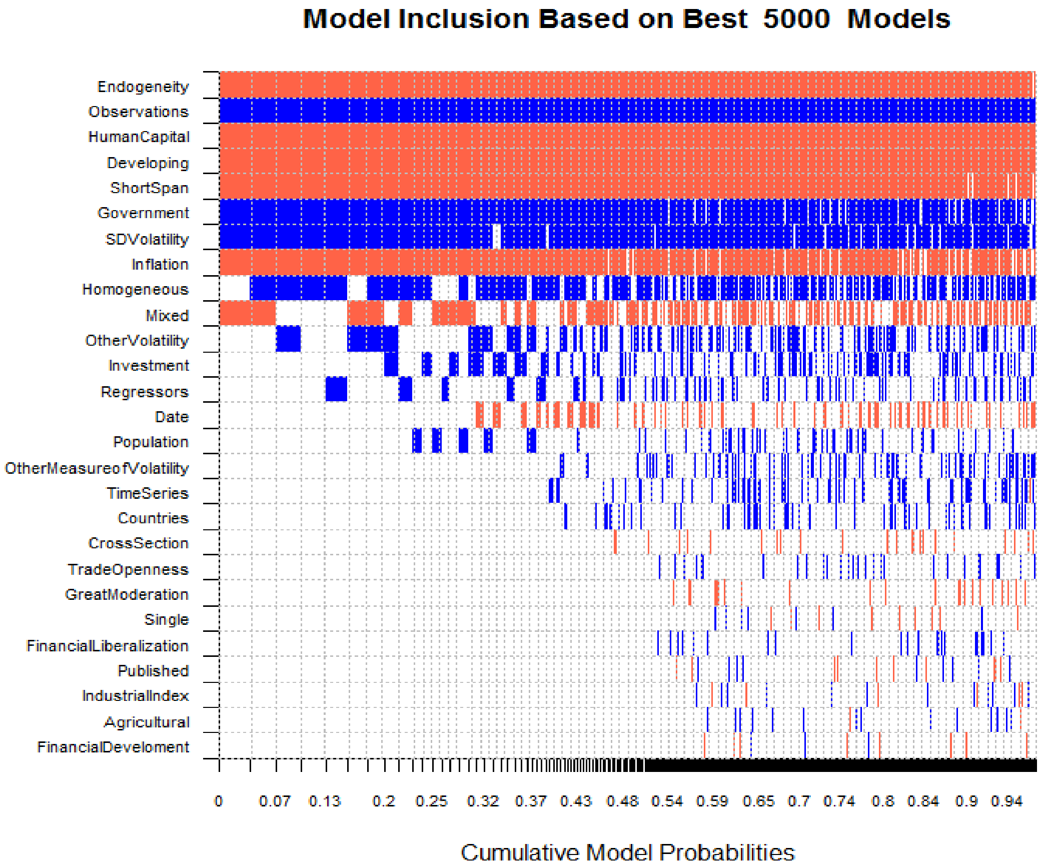
Funnel Plot



Notes: Presence of symmetry suggests the absence of publication bias and vice versa; an asymmetrical funnel plot indicates a possible publication bias. The dotted line shows the average effect (r = *-0.049*).

Figure 4:

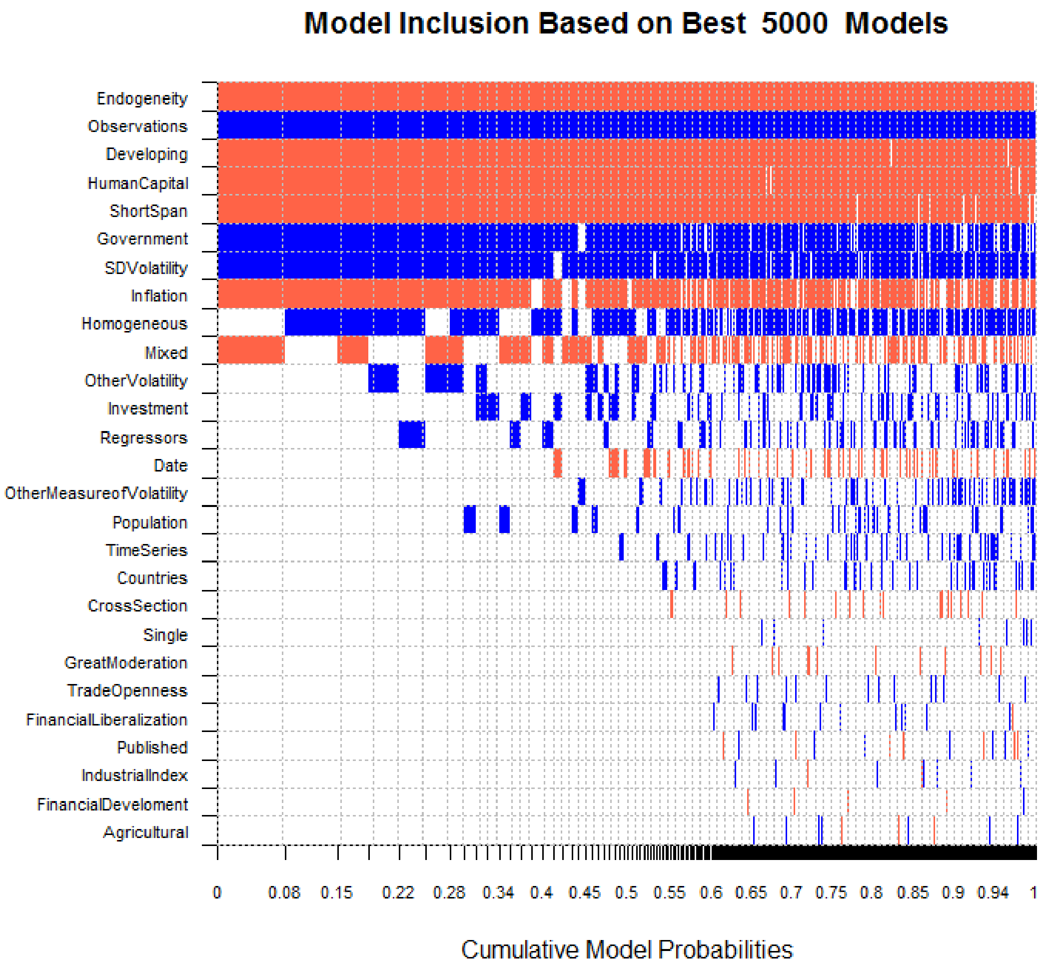
Bayesian Map I



Notes: The vertical axis measures the cumulative posterior model probabilities, while the vertical one depicts the moderator variables that are explained in Table 1. Each column shows different model. Each variable in the left axis is sorted according to posterior inclusion probability in descending order meaning that variables on the top appear more frequently across different models than the ones in the bottom. Red colour (light grey) shows negative sign, while blue colour (dark grey) shows positive sign. Blank entries mean that the variable is not included in the model. 5000 models with the highest posterior probabilities are shown, while assuming unit information prior as parameters' prior and uniform model prior.

Figure 5:

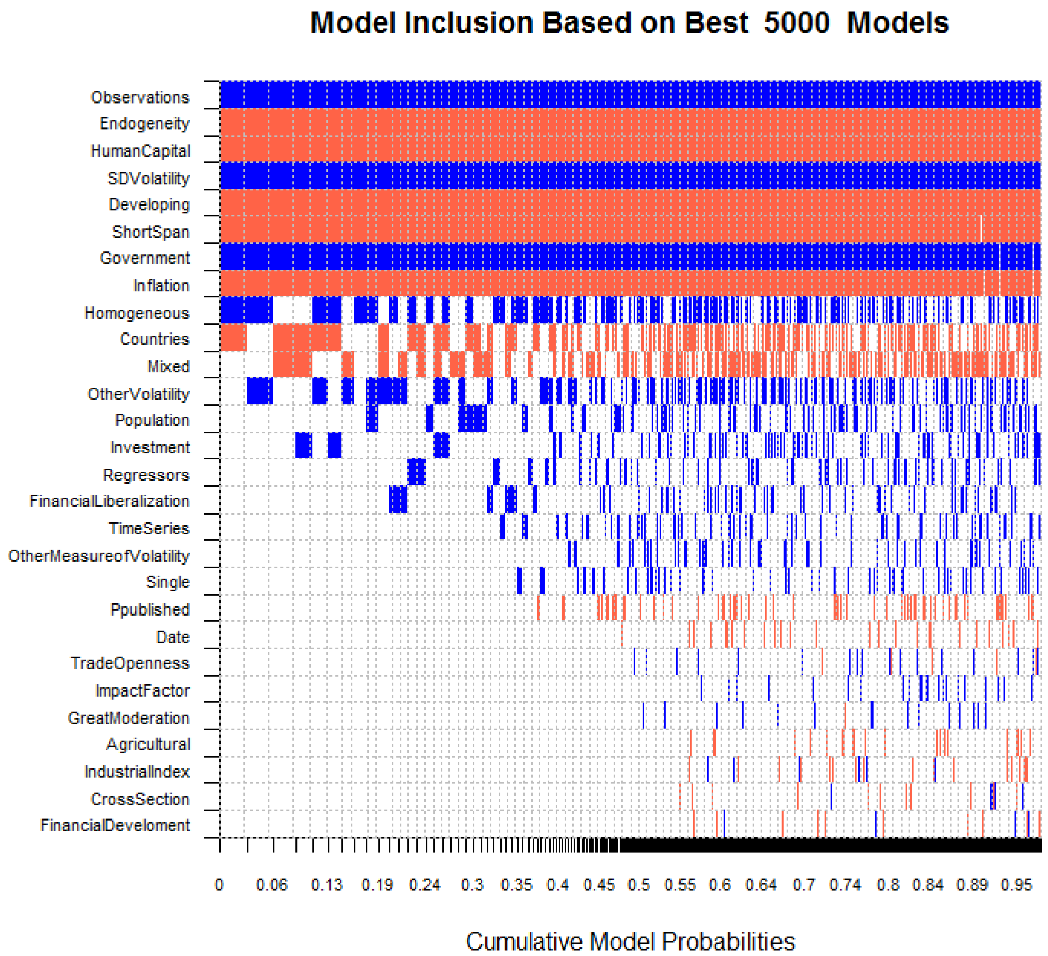
Bayesian Map II (Robustness: Alternative Priors)



Notes: The vertical axis measures the cumulative posterior model probabilities, while the vertical one depicts the moderator variables that are explained in Table 1. Each column shows different model. Each variable in the left axis is sorted according to posterior inclusion probability in descending order meaning that variables on the top appear more frequently across different models than the ones in the bottom. Red colour (light grey) shows negative sign, while blue colour (dark grey) shows positive sign. Blank entries mean that the variable is not included in the model. 5000 models with the highest posterior probabilities are shown, while assuming Zellner's *g* prior as parameters' prior and beta-binomial model prior.

Figure 6:

Bayesian Map III (Robustness: Only Published Papers)



Notes: See the notes in Table 4. Here, we include only published papers.

Appendix: Studies Used in the Meta-Analysis

1. Aghion, P., Angeletos, G.M., Banerjee, A., & Manova, K. (2010). 'Volatility and Growth: Credit Constraints and the Composition of Investment', *Journal of Monetary Economics*, 57, 246-265.

2. Aghion, P. & Banerjee, A. (2005). '*Volatility and Growth*', Oxford University Press.

3. Andreou, E., Pelloni, A., & Sensier, M. (2013). 'Is Volatility Good for Growth? Evidence from the G7', CEIS Research Paper 258, Tor Vergata University.

4. Araújo, E., Carpena, L., & Cunha, A. B. (2008). 'Brazilian Business Cycles and Growth from 1850 to 2000', *Estudos Econômicos (São Paulo), 38*, 557-581.

5. Badinger, H. (2010). 'Output Volatility and Economic Growth', *Economics Letters, 106*, 15-18.

6. Badinger, H. (2012). 'Cyclical Expenditure Policy, Output Volatility and Economic Growth', *Applied Economics, 44*, 835-851.

7. Beaumont, P.M., Norrbin, S.C., & Yigit, F.P. (2008). 'Time Series Evidence on the Linkage between the Volatility and Growth of Output', *Applied Economics Letters*, 15, 45-48.

8. Berument, M.H., Dincer, N.N., & Mustafaoglu, Z. (2012). 'Effects of Growth Volatility on Economic Performance - Empirical Evidence from Turkey', *European Journal of Operational Research, 217*, 351-356.

9. Bhar, R., & Mallik, G. (2013). 'Inflation Uncertainty, Growth Uncertainty, Oil Prices, and Output Growth in the UK', *Empirical Economics, 45*, 1333-1350.

10. Bisio, L., & Ventura, L. (2013). 'Growth and Volatility Reconsidered: Reconciling Opposite Views', *ISRN Economics, 2013*.

11. Bredin, D., & Fountas, S. (2005). 'Macroeconomic Uncertainty and Macroeconomic Performance: Are they Related?', *The Manchester School*, *73*, 58-76.

12. Bredin, D., & Fountas, S. (2009). 'Macroeconomic Uncertainty and Performance in the European Union', *Journal of International Money and Finance, 28*, 972-986.

13. Bredin, D., Elder, J., & Fountas, S. (2009). 'Macroeconomic Uncertainty and Performance in Asian Countries', *Review of Development Economics, 13*, 215-229.

14. Brzozowski, M. (2011). 'The Interplay between Labor Market Rigidity and Volatility-Growth Nexus', *International Review of Applied Economics*, 25, 405-418.

15. Burnside, C., & Tabova, A. (2009). 'Risk, Volatility, and the Global Cross-Section of Growth Rates', No. w15225, National Bureau of Economic Research.

16. Caporale, T., & McKiernan, B. (1996). 'The Relationship between Output Variability and Growth: Evidence from Post War UK Data', *Scottish Journal of Political Economy*, 43, 229-236.

17. Caporale, T., & McKiernan, B. (1998). 'The Fischer Black Hypothesis: Some Time-Series Evidence', *Southern Economic Journal*, 64, 765-771.

18. Chatterjee, P., & Shukayev, M. (2006), 'Are Average Growth Rate and Volatility Related?', Bank of Canada working paper 2006-24.

19. Clévenot, M., & Mbome, M. S. (2014). 'Reassessing Vulnerability to Macroeconomic Volatility: A Nonstationary Panel Approach', CEPN Working paper.

20. Conrad, C., Karanasos, M., & Zeng, N. (2010). 'The Link between Macroeconomic Performance and Variability in the UK', *Economics Letters*, 106, 154-157.

21. Dabušinskas, A., Kulikov, D., & Randveer, M. (2013). 'The Impact of Volatility on Economic Growth', No. wp2012-7, Bank of Estonia.

22. Dawson, J. W., & Stephenson, E. F. (1997). 'The Link between Volatility and Growth: Evidence from the States', *Economics Letters*, 55, 365-369.

23. Dejuan, J., & Gurr, S. (2004). 'On the Link between Volatility and Growth: Evidence from Canadian Provinces', *Applied Economics Letters, 11*, 279-282.

24. Döpke, J. (2004). 'How Robust is the Empirical Link between Business-cycle Volatility and Long-run Growth in OECD Countries?', *International Review of Applied Economics, 18*, 103-121.

25. Easterly, W., & Kraay, A. (2000). 'Small States, Small Problems? Income, Growth, and Volatility in Small States', *World Development*, 28, 2013-2027.

26. Edwards, J. A. (2007). 'Dynamics of the Cross-country Growth/Volatility Relationship', *Global Economy Journal, 7*, 1-20.

27. Ezcurra, R. (2010). 'Sectoral Volatility and Regional Growth in the European Union', *Environment and Planning C: Government and Policy*, 28, 369-380.

28. Ezcurra, R. & Vicente. R. (2013). 'Volatility and Regional Growth in Europe: Does Space Matter?', In ERSA conference papers, No. ersa13p133, European Regional Science Association.

29. Falk, M., & Sinabell, F. (2009). 'A Spatial Econometric Analysis of the Regional Growth and Volatility in Europe', *Empirica, 36*, 193-207.

30. Fang, W. S., & Miller, S. M. (2008). 'The Great Moderation and the Relationship between Output Growth and its Volatility', *Southern Economic Journal*, 74, 819-838.

31. Fang, W., & Miller, S. M. (2009). 'Modelling the Volatility of Real GDP Growth: The case of Japan Revisited', *Japan and the World Economy, 21*, 312-324.

32. Fang, W., & Miller, S. M. (2014). 'Output Growth and its Volatility: The Gold Standard through the Great Moderation', *Southern Economic Journal, 80*, 728-751.

33. Fang, W., Miller, S. M., & Lee, C. (2008). 'Cross-country Evidence on Output Growth Volatility: Nonstationary Variance and GARCH Models', *Scottish Journal of Political Economy, 55*, 509-541.

34. Fatás, A. (2002). 'The Effects of Business Cycles on Growth', Vol. 156, Banco Central de Chile.

35. Fatás, A., & Mihov, I. (2009). '*Macroeconomic Policy: Does it Matter for Growth?; the Role of Volatility',* World Bank.

36. Fatás, A., & Mihov, I. (2013). 'Policy Volatility, Institutions, and Economic Growth', *The Review of Economics and Statistics, 95*, 362-376.

37. Fountas, S., & Karanasos, M. (2006). 'The Relationship between Economic Growth and Real Uncertainty in the G3', *Economic Modelling*, 23, 638-647.

38. Fountas, S., & Karanasos, M. (2008). 'Are Economic Growth and the Variability of the Business Cycle Related? Evidence from five European Countries', *International Economic Journal, 22*, 445-459.

39. Fountas, S., Karanasos, M., & Mendoza, A. (2004). 'Output Variability and Economic Growth: the Japanese case', *Bulletin of Economic Research, 56*, 353-363.

40. Furceri, D. (2009). 'Fiscal Convergence, Business Cycle Volatility, and Growth', *Review of International Economics, 17*, 615-630.

41. García-Herrero, A., & Vilarrubia, J. (2007). 'The Laffer Curve of Macroeconomic Volatility and Growth: Can it be Explained by the Different Nature of Crises?', *Money Affairs*, 44, 43-60.

42. Garrison, C. B., & Lee, F. Y. (1995). 'The Effect of Macroeconomic Variables on Economic Growth Rates: A Cross-country Study', *Journal of Macroeconomics*, 17, 303-317.

43. Grier, K. B., & Perry, M. J. (2000). 'The Effects of Real and Nominal Uncertainty on Inflation and Output Growth: Some GARCH-M Evidence', *Journal of Applied Econometrics*, 15, 45-58.

44. Grier, K. B., & Tullock, G. (1989). ’An Empirical Analysis of Cross-national Economic Growth, 1951–1980’, *Journal of Monetary Economics, 24*, 259-276.

45. Grier, K. B., Henry, Ó. T., Olekalns, N., & Shields, K. (2004). ‘The Asymmetric Effects of Uncertainty on Inflation and Output Growth’, *Journal of Applied Econometrics*, 19, 551-565.

46. Henry, O. T., & Olekalns, N. (2002). ’The Effect of Recessions on the Relationship between Output Variability and Growth’, *Southern Economic Journal*, 68, 683-692.

47. Hnatkovska, V., & Loayza, N. (2004). ‘Volatility and Growth’, Vol. 3184, World Bank.

48. Imbs, J. (2007). ‘Growth and Volatility’, *Journal of Monetary Economics, 54*, 1848-1862.

49. Jetter, M. (2013). ‘Volatility and Growth: An Explanation for the Disagreement’, Available at SSRN 2285668.

50. Jetter, M. (2014). ‘Volatility and Growth: Governments are Key’, *European Journal of Political Economy*, 36, 71-88.

51. Karanasos, M., & Schurer, S. (2005). ‘Is the Reduction in Output Growth Related to the Increase in its Uncertainty? The case of Italy’, *WSEAS Transactions on Business and Economics, 3*, 116-122.

52. Kedir, A. M., & Bani, N. Y. M. (2012). ‘Panel Data Evidence on the Role of Education in the Growth-Volatility Relationship’, University of Leicester, No. 12/04.

53. Kim, J., & Kim, J. (2010). ‘Volatility and Growth: An Alternative Interpretation’, *Journal of Economic Research*, 15, 233-247.

54. Kim, J. R., & Lim, G. Y. (2009). ‘Volatility and Growth: the Case of the US and UK’, Mimeo.

55. Kneller, R., & Young, G. (2001). 'Business Cycle Volatility, Uncertainty and Long-run Growth', *The Manchester School, 69*, 534-552.

56. Kormendi, R.C., & Meguire, P.G. (1985). 'Macroeconomic Determinants of Growth: Cross-country Evidence', *Journal of Monetary Economics, 16*, 141-163.

57. Kose, M. A., Prasad, E. S., & Terrones, M. E. (2005). 'Growth and Volatility in an Era of Globalization', *IMF Economic Review, 52*, 31-63.

58. Kose, M. A., Prasad, E. S., & Terrones, M. E. (2006). 'How Do Trade and Financial Integration Affect the Relationship between Growth and Volatility?', *Journal of International Economics, 69*, 176-202.

59. Kroft, K., & Lloyd-Ellis, H. (2002). 'Further Cross-country Evidence on the Link between Growth, Volatility and Business Cycles', Queens University, Department of Economic, Working Paper.

60. Lee, J. (2010). 'The Link between Output Growth and Volatility: Evidence from a GARCH Model with Panel Data', *Economics Letters*, 106, 143-145.

61. Lemoine, M., & Mougin, C. (2010). 'The Growth-Volatility Relationship: New Evidence Based on Stochastic Volatility in Mean Models', Banque de France.

62. Lin, S. C., & Kim, D. H. (2014). 'The Link between Economic Growth and Growth Volatility', *Empirical Economics*, 46, 43-63.

63. Macri, J., & Sinha, D. (2000). 'Output Variability and Economic Growth: The case of Australia', *Journal of Economics and Finance, 24*, 275-282.

64. Mallik, G., & Chowdhury, A. (2011). 'Effect of Inflation Uncertainty, Output Uncertainty and Oil Price on Inflation and Growth in Australia', *Journal of Economic Studies, 38*, 414-429.

65. Martin, P., & Rogers, C.A. (2000). 'Long-term Growth and Short-term Economic Instability', *European Economic Review, 44*, 359-381.

66. Neanidis, K. C., & Savva, C. S. (2013). 'Macroeconomic Uncertainty, Inflation and Growth: Regime-dependent Effects in the G7', *Journal of Macroeconomics, 35*, 81-92.

67. Norrbin, S. C., & Yigit, F. P. (2005). 'The Robustness of the Link between Volatility and Growth of Output', *Review of World Economics*, 141, 343-356.

68. Ponomareva, N., & Katayama, H. (2010). 'Does the Version of the Penn World Tables Matter? An Analysis of the Relationship between Growth and Volatility', *Canadian Journal of Economics/Revue canadienne d'économique, 43*, 152-179.

69. Popov, A. A. (2011). 'Output Growth and Fluctuations: The Role of Financial Openness', ECB Working paper 1368.

70. Posch, O., & Wälde, K. (2011). 'On the Link between Volatility and Growth', *Journal of Economic Growth, 16*, 285-308.

71. Rafferty, M. (2002). 'Black's Hypothesis and Developed Economies', *Journal of Economics and Finance, 26*, 309-326.

72. Rafferty, M. (2005). 'The Effects of Expected and Unexpected Volatility on Long-run Growth: Evidence from 18 Developed Economies', *Southern Economic Journal*, 71, 582-591.

73. Rafferty, M. C. (2004). 'Growth-Business Cycle Interaction: A Look at the OECD', *International Advances in Economic Research, 10*, 191-201.

74. Ramey, G., & Ramey, A. (1995). 'Cross-Country Evidence on the Link Between Volatility and Growth', *The American Economic Review, 85*, 1138-1151.

75. Rodriguez, C. M. (2014). 'Financial Development, Fiscal Policy and Volatility: Their Effects on Growth', *The Journal of International Trade & Economic Development, 23*, 223-266.

76. Šergo, Z. (2010). 'Is there Volatility-Growth Trade-off? The case of Croatia-1920 to 2008', *Ekonomski pregled, 61*, 151-186.

77. Shields, K., Olekalns, N., Henry, Ó. T., & Brooks, C. (2005). 'Measuring the Response of Macroeconomic Uncertainty to Shocks', *The Review of Economics and Statistics, 87*, 362-370.

78. Siegler, M. V. (2005). 'International Growth and Volatility in Historical Perspective', *Applied Economics Letters, 12*, 67-71.

79. Speight, A. E. (1999). 'UK Output Variability and Growth: Some Further Evidence', *Scottish Journal of Political Economy*, 46, 175-184.

80. Tochkov, K., & Tochkov, K. (2009). 'Is Higher Volatility Associated with Lower Growth? International Evidence from South Korea', *The Empirical Economics Letters, 8*, 625-629.

81. Trypsteen, S. (2014). 'Cross-Country Interactions, the Great Moderation and the Role of Volatility in Growth', CFCM working paper, University of Nottingham.

82. Tsouma, E. (2014). 'The Link between Output Growth and Real Uncertainty in Greece: A Tool to Speed up Economic Recovery?', *Theoretical Economics Letters*, 4, 91-97.

83. Turnovsky, S. J., & Chattopadhyay, P. (2003). 'Volatility and Growth in Developing Economies: Some Numerical Results and Empirical Evidence', *Journal of International Economics*, 59, 267-295.

84. Van der Ploeg, F., & Poelhekke, S. (2009). 'Volatility and the Natural Resource Curse', *Oxford Economic Papers*, 61, 727-760.