Volatility and Growth: A not so Straightforward Relationship

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Abstract: Conflicting theoretical approaches and diverse empirical evidence exist on the relationship between business cycle volatility and economic growth. While the average reported effect of volatility on growth is negative, the empirical estimates vary substantially across studies. We identify the factors that explain this 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 can explain the differences in the reported estimates. Finally, the literature is found to be free of publication bias.

Keywords: Economic Growth, Volatility, Meta-Analysis, Bayesian Model Averaging, Ordered Probit Model

*JEL Classification: C83, E32, O40*

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1. Introduction

The connection between business cycle volatility and economic growth has been extensively investigated in modern macroeconomics (Cooley and Prescott, 1995; Fatás, 2002; Aghion and Banerjee, 2005; Hnatkovska and Loayza, 2005). The direction of the effect of volatility on economic growth, though, is ambiguous and no consensus exists in either the theoretical or the empirical literature. Several theoretical models attempt to identify the impact of volatility on growth with divergent conclusions.[1] Motivated by the absence of a clear theoretical consensus, researchers attempt to resolve this issue empirically. The work of Ramey and Ramey (1995) gave rise to an extant empirical literature exploring this link. The reported estimates of the empirical contributions vary widely, as **Figure 1** shows. Most of the empirical studies suggest a negative association between business cycles and economic growth (Ramey and Ramey, 1995; Martin and Rogers, 2000; Kneller and Young, 2001; Van der Ploeg and Poelhekke 2009; Badinger, 2010); several others (Kormendi and Meguire, 1985; Caporale and McKiernan, 1996; Fountas and Karanasos, 2006) point to a positive link, while a few studies report a lack of association between the two variables (Speight, 1999; Grier and Perry, 2000; Fang and Miller, 2008).[2] As a result, 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.

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[1] Several theoretical foundations exist suggesting either a positive (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 cycle volatility and growth. See Priesmeier and Stahler (2011), Aghion and Banerjee (2005) and Aghion and Howitt (2006) for summary reviews of the theoretical literature.

[2] 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 (Kormendi and Meguire, 1985; Grier and Tullock, 1989; Ramey and Ramey, 1995). On the other hand, several empirical contributions utilize the generalized auto-regressive conditional heteroskedasticity (GARCH) model to analyze the relationship between output fluctuations and growth (Caporale and McKiernan, 1998; Grier and Perry, 2000; Fountas and Karanasos, 2006). See Fatás (2002), Dopke (2004) and Norrbin and Yigit (2005) for extensive reviews of the empirical literature.

Figure 1

Reported Estimates over Time
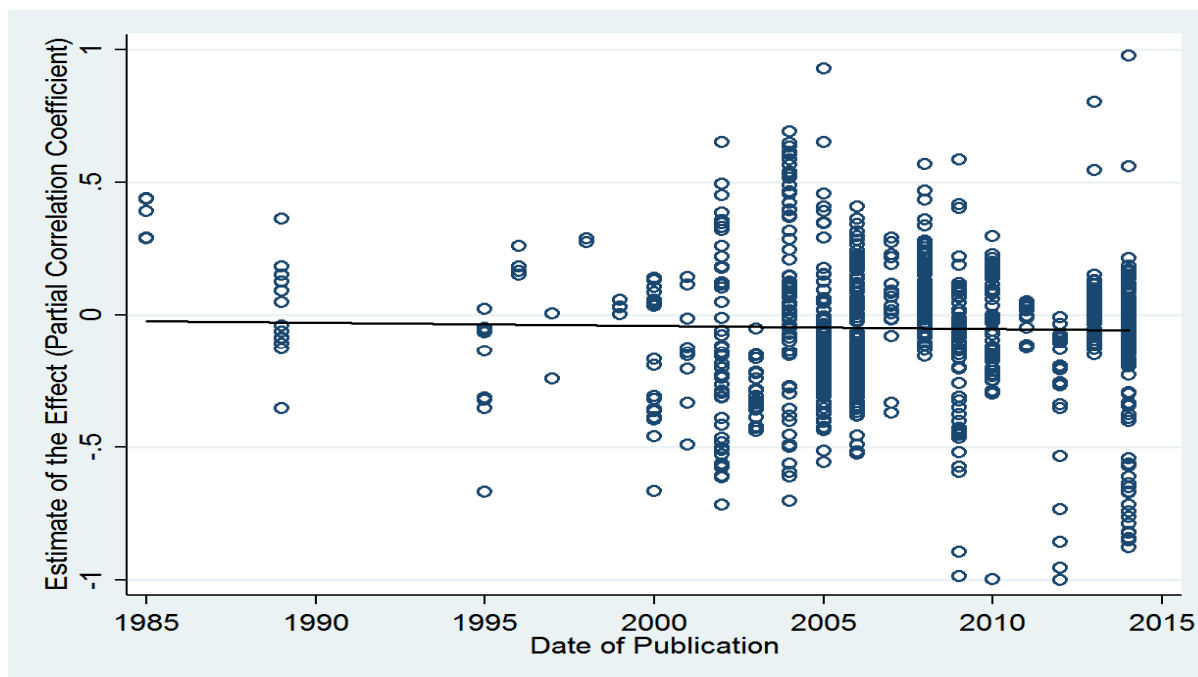
Notes: The figure depicts the estimates (partial correlation coefficients) of the effect of volatility on growth reported in the empirical literature over time. The horizontal axis shows the publication year of the examined studies.

This paper uses more than one thousand estimates on the effect of output volatility on growth. From this set of point estimates, 41% indicate a statistically significant negative effect, 17% find a statistically significant positive effect, and 42% are not significant. The empirical literature reports, on average, a negative impact of volatility on growth of -0.05. As **Figure 1** reveals, the individual estimates vary heavily across studies. The absence of conclusive empirical evidence motivates a quantitative synthesis of research to understand why so diverse empirical findings emerge. Meta-analysis constitutes a systematic quantitative review method designed 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 (see for example, Card and Krueger, 1995; Card *et al.*, 2010; Chetty *et al.*,

2012; Doucouliagos *et al.*, 2012; Gechert, 2015; Havranek *et al.*, 2017; Huang and Sim, 2018).

To the best of our knowledge, this is the first meta-analytic study on the literature of volatility and growth.[3] We collect and analyze 1010 estimates on the volatility-growth nexus, as reported in 84 empirical studies over the period 1985-2015. Our meta-analysis relies on two alternative methodological approaches: 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 modeling uncertainty stemming from the large number of potential explanatory variables in the meta-regression specification. The ordered probit model overcomes 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 both approaches, we account for five groups of potential research design factors: i) differences in variables used, ii) modeling 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. These findings are robust to a series of alternative techniques and robustness checks. Specifically, we find that the choice of volatility measure matters; the use of a SD instead of a GARCH measure appears to be a key determinant of the observed heterogeneity of the collected coefficients. Studies that use GARCH-based measures of volatility tend to give less positive results compared to those using SD measures. Additionally, certain aspects of the volatility-growth equation specification can explain the diverse estimates. The

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[3] The terms volatility, variability, business cycle volatility and uncertainty are typically used interchangeably in the empirical literature. We follow this convention throughout this paper.

presence of proxies for human capital, government size, and the inflation rate are significant factors. The results show that studies accounting for the impact of human capital and the inflation rate in the empirical modeling 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. Moreover, several aspects of data characteristics emerge as decisive in explaining the heterogeneity of the literature. Such aspects include the number of observations, the short-span of datasets and the presence of developing countries in the dataset. In addition, our evidence confirms that the negative relationship is more prominent in developing countries rather than in developed ones. On the other hand, 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** analyzes 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 (Cooley and Prescott, 1995; Aghion and Banerjee, 2005). Subsequently, several theoretical contributions have focused on the relationship between volatility and growth, providing alternative rationales for either a positive or a negative link.

Two broad strands exist in the literature on the link between business cycles and economic growth. The first strand 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 second strand 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, 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, emphasizing the role of innovation in production. During 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 point to a negative relation between volatility and 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.

Various alternative explanations exist for a negative relationship between volatility and growth. Bernanke (1983) and Pindyck (1991) 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. Furthermore, Dehejia and Rowe (1998) develop a neo-Keynesian model and show that a more severe business cycle, driven by fluctuations in monetary velocity, reduces the productivity of capital and, therefore, reduces the growth rate. 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. Long-run growth is more sensitive to business cycle volatility in economies where the degree of financial development is lower.

2.2. The Empirics of Volatility and Growth

The empirical literature is even more rich than the theoretical one but nevertheless the abounding evidence remain equally ambiguous. The empirical contributions on the volatility-growth nexus follow two main trajectories. The bulk of the empirical studies follow the empirical literature on growth determinants. That is, volatility is treated as one of the explanatory variables of growth (e.g., Kormendi and Meguire, 1985; Grier and Tullock, 1989; Ramey and Ramey, 1995; among others). Another set of studies relies on generalized 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 to investigate the relationship between growth and volatility as part of a 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 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 the model:

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

where $\Delta y_{i,t}$ is the growth rate of output for country i in year t; 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; θ is a vector of coefficients, which is assumed to be common across countries; finally, $\varepsilon_{i,t}$ 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, however, 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 typically takes the form:

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

with

$$\sigma_t^2 = \delta_0 + \delta_1\,e_{t-1}^2 + \delta_2\,\sigma_{t-1}^2, \tag{4}$$

where Ω_t is the available information set and σ^2_t 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). Once more, 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 upholds 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 contributions corroborate the results of Ramey and Ramey (1995), including Martin and Rogers (2000), Kneller and Young (2001), Aghion and Banerjee (2005), Van der Ploeg and Poelhekke (2009) and Aghion *et al*. (2010). 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 indicates 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. For instance, Norrbin and Yigit (2005) produce evidence of a robust negative relationship between the volatility and growth of output and 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.

In a similar vein, Chatterjee and Shukayev (2006) show that Ramey and Ramey's results are not robust to either the definition of the growth rate or the composition of the sample. They conclude that the hypothesized relationship is not statistically significant. Dopke's (2004) results, based on a wide range of estimation techniques, 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, he 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. However, the evidence, using disaggregated firm-level data, from the study of Chong and Gradstein (2009), provides empirical support for the negative volatility-growth relationship.

The second strand in the literature consists of studies employing time series techniques (e.g., 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 in the UK and the US, whereas Fountas and Karanasos (2006) find a positive relationship in Germany and Japan. In contrast, Grier and Perry (2000) and Fountas and Karanasos (2006) conclude that no relationship exists in the US. Similarly, Fang and Miller (2008), accounting for possible structural changes in the volatility process, report a non-significant relationship between output growth rate and its volatility in the US. Lee (2010) extends the GARCH-in-mean methodology into a dynamic panel context and provides evidence for the G7 countries, showing that while higher output growth is associated with higher volatility, higher growth does not increase economic uncertainty.

Finally, several papers explore the link between business cycle volatility and 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 of 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 exhibit higher volatility and a pronounced negative correlation between volatility and growth. Furceri (2009) also finds that business cycle volatility affects negatively output growth through higher levels of fiscal convergence across countries, while Posch and Wälde (2011) show that the negative coefficient is affected sizeably when controlling for taxes in the conventional Ramey and Ramey specification. Finally, Jetter (2014) suggests that in addition to a direct positive effect of volatility on growth, a negative indirect effect exists, 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 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 repeated the same process in *Econlit* and *Scopus*. The search includes all combinations of the keywords 'growth', 'economic growth' and 'output growth', with 'volatility', 'variability' and 'uncertainty'. This process produced 160 papers in total.[4] Our inclusion strategy consisted of three criteria. The main criterion for a study to be included in the meta-data sample is to report at least one estimated coefficient of the effect of volatility on output growth. Therefore, we excluded papers that make a theoretical (not empirical) contribution to the literature. The second inclusion criterion is the definition of volatility. More precisely, we are interested in studies that focusing on any proxy of economic activity's volatility. This excludes studies that are examining other types of volatility (such as political volatility). This kind of studies appeared in our original pool of papers since the words 'growth' and 'volatility' are frequently used in their titles. The final inclusion criterion is the reporting of a measure of estimate's precision (standard errors, *t*-statistics or *p*-values). Therefore, we excluded studies that report statistical significance by using only stars or bold printing. In total, 84 papers meet our inclusion criteria. The full list of these studies is provided in the Appendix.

Figure 2 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 Ramey and Ramey (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 the Great Moderation. The financial

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[4] We pursue the data collection process following the methodological steps suggested in Stanley *et al*. (2013).

turbulence of 2008-9 and the subsequent European sovereign crisis, both associated with higher levels of economic variability, have motivated interest in re-examining the volatility-growth relationship. 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 2

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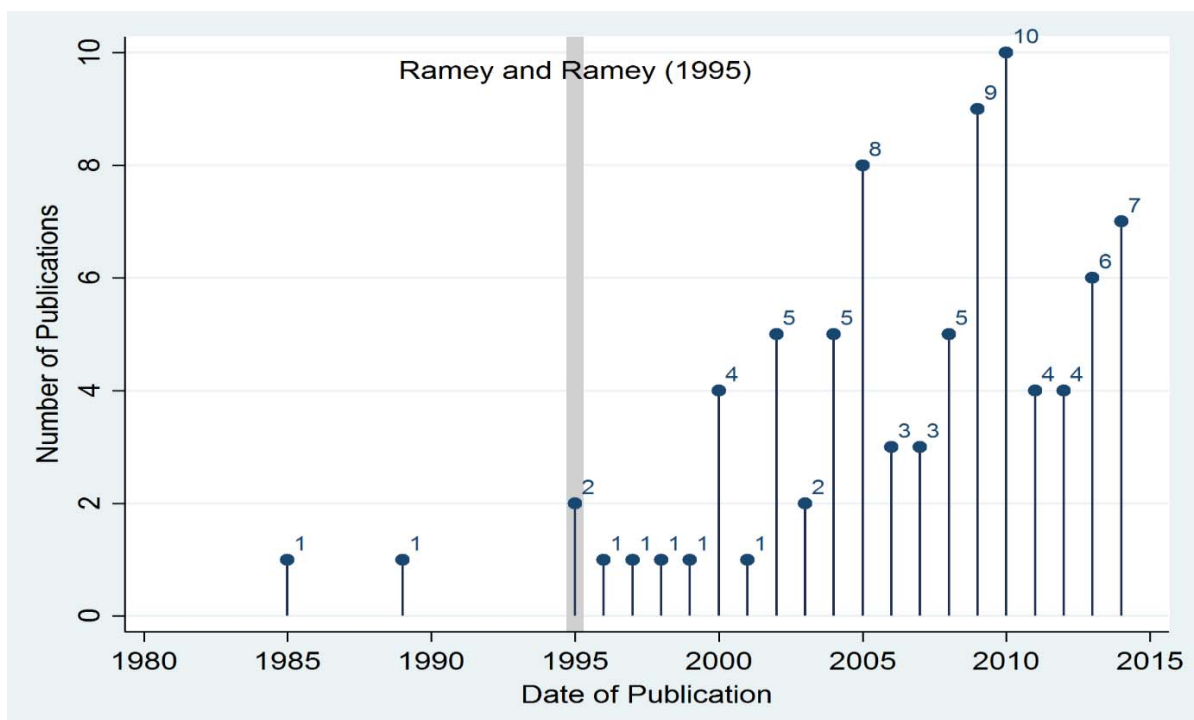
Notes: The figure shows the evolution of the empirical literature over time. Numbers indicate the number of published studies for each year. The shade line shows the year when the most influential study (Ramey and Ramey, 1995) was published. Even though the paper is not the first empirical study, it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

To obtain an overview of the meta-analytic data set we report the boxplot in **Figure 3**. We show the degree of dispersion of the estimates across and within studies, using the partial correlation coefficients from the 84 collected papers. Our analysis relies on the 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 the 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 estimates comparable regardless of the different volatility proxies used. The full sample of 84 studies includes 70 published papers in peer-reviewed journals and the remaining 14 are working papers. Following the current consensus in meta-analytic literature, we do not exclude the working papers from our analysis (Stanley, 2001).[5] 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 explicitly model this feature in the next section.

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

Figure 3

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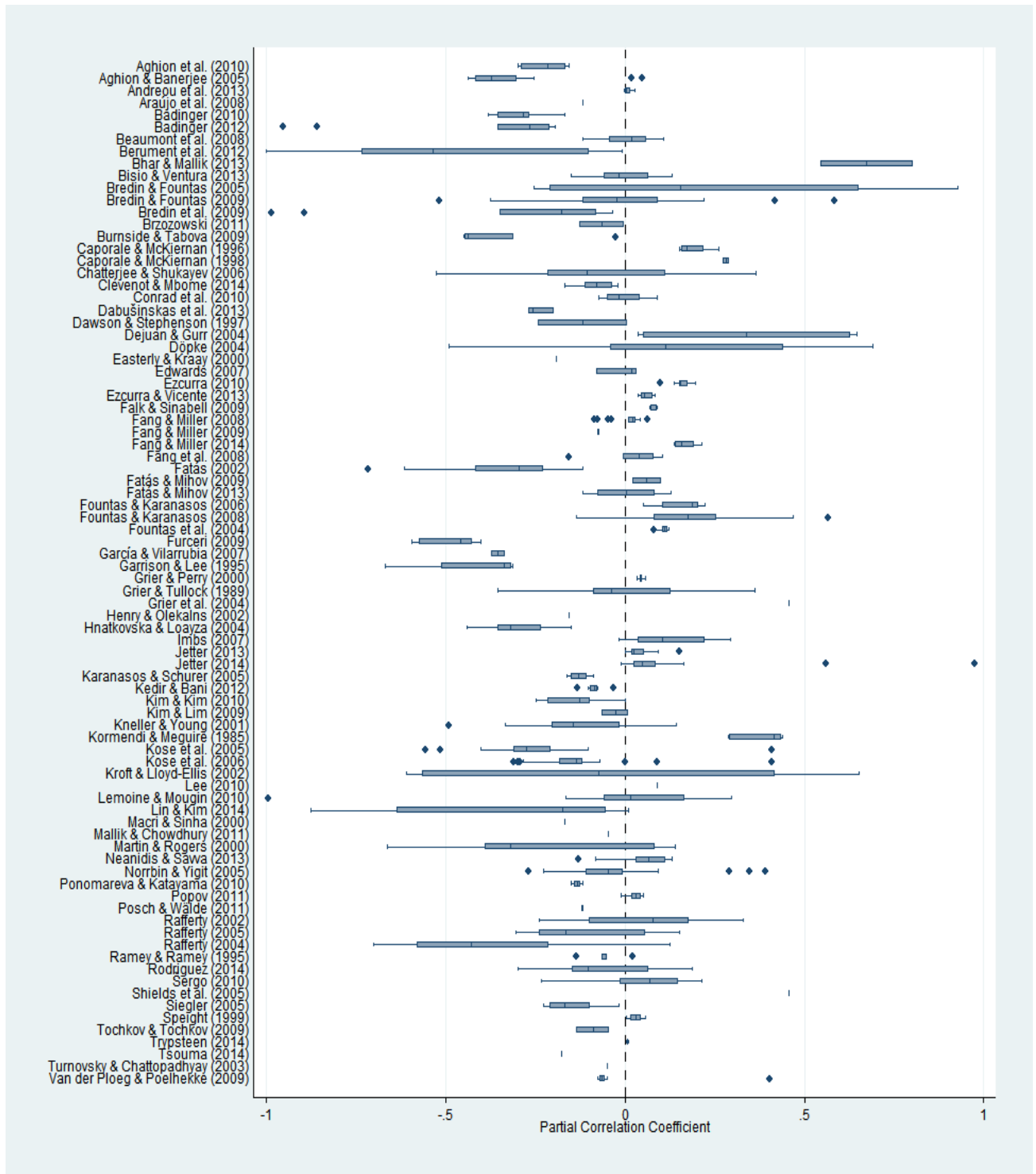
Notes: The figure depicts the boxplot of the collected estimates from the 84 empirical studies. For better exposition of the observed heterogeneity across studies, we have used partial correlation coefficients. Studies are sorted alphabetically. The full list of papers is provided in the Appendix.

The first step in analyzing the meta-analytic data on the volatility-growth nexus consists in examining the relationship of the estimated effects with their corresponding precision. We report the funnel plot in **Figure 4**; that is, the scatter plot of the partial correlation coefficients along with their inverse standard errors.

Figure 4

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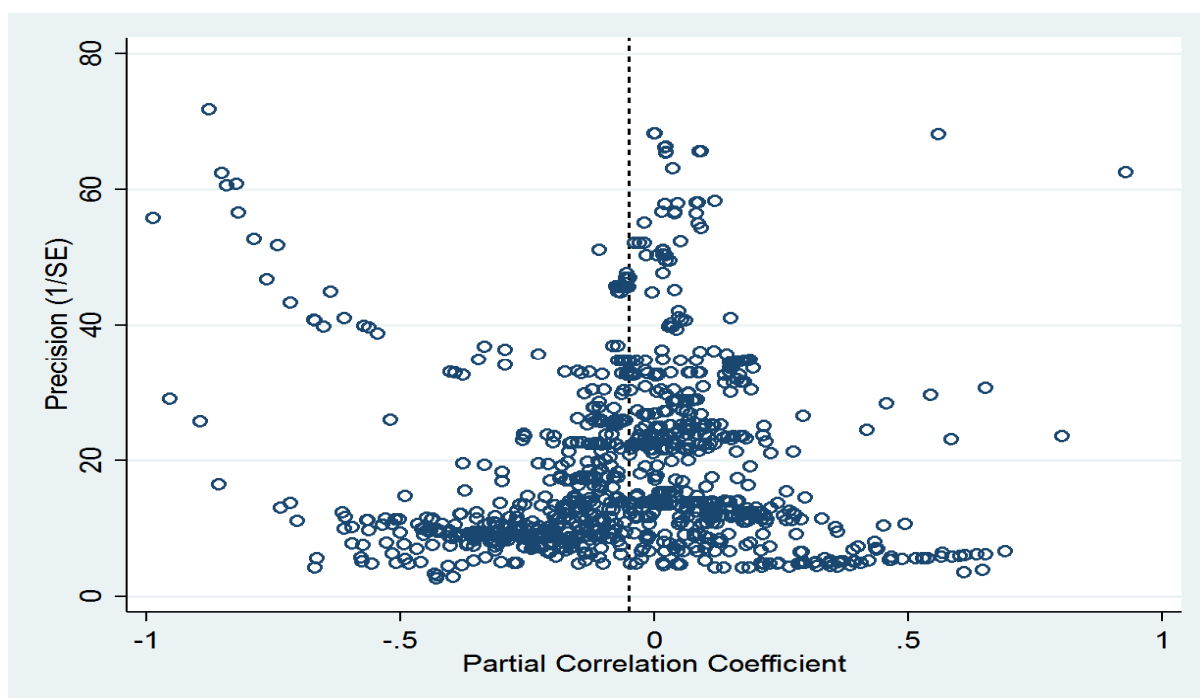
Notes: Presence of symmetry suggests the absence of publication bias and vice versa; an asymmetrical funnel plot indicates a possible publication bias. The dotted line shows the average effect ($r = -0.049$).

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) average of the partial correlation coefficients. The unweighted mean of the reported estimates equals -0.049, suggesting that the effect of volatility on growth is on average negative. Following Doucouliagos (2011), this average partial correlation can be considered as a small effect in economics. This result should be interpreted cautiously. As we discuss in more detail in **Section 4** and **6**, the dispersion of estimates is vast. The number of negative estimates, however, 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 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 (i.e., the mean is weighted by the inverse of the number of observations that are reported in each study). This evidence should be cautiously interpreted as the average effect may be a biased estimate of the true effect due to publication bias (Doucouliagos and Stanley, 2013). Both plots in **Figures 3** and **4** as well as the mean estimates in **Table 1,** make apparent that a substantial heterogeneity of the estimates both within and across studies. Thus, the emerging challenge is to model this observed heterogeneity.

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% denote 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.

4. Modeling Heterogeneity

In the absence of an a priori theory regarding the types of moderators, we should consider as many aspects of the literature as possible. **Table 2** lists all the potential moderator variables collected from the 84 empirical studies along with a short description and their summary statistics. We group the moderators into five broad categories, which capture the characteristics for: i) variable selection, ii) modeling specifications, iii) datasets, iv) estimation methods, and v) publication bias.

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.

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 most 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. Treating the estimates that use either GDP growth or GDP per capita growth, as base category 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 modeling volatility. In the first set of studies, the usage of standard deviation of growth rates was the norm. Even though, GARCH modeling 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 modeling 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.[6]

The specification of the estimated model typically involves a large number of conditional variables. Overall, this group of moderator variables help us to identify whether there is any variation in the reported estimates due to the selection of different variables as control set. Trying to be as inclusive as possible, we construct eleven moderator variables. The first one is the number of total regressors and proxies how parsimonious a model is. We use additional dummy variables related to whether the estimated equations include proxies that measure one of the following variables including: population; government size; inflation rate; measures of investment; measures of human capital; agricultural production or primary sector of the economy;

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

financial development; financial liberalization; and 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 can identify several potential factors of data 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 the 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 the value 1 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 categorization may not be sufficient enough, we also take into account an additional country-group feature. Since 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 the value of 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 the value of 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.[7] Assuming as a large time-span dataset that covers at least 40 years, we create a dummy ('Short span') that takes the value of 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 the Great Moderation, that is the period between 1985 and 2007 (Bernanke, 2004; Davis and Kahn, 2008). So, we put 1 when at least ten years of this period are covered.[8]

The forth group of moderator variables consists of a dummy capturing differences in the econometric methodology. In the volatility-growth literature the different econometric techniques mostly pertain to the volatility measures, and the proxy that distinguishes between panel, time series or cross-section dataset. For example, the GARCH methodology constitutes an approach for calculating 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 (IV/GMM/2SLS) that account for endogeneity and 0 otherwise.

The last group of moderator variables deals with publication features that are captured by three variables. The first is the most typical variable in meta-analysis; i.e., a dummy ('Published') taking 1 when the study has been published in peer-reviewed journal and 0 when it is in a working-paper form. Additionally, we include a trend

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

[8] We do not include a dummy variable for the period over which each effect has been estimated. The reason is that the time span used in this literature contain periods that coincide across different studies. For instance, the period 1980-2000 is a common sub-period used by studies which focus on both shorter and longer periods. In this way, such a dummy would lose any economic context.

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 to test whether the quality of the journal plays a role.

5. Meta-Regression Analysis and Results

The key objective and contribution of our analysis is to identify the factors that affect the volatility-growth relationship as reflected in the estimated coefficients of the empirical literature. The previous section discussed the role of 27 potential moderator variables. This section explores which of these factors systematically affect the estimation outcomes using the following linear meta-regression 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 jth 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 evident considering the need of applied researchers for reporting robust results (Lu and White, 2014). One way to deal with model uncertainty is to use the Bayesian Model Averaging (BMA) approach. Originally applied in growth econometrics (Fernandez *et al*. 2001), this method has recently become popular in macroeconomics (Moral-Benito and Roehn, 2016) and in meta-analysis studies (Havranek and Rusnak, 2013; Havranek *et al*., 2017). Starting from the 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 $M_1,\ldots,M_\mu$, models, 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, $p(M_\mu \mid r)$. More precisely, the best models are the ones with higher posterior model probability (PMP). According to the 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 $p(r \mid M_\mu, Z)$ 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 the regressors that consistently 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 greater its explanatory power.

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) algorithm. 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.[9] In the next section, we assume an alternative set of priors in order to test the robustness of our results.

Figure 5 depicts a map, which is a useful visualization of our results. In this map, the 5000 models with the highest posterior inclusion probabilities are summarized. 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 diminishes. 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 as compared to the ones in the bottom. The red color (lighter grey) indicates that the variable is included, and its estimated sign is negative, while the blue color (darker grey) indicates a positive sign.

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

Figure 5

Bayesian Map I
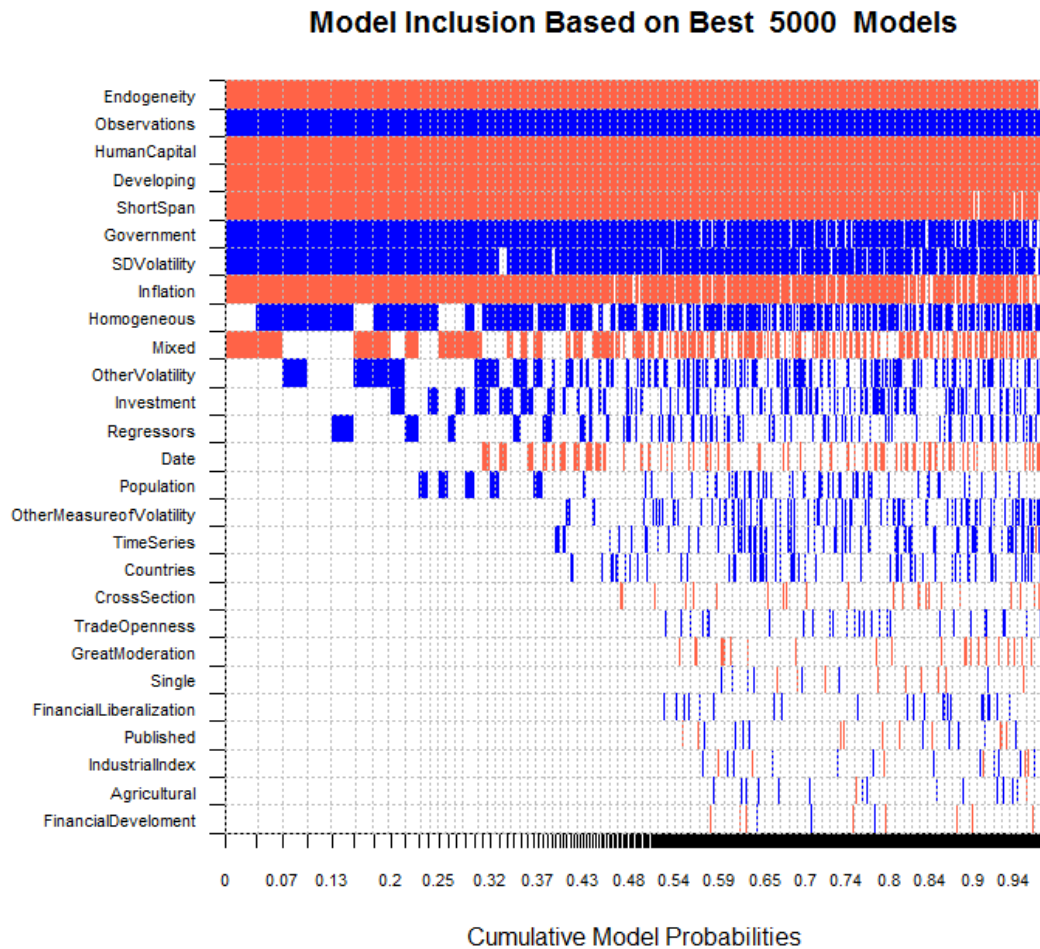
Model Inclusion Based on Best 5000 Models

Cumulative Model Probabilities

Notes: The horizontal 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 color (light grey) shows negative sign, while blue color (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.

According to the best model from the BMA results, nine variables seem to play the most significant role in explaining the heterogeneity of the estimated coefficients. As the red/blue color intensity shows, these variables appear to the majority of the estimated models. 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.[10] 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 characteristics, our results suggest 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 on the estimates; the variable 'other measure of volatility' appears only in a small sample of models and its PIP is rather low. Finally, the choice of the dependent variable does not seem to play any role in the reported estimates.

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[10] The posterior means and standard deviations are conditional on the variables included in the model.

Table 3

Bayesian Model Averaging Estimates

Categories	Variable	Bayesian Model Averaging			Frequentist check (OLS)		
		PIP	post Mean	post SD	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.

Another message from **Figure 5** 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)

who reported more negative coefficients of volatility when they consider secondary school enrolment. This reaffirm also the view of Cohen and Soto (2007) on the importance of the inclusion of human capital measures on growth regressions. In other words, human capital appears to be a key factor in explaining the negative relationship between growth and volatility. The same holds for the inflation rate, a finding that corroborates 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 its primary focus on growth volatility, also examines 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). In contrast 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. On theoretical grounds, Martin and Rogers (1997) and Blackburn (1999) discuss the advantages of stabilization policies in reducing volatility. In addition, Furceri (2009) examines whether the existence of fiscal convergence (i.e., similar government budget positions) alleviates the business cycle variability. Our evidence on the proxy of government size as a significant factor for the volatility-growth relationship is in accordance with Jetter (2014). Specifically, he supports the view that expansionary government policies can act as an insurance mechanism in volatile times. Thus, not accounting for the government size may lead to erroneous results. This result reaffirms also the findings of Posch and Wälde (2011), who show that controls for fiscal measures should be included in the standard growth-volatility regressions.

Interestingly, the evidence from our meta-data set suggests that there is no systematic pattern of credit growth effects on the volatility-growth relationship. This probably reflects the fact that a small group of studies allow for this channel in their

specifications. Furthermore, there is no evidence of any significant effects of trade openness, a finding consistent with previous evidence on the limited role of trade (e.g., Fatás; 2002 and Hnatkovska and Loayza; 2005).

Several aspects of the data characteristics appear to explain the magnitude of the estimated effects. First, 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 a less positive relationship. Focusing on the sample countries considered allows for some intriguing findings. Studies focusing on developing countries tend to report a less positive relationship between growth and volatility. This implies that developed countries are more robust to the perils of volatility, while volatility can be more damaging for developing countries. To the best of our knowledge, there are not studies that compare the effects of volatility across different groups of countries (e.g., developed vs. developing economies). In contrast, there are studies examining the specific groups of countries, such as Bredin *et al*. (2009) who restrict their focus only on Asian economies. This gap in the literature may motivate new relevant research. Finally, the choice among cross-sectional, time series and panel data does not seem to systematically affect the direction and magnitude of the reported estimates.

The last evidence regarding the data characteristics refers to the homogeneous data sets. It seems that when the analysis covers more homogeneous country-sets, leads to the reporting of more positive estimates. Although this finding has marginal statistical significance (*PIP = 0.721*), it suggests that the hypothesis of a negative relation is valid when the dataset consists of heterogeneous sets. When the countries under consideration share similar characteristics, the evidence of a negative relationship weakens. This result is consistent with Norrbin and Yigit (2005) who find a strong negative relationship between volatility and growth in a sample of 76 economies. When the authors confine their sample to OECD countries this relationship becomes weaker. Finally, the moderator pertaining to the econometric methods appears to be significant in almost all estimated models; studies that consider

endogeneity issues report more negative estimates. This implies that neglecting endogeneity may cause an upward bias.

Ioannidis *et al*. (2017) report that many fields in economics research suffer from this bias. However, as far as the publication characteristics are concerned in our analysis, 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. Consequently, the growth-volatility relationship emerges as one of the few empirical questions 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 relevant knowledge about the parameters and the model's size (Ley and Steel, 2009). To compare these results with the previous ones we show the map of 5000 models in **Figure 6**. The factors that seem to be significant 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 statistically significant. 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 to control for the quality of the journals used. As **Figure 7** 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 studies published in peer-reviewed journals. This result confirms the absence of publication bias in the literature.

Figure 6

Bayesian Map II (Robustness: Alternative Priors)
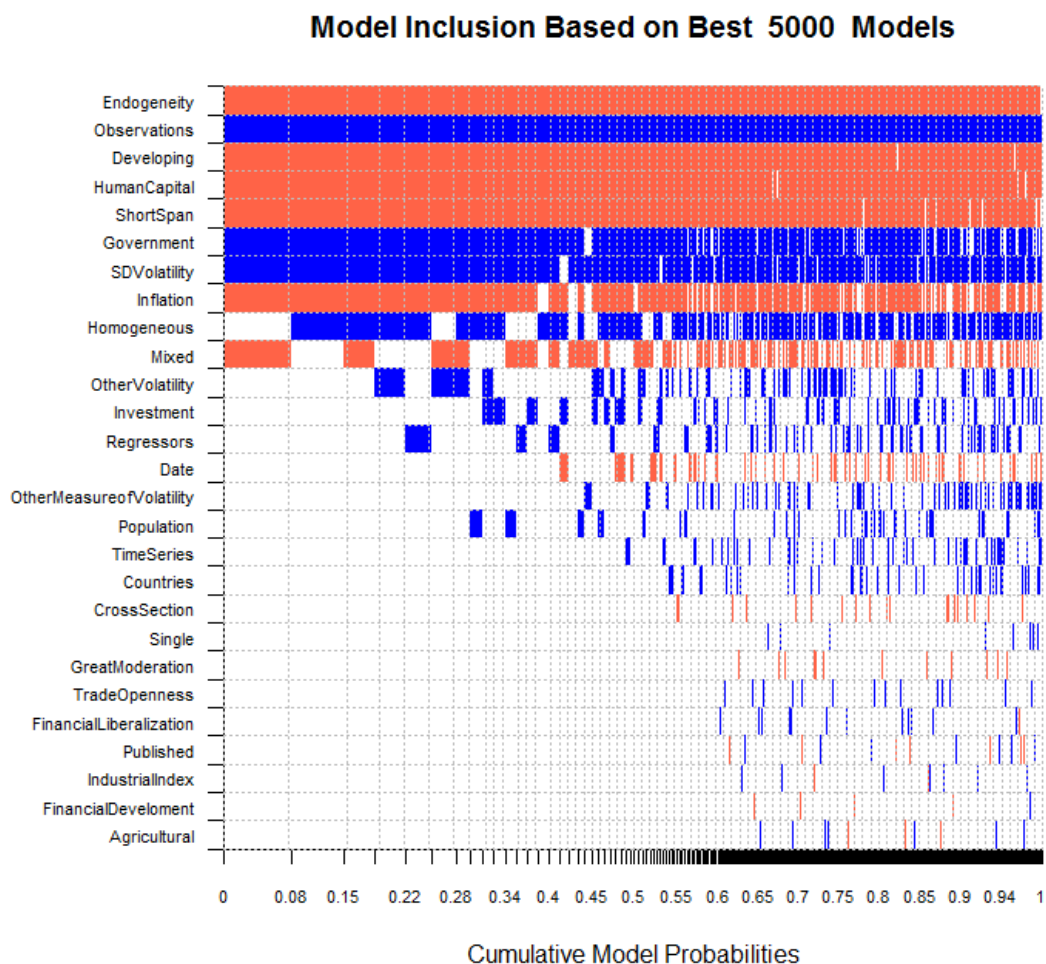
Model Inclusion Based on Best 5000 Models

Cumulative Model Probabilities

Notes: The horizontal 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 color (light grey) shows negative sign, while blue color (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 7

Bayesian Map III (Robustness: Only Published Papers)
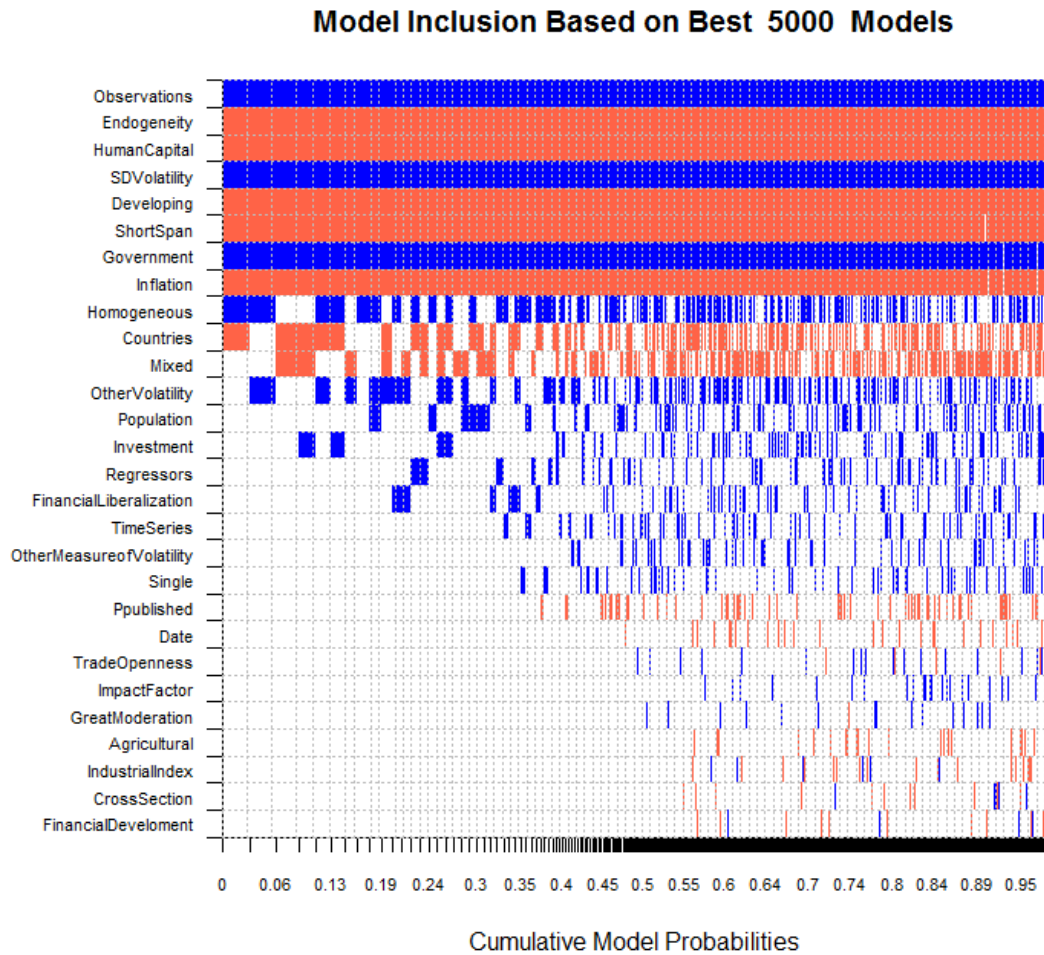
Notes: See the notes in Table 4. Here, we include only published papers.

Table 4

Bayesian Model Averaging (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).

6.2 Further Evidence

One basic feature of the literature examined in this paper is that the very notion of volatility is treated by employing 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**). Furthermore, we chose to use partial correlation coefficients to make the reported effects comparable. Even though the

partial correlation can prevent us from 'comparing apples with oranges', one critical 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. We can now write the model 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}, 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. Most of these positive estimates (62%), however, are insignificant. On the contrary, the 75% of negative coefficients is statistical significant.

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).

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.[11] 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

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[11] We have also performed the probit analysis adopting the 5% significance level as threshold. The results are qualitatively similar. These results are available upon request.

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 initial findings that the literature is bias free. As a final robustness test, we estimate a panel ordered probit to control for the fact that 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:

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 R²		0.225			
Log Likelihood		-850.467			
X² Test		489.615			
X² 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	Insignificant	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.

7. Conclusion

Ample evidence on the impact of business cycle volatility on economic growth has been produced over the last decades based on a set of diverse empirical studies. Despite the plethora of empirical estimations, no conclusive evidence exists on the effect of volatility on growth. Motivated by a number of divergent theoretical models and empirical results, this paper analyzes the existing empirical literature to identify the factors that affect the reported results. Identifying the sources of the heterogeneity of the estimates can guide the focus of future research efforts. While most of the evidence points to a negative effect of volatility on growth, the estimates vary considerably across the empirical studies. We conduct a meta-analysis that explores a wide range of potential factors to explain the sources of this heterogeneity. We use 27 explanatory variables, grouped into 5 categories. Two critical empirical challenges emerge in this process, namely model uncertainty and incomparability of the estimated coefficients across studies. To this end, we employ two distinct approaches, a Bayesian Model Averaging method that captures the model uncertainty and an ordered probit model, to deal with the incomparability of the estimates.

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 less positive 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 in less positive estimates, while the use of proxies for government size tend to support a positive relationship. In addition, the negative relationship is found to be stronger for samples of developing countries. Other aspects of data and estimation characteristics are decisive in explaining the diversity of the estimates. Finally, our analysis shows that the empirical literature on volatility and growth is one of the fields

in the economics research that is free from publication bias. This reflects the fact that both hypotheses of a positive and a negative link between business cycle volatility and growth enjoy theoretical and empirical support in this literature.

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