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D. Bakas, G. Chortareas, G. Magkonis

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Volatility and Growth: A not so Straightforward Relationship

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

[a] *Nottingham Business School, Nottingham Trent University, UK*
[b] *King's Business School, King's College London, UK*
[c] *Portsmouth Business School, University of Portsmouth, UK*
[d] *Rimini Centre for Economic Analysis (RCEA), Canada*
[e] *Data Analytics in Finance and Macro (DAFM) Research Centre, King's College London, UK*

Abstract

Conflicting theoretical models and diverse empirical evidence characterize research analysing 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 in 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 all explain the differences in the reported estimates. Finally, the literature is free of publication bias.

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

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[*] *E-mail addresses*: dimitrios.bakas@ntu.ac.uk (D. Bakas), georgios.chortareas@kcl.ac.uk (G. Chortareas) and georgios.magkonis@port.ac.uk (G. Magkonis).

1. Introduction

The connection between business cycle volatility and economic growth has been subjected to intensive investigation in modern macroeconomics (Cooley and Prescott, 1995; Fatás, 2002; Aghion and Banerjee, 2005; Hnatkovska and Loayza, 2005). The directionality 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 have thus attempted to resolve this issue empirically. The work of Ramey and Ramey (1995) gave rise to an extensive empirical literature exploring this link. The reported estimates of the empirical contributions vary widely, as shown in Figure 1. Most 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); but 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 and magnitude of the relationship between growth and volatility on either theoretical or empirical grounds.

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[1] Various studies 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 by employing growth regressions (Kormendi and Meguire, 1985; Grier and Tullock, 1989; Ramey and Ramey, 1995). On the other hand, several empirical contributions utilize generalized auto-regressive conditional heteroskedasticity (GARCH) models to analyse the relationship between business cycle volatility 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.

This paper uses more than one thousand estimates of the effect of output volatility on growth.[3] 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 greatly across studies. The absence of conclusive empirical evidence motivates a quantitative synthesis of research to understand the reasons behind such diverse empirical findings. Meta-analysis constitutes a systematic quantitative review method designed to explore the sources of heterogeneity in an 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 exploring the link between volatility and growth. We collect and analyse 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 us to address modelling uncertainty stemming from the large number of potential explanatory variables in the meta-regression specification. The ordered probit model overcomes potentially erroneous inference arising from the incomparability of alternative volatility measures. The empirical literature uses alternative measures for output volatility; e.g., standard deviation (SD) or generalized auto-regressive conditional heteroskedasticity (GARCH). This diverse set of volatility

[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.

measures may give rise to 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, ii) modelling specifications, iii) dataset characteristics, iv) differences in estimation strategies and v) publication characteristics.

Our results show that specific 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 in the coefficients. Studies that use GARCH-based measures of volatility tend to give less positive results compared to those using SD measures. Additionally, the presence of proxies for human capital, government size, and the inflation rate are significant factors explaining the diverse estimates. Our 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. Data characteristics that are found to be important in explaining the heterogeneity in the literature include the number of observations, the length of the time period used 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. Controlling for the period of the great moderation does not account for variations in 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 presents 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 were typically treated as separate 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, 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 theoretical 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 new technology replaces old, 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 average growth rate of output. More recently, models incorporating the mechanism of 'creative destruction' have sought to provide alternative explanations for the positive relationship, for example through a 'disciplining' effect (Aghion and Saint-Paul, 1998), a 'cleaning-up' effect (Caballero and Hammour, 1994) or an 'opportunity costs' effect (Hall, 1991).

On the other hand, several approaches that model growth as an endogenous process point to a negative relation conceptualized 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 outcome 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 other 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. Thereby, a higher level of business cycle volatility leads to a reduced level of investment and, consequently, to a lower level of capital accumulation and thus lower output growth. Dehejia and Rowe (1998) develop a neo-Keynesian model and show that a more pronounced 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 drives 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 the evidence remains 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 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 equations for both 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 for the simultaneous estimation of equations for the conditional mean and variance of output growth. The empirical model typically takes the form:

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

with

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

where 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 and support the Schumpeterian view. Specifically, Kormendi and Meguire (1985) by measuring output volatility as the SD of the growth rate, and utilizing a cross-section of 47 countries, find a positive relationship. Grier and Tullock (1989), considering a broader sample of countries and employing pooled cross-section data analysis, provide evidence that upholds the positive link.

In contrast to these early findings, Ramey and Ramey (1995), using panel data in 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. Their 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 business cycle volatility, where the latter 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 in both aspects. 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, by employing different choices of countries, alternative time periods, estimation methodologies and measurement of key variables.

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 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 relationship between growth and volatility becomes positive. However, the evidence, using disaggregated firm-level data, from the study of Chong and Gradstein (2009), provides empirical support to 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. Studies using this approach arrive at conflicting results. Fountas and Karanasos (2006) find a positive relationship in Germany and Japan. Caporale and McKiernan (1996) find a positive relationship in the UK and the US, whereas Grier and Perry (2000) and Fountas and Karanasos (2006) find no such relationship for the US. Similarly, Fang and Miller (2008) by accounting for possible structural changes in the volatility process, also report a non-significant relationship between US growth and volatility. 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 through which growth and volatility can be affected. Aghion and Banerjee (2005) focus on the channel of financial development as an important determinant of the negative association between the two variables. Aghion *et al*. (2010) extend this view by 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 the most extensive available 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 focus on any proxy of the volatility of economic activity. This excludes

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

studies that examine other types of volatility (such as political volatility), which appeared in our initial search since the words 'growth' and 'volatility' are frequently used in their titles. The final inclusion criterion is the reporting of a measure of the 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 online appendix.

Figure 2 portrays how the empirical volatility-growth literature has evolved over time. After the initial publication of Kormendi and Meguire (1985), and with the exception of Grier and Tullock (1989), there is a gap of almost one decade in the empirical literature. The interest in business cycle volatility and its effects on growth is triggered by the study of Ramey and Ramey (1995), with a clearly increasing trend from the mid-1990s. A further surge of papers coincides with the end of the Great Moderation. The financial 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 also partly reflects the absence of an empirical consensus.

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, given 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^{th} observation from the j^{th} 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 14 working papers. Following the current consensus in the meta-analytic literature, we do not exclude 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 in the estimates, both within and across these 84 empirical studies. We explicitly model this feature in the next section. The first step in analysing the meta-analytic data on the volatility-growth nexus consists of 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 against their inverse standard errors.

The funnel plot appears reasonably 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 symmetry is an indication that publication bias is unlikely to exist. In other words, editors and referees do not tend to prefer one specific empirical outcome over another. In Section 4, we explicitly investigate publication bias, controlling for several publication characteristics within the sample. As is evident from both the boxplot and the funnel plot, the values of partial correlation coefficients cover more or less 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 small, although this result should be

[5] Considering only the published peer-reviewed journal articles does not alter our results (see Section 6).

interpreted cautiously. As we discuss in more detail in Sections 4 and 6, the dispersion of estimates is vast. The number of negative estimates, however, is greater than positive ones, resulting in a negative average effect which is very close to zero. Furthermore, the interval between the 5th and 95th percentile (-0.492 to 0.361) implies substantial uncertainty about the true average effect. The estimate of the negative average 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 interpreted cautiously as the average effect may be a biased estimate of the true effect due to possible publication bias (Doucouliagos and Stanley, 2013). The plots in Figures 3 and 4 and the mean estimates in Table 1 make apparent the heterogeneity of estimates, both within and across studies. Thus, the emerging challenge is to model this observed heterogeneity.

4. Modelling 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 categories, which capture the characteristics for: i) variable selection, ii) modelling specifications, iii) datasets, iv) estimation methods, and v) publication bias.

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 GDP growth (or GDP per capita growth) as the dependent variable, some researchers use the industrial production index instead. Therefore, the first moderator controls for whether the measurement of growth plays a role. Treating the estimates that use either GDP growth or GDP per capita growth as the 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 0 otherwise.

The next important design issue is the measurement of volatility. As we have discussed above, there are different ways of modelling volatility. In the first set of studies, the standard deviation of growth rates was the norm. Even though, GARCH modelling became popular, especially in the 2000s, some authors continued to prefer using the standard deviation. We create two dummies, taking as the base the estimates that use GARCH modelling. The first dummy ('SD volatility') takes the value of 1 when standard deviation is used and 0 in all the remaining cases. The second dummy ('other measure of volatility') takes the value of 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. This group of moderator variables help us to identify whether there is any variation in the reported estimates resulting from the selection of different variables as the control set. Trying to be as inclusive as possible, we construct eleven moderator variables. The first one is the number of total regressors, which 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: population; government size; inflation rate; measures of investment; measures of human capital; agricultural production or primary sector of the economy; 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 an additional macroeconomic variable. For instance, some GARCH studies include inflation volatility (e.g., Grier and Perry, 2000), while other studies (e.g., Fatás and Mihov, 2013) have used proxies of policy volatility.

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

The third category focuses on several aspects of the datasets used. Since our pool of primary papers is fairly large, covering almost two decades, we can identify several potential factors of data heterogeneity. We start with a measure for the number of observations. We also distinguish between studies that use panel data (almost half of all studies) and those that use time series or 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-sectional data. Another important factor 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 differentiation is to separate developed (base category) from developing economies – for which the dummy 'developing' takes the value 1. For cases analysing both developed and developing countries, we include the dummy ('mixed').

Despite the foregoing, we also need to take into account an additional country-group feature. Since most of the studies use many different combinations of countries, we investigate 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 example, Euro Area, Latin America or Sub-Saharan Africa). We create a dummy ('homogeneous') that takes the value of 1 when the paper focuses on a homogeneous set of countries. Following on from this, we also need to distinguish those studies that analyse a single country or include multiple 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 thus distinguish between long and short time-span studies.[7] We define long time-span as covering at least 40 years, and thus create a dummy ('Short span') that takes the value of 1 the data run for less than 40 years and 0 otherwise. Lastly, we examine whether the dataset covers the period of the Great Moderation, that is the period between 1985 and 2007 (Bernanke,

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

2004; Davis and Kahn, 2008). We create a dummy ('Great moderation') that takes the value of 1 when at least ten years of this period are covered.[8]

The fourth category of moderators captures differences in the econometric methodology. In the volatility-growth literature the different econometric techniques pertain mostly to the volatility measures, and the proxy that distinguishes between panel, time series or cross-sectional 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 takes the value of 1 when the results come from estimation methods (IV/GMM/2SLS) that account for endogeneity, and 0 otherwise.

The last category of moderators deals with publication features and is 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 working-paper form. We also include a trend variable ('Publication date') from 1985 (the date of the oldest paper we found) to 2015 (the most recent paper). 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 has discussed the role of 27 potential

[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.

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 j^{th} study. Given the large number of moderators, model uncertainty becomes quite significant as the 'general-to-specific' approach may lead to erroneous results. The seriousness of this problem becomes evident when considering the need of applied researchers to report 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 statistical inference does not rely on individual regressions. On the contrary, as its name suggests it gives a 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, the posterior probability density for each model M_μ 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 for 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 the Bayes rule the PMP of model M_μ is equal to:

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

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 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:

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

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, with 27 explanatory variables, the number of all potential models is more than 134 million. Given 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 in descending order according to their PIP. In other words, variables at the top of the axis play a more significant role in explaining heterogeneity, compared to the ones at the bottom. The red colour (lighter grey) indicates that the variable is included, and its estimated sign is negative, while the blue colour (darker grey) indicates a positive sign.

According to the best model from the BMA results, nine variables appear to play the most significant role in explaining the heterogeneity of the estimated coefficients. As the red/blue colour intensity shows, these variables appear in 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 a proxy for volatility tend to report less negative estimates than the studies using GARCH-based measures. The use of other methods 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 play a role in the reported estimates.

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

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

Another message from Figure 5 and Table 3 is that model specification matters: the choice of variables that a researcher includes in Equation (2) is an important factor affecting 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 with the evidence provided by Aghion and Banerjee (2005), who reported more negative coefficients of volatility when they considered secondary school enrolment. This reaffirms also the view of Cohen and Soto (2007) on the importance of the inclusion of human capital measures in 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 government size is considered, more positive estimates are reported. The role of the government has attracted 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) across countries alleviates 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 finds that expansionary government policies can act as an insurance mechanism in volatile times. Thus, not accounting for 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 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 only a small number of studies allows for this channel in their specifications. Furthermore, there is no evidence of any significant effect of trade openness, a finding consistent with previous studies (e.g., Fatás; 2002 and Hnatkovska and Loayza; 2005).

Several aspects of the data characteristics appear to help 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 to Asian economies. This gap in the literature may motivate new relevant research. Finally, the choice between 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 homogeneity of data sets. More homogeneous country-sets appear to lead 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 diverse sample of 76 economies. When the authors confine their sample to OECD countries this relationship becomes weaker. Finally, the moderator pertaining to 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, no variable appears to have any systematic influence on the partial correlation coefficient. 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 are not driven by preferential reporting or publication decisions. Consequently, the growth-volatility relationship emerges as one of the few empirical questions that are free from 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 no relevant knowledge about the parameters and the model's size (Ley and Steel, 2009). To compare these results with our initial findings we show the map of 5000 models in Figure 6. The factors that we find 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 displays 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 other findings, 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 being 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. [11]

6.2 Further evidence

One basic feature of the literature examined in this paper is that the very notion of volatility is analysed 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 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 combined. With the aim of excluding this possibility and offering reassurance that our previous results are robust, we follow an alternative analysis. Given variations in the exact definition of volatility, we focus our attention only on the sign and statistical significance of the estimates, neglecting their value. This leads us to use 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

[11] As a final robustness check, we restrict our sample to well-established journals. Therefore, we only include papers from journals that are classified as 4*, 3* or 2* in the ABS-2015 list. The results using this sample of studies remain quantitatively and qualitatively the same. These additional results can be provided upon request. We thank an anonymous referee for this suggestion.

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:

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

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 a threshold the 10% level of significance, Table 5 gives a quantitative overview of the collected meta-dataset. Interestingly, only just below 50% of the empirical estimates are positive. Most of these (62%), however, are insignificant. On the other hand, 75% of the negative coefficients are statistically significant.

Since the estimated coefficients from an ordered probit model are not straightforward to interpret 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., finding a significant negative, an insignificant (positive or negative), or significant positive estimate) when the dummy switches from 0 to 1. For the case of continuous moderator variables, the marginal effects show the probability change from an increase in the dependent variable by one unit.

Table 6 shows the results. Overall, the probit analysis confirms the results found by the BMA.[12] Apart from the measure of volatility and the time-span of the data used, all of the other variables from 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 for human capital and inflation rate increase the probability of finding a negative effect, while the opposite is true for 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 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 as the pooled estimates.

7. Conclusion

Ample evidence on the impact of business cycle volatility on economic growth has been produced over recent decades by numerous, diverse empirical studies. Despite the plethora of analyses, no conclusive evidence exists on the effect of volatility on growth. 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. Identifying the sources of the heterogeneity of the estimates can guide the focus of future research efforts.

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

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 with more traditional measures. Moreover, certain aspects of the empirical design influence 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 promote a positive link. In addition, the negative relationship is found to be stronger for samples of developing countries. Other aspects of data and estimation characteristics are also 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 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.

References

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

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

Aghion, P. and Howitt, P. (2006). 'Joseph Schumpeter Lecture Appropriate Growth Policy: A Unifying Framework', *Journal of the European Economic Association*, 4, 269-314.

Aghion, P. and 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., and 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*, Hoover Institution Press, Stanford, CA.

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

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

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

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

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

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

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

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

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

Chatterjee, P. and Shukayev, M. (2006). 'Are Average Growth Rate and Volatility Related?', Working Paper 2006-24, Bank of Canada, Ottawa.

Chetty, R., Guren, A., Manoli, D. and Weber, A. (2012). 'Does Indivisible Labor Explain the Difference Between Micro and Macro Elasticities? A Meta-Analysis of Extensive Margin Elasticities', *NBER Macroeconomics Annual*, 27, 1-56, Cambridge, MA.

Chong, A. and Gradstein, M. (2009). 'Volatility and Firm Growth', *Journal of Economic Growth*, 14, 1-25.

Cohen, D. and Soto, M. (2007). 'Growth and Human Capital: Good Data, Good Results', *Journal of Economic Growth*, 12, 51-76.

Cooley, T.F. and Prescott, E.C. (1995). 'Economic Growth and Business Cycles', In: Cooley, T.F. (Ed.), *Frontiers of Business Cycle Research*, Princeton University Press, Princeton, NJ.

Davis, S.J. and 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.

Dehejia, V.H. and Rowe, N. (1998). 'The Effect of Business Cycles on Growth: Keynes vs. Schumpeter', *Economic Inquiry*, 36, 501-511.

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, Melbourne.

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

Doucouliagos, H. and 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. and 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. and Robins, R.P. (1987). 'Estimating Time Varying Risk Premia in the Term Structure: The ARCH-M Model', *Econometrica*, 55, 391-407.

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

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

Fountas, S. and 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.

Gechert, S. (2015). 'What Fiscal Policy is Most Effective? A Meta-Regression Analysis', *Oxford Economic Papers*, 67, 553-580.

Grier, K. and 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. and 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. and 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. and 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, Cambridge, MA.

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

Havranek, T., Rusnak, M., and Sokolova, A. (2017). 'Habit Formation in Consumption: A Meta-Analysis', *European Economic Review*, 95, 142-167.

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

Huang, K., and Sim, N. (2018). 'Why Do the Econometric-Based Studies on the Effect of Warming on Agriculture Disagree? A Meta-Analysis', *Oxford Economic Papers*, 70, 392-416.

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

Ioannidis, J.P.A., Stanley, T.D. and Doucouliagos, C., (2017). 'The Power of Bias in Economics Research', *The Economic Journal*, 127, F236-F265.

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

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

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

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

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

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

Kydland, F.E. and 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. and 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. and Plosser, C.I. (1987). 'Sectoral vs. Aggregate Shocks in the Business Cycle', *American Economic Review*, 77, 333-336.

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

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

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

Moral-Benito, E. and Roehn O. (2016). 'The Impact of Financial Regulation on Current Account Balances', *European Economic Review*, 81, 148-166.

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

Norrbin, S.C. and 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.

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

Priesmeier, C. and 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. and 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*', McGraw-Hill, New York, NY.

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

Shields, K., Olekalns, N., Henry, Ó.T. and Brooks, C. (2005). 'Measuring the Response of Macroeconomic Uncertainty to Shocks', *The 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. and Doucouliagos, H. (2012). '*Meta-Regression Analysis in Economics and Business*, Routledge, Oxford.

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

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

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% 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.
Source: Authors' calculations.

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 volatility	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 agricultural (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 liberalization 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 is 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 era	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 a single country is examined	0.309	0.462
Endogeneity-Econometric Method			
Endogeneity	D=1, if the econometric method takes into account endogeneity	0.205	0.404
Publication Characteristics			
Published	D=1, if the study is published	0.792	0.406
Publication date	A trend variable where 1 is the year of the 1st publication (1985)	23.513 (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.
Source: Authors' calculations.

Table 3: Bayesian Model Averaging and OLS Estimates

Categories	Variable	*PIP*	*post Mean*	*post SD*	*Coefficient*	*SD*	*P-value*
		Bayesian Model Averaging			*Frequentist check (OLS)*		
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.
Source: Authors' calculations.

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).
Source: Authors' calculations.

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).
Source: Authors' calculations.

Table 6: Pooled Ordinal Probit Model

Categories	Variable	*Estimated Coefficient*	*Marginal Effects*		
			Significantly negative	*Insignificant*	*Significantly 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.
Source: Authors' calculations.

Table 7: Panel Ordinal Probit Model

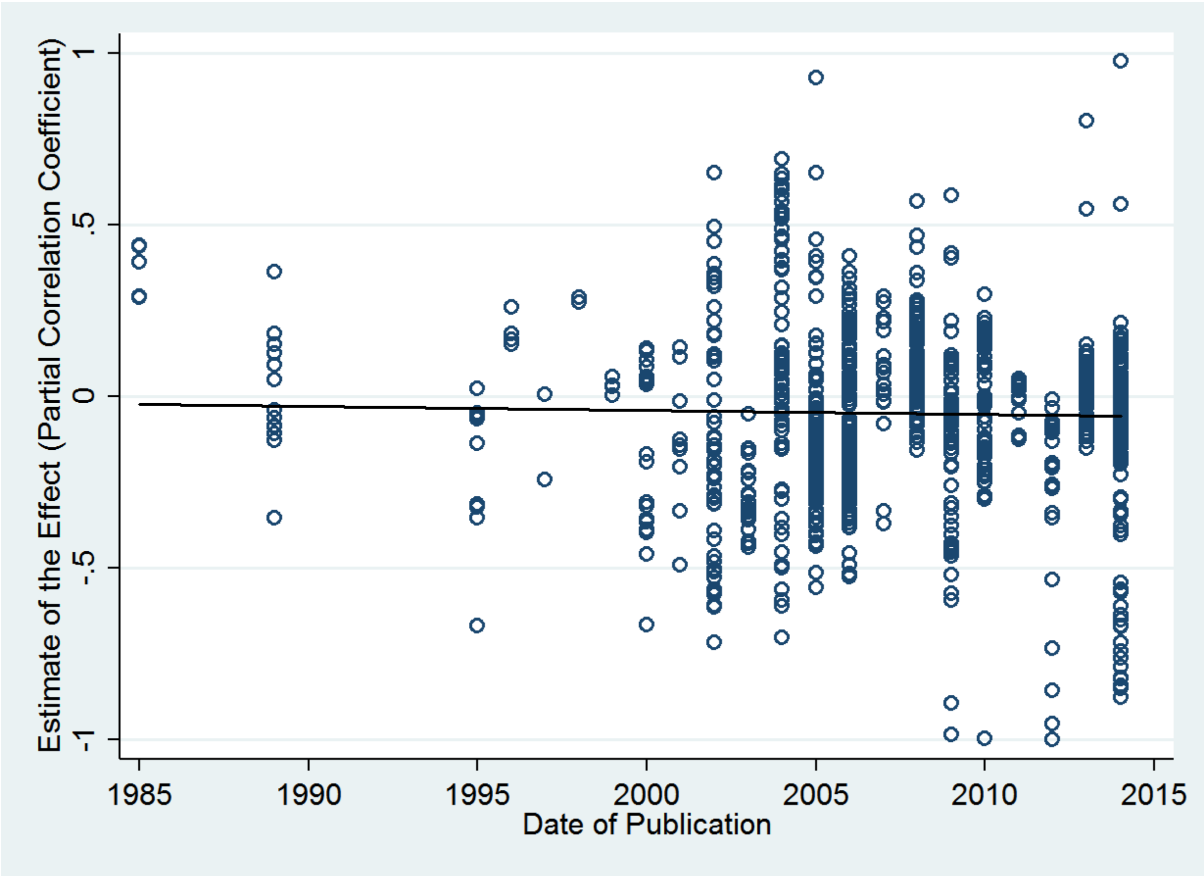
Categories	Variable	*Estimated Coefficient*	*Marginal Effects* *Significantly negative*	*Insignificant*	*Significantly positive*
Variable Characteristics					
	Industrial index	0.448	-0.173	0.081	0.092
		(1.11)	(-1.11)	(1.03)	(1.12)
	SD volatility	-0.132	0.051	-0.024	-0.027
		(-0.38)	(0.38)	(-0.37)	(-0.38)
	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.
Source: Authors' calculations.

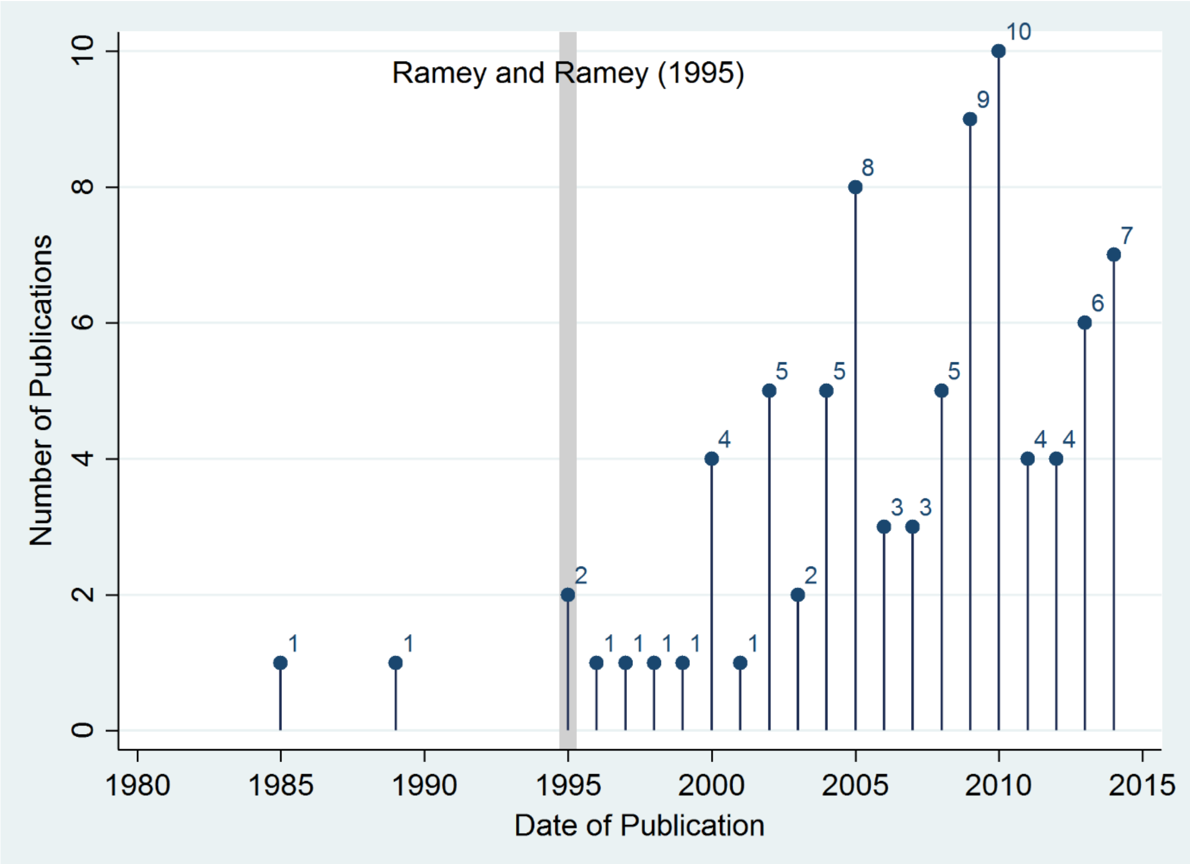
Figures

Figure 1: Reported Estimates over Time



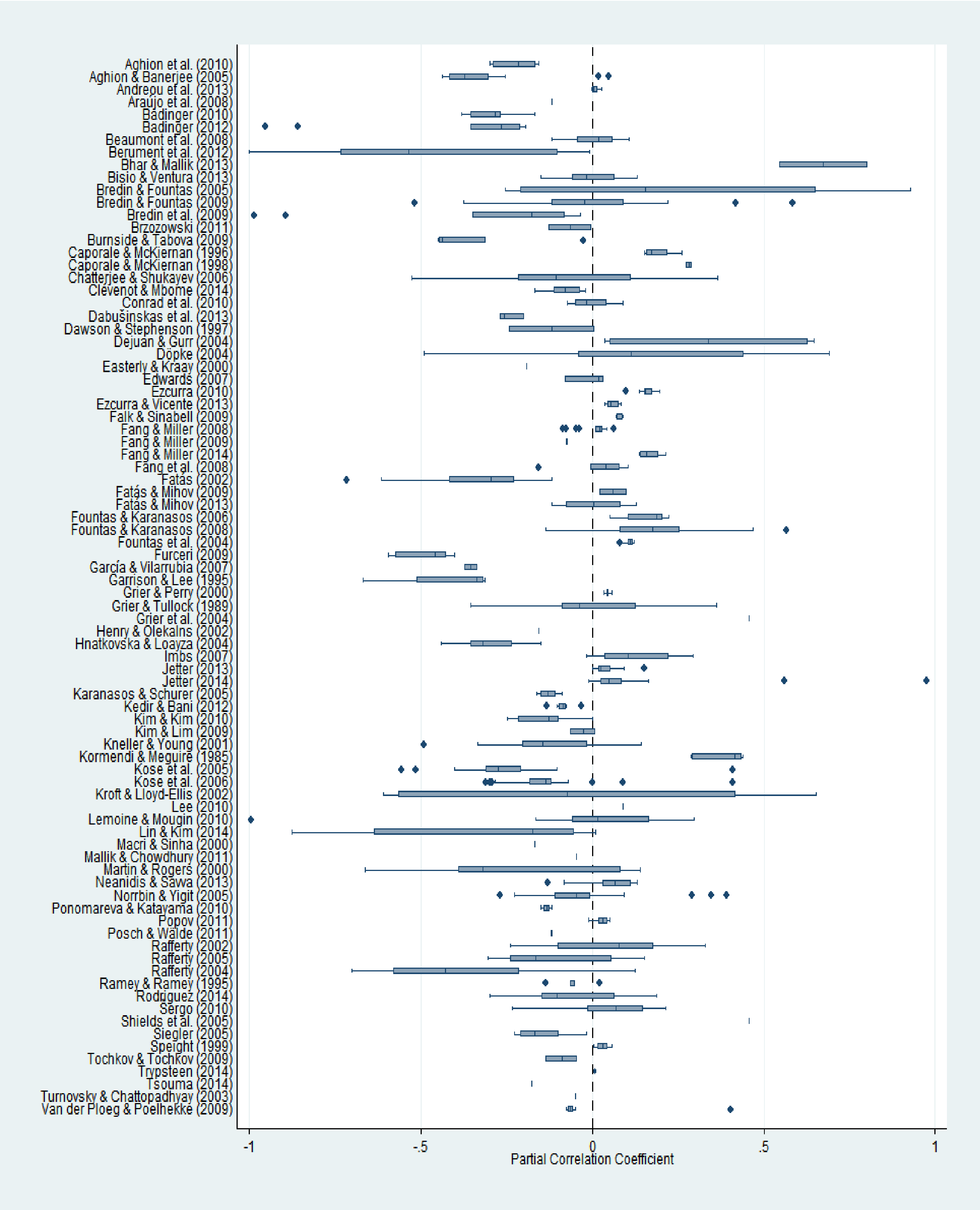
Notes: The figure depicts the estimates (partial correlation coefficients) of the effect of volatility on growth reported in the empirical literature over time. The horizontal axis shows the publication year of the examined studies.
Source: Authors' calculations.

Figure 2: Number of Publications over Time



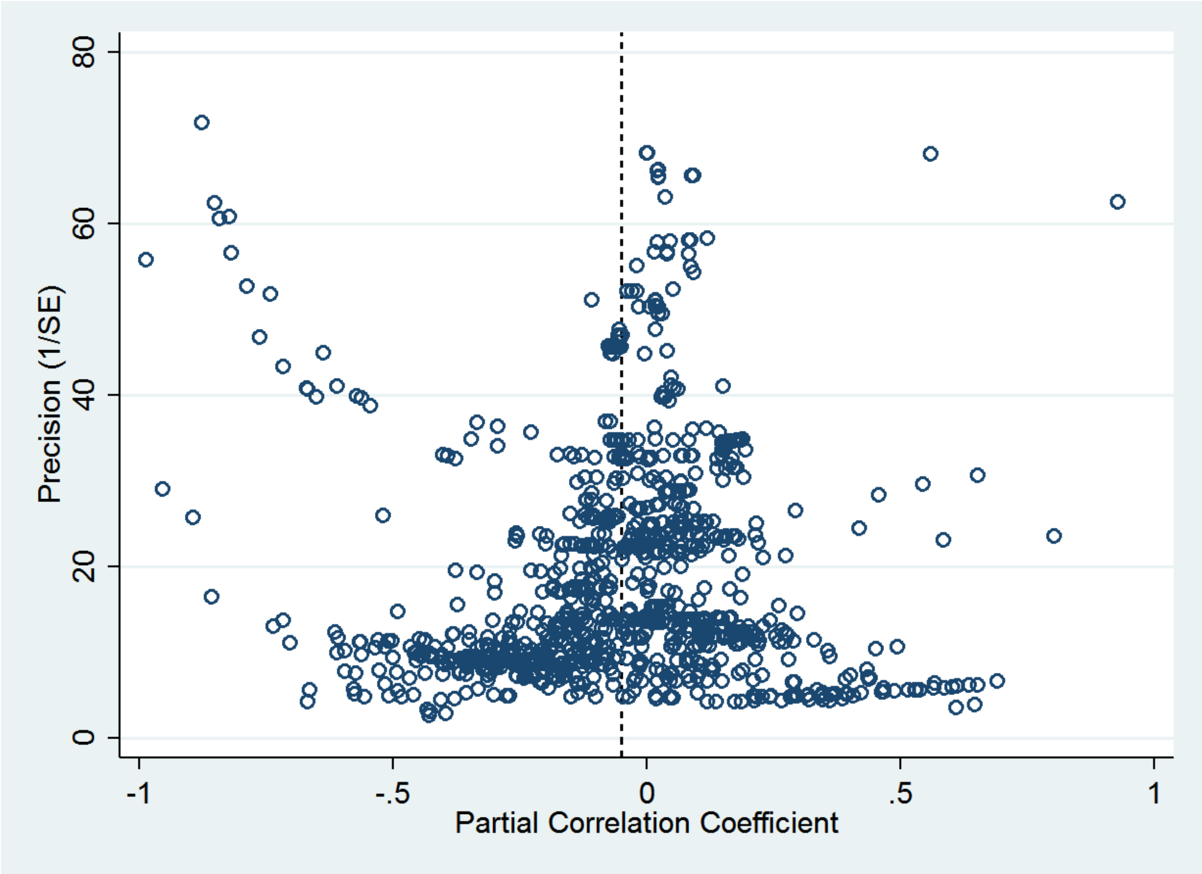
Notes: The figure shows the evolution of the empirical literature over time. Numbers indicate the number of published studies for each year. The shade line shows the year when the most influential study (Ramey and Ramey, 1995) was published. Even though the paper is not the first empirical study, it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

Figure 3: Boxplot



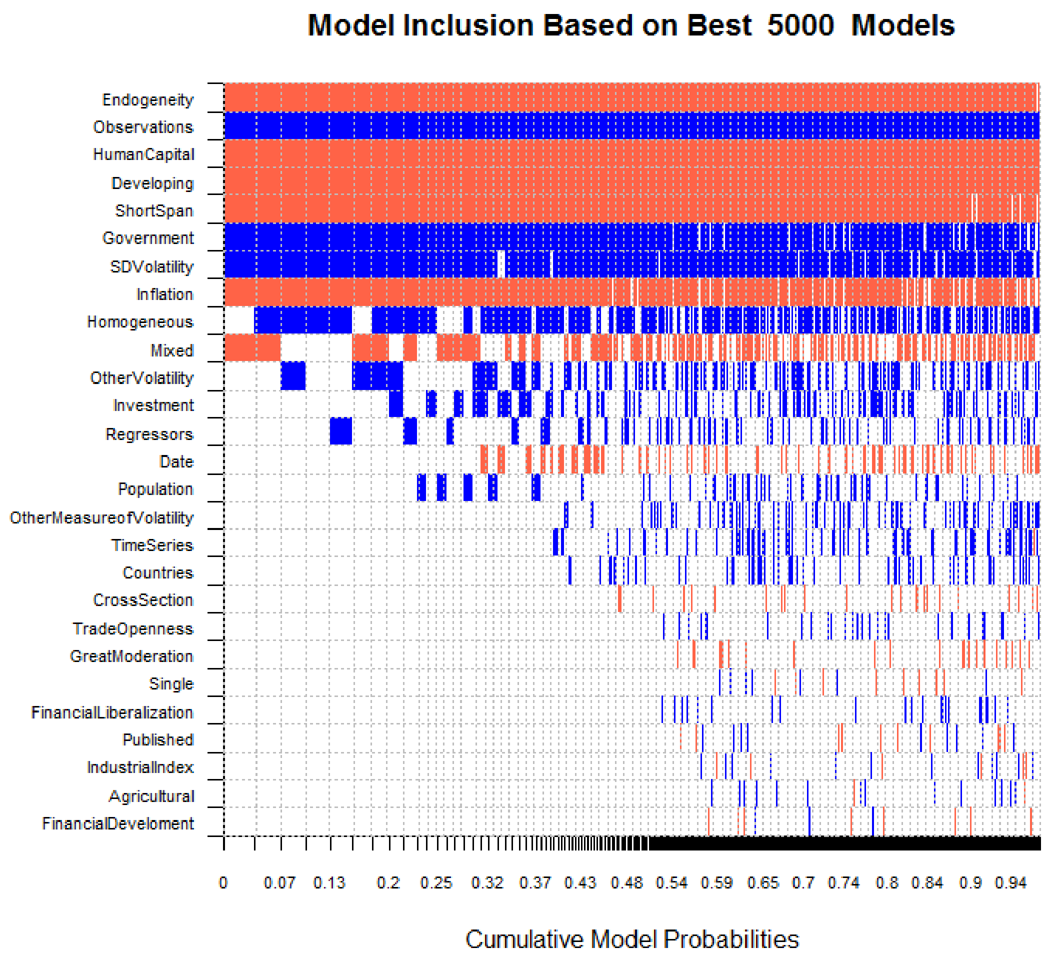
Notes: The figure depicts the boxplot of the collected estimates from the 84 empirical studies. For better exposition of the observed heterogeneity across studies, we have used the partial correlation coefficient. Studies are sorted alphabetically. The full list of papers is provided in the online appendix.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

Figure 4: Funnel Plot



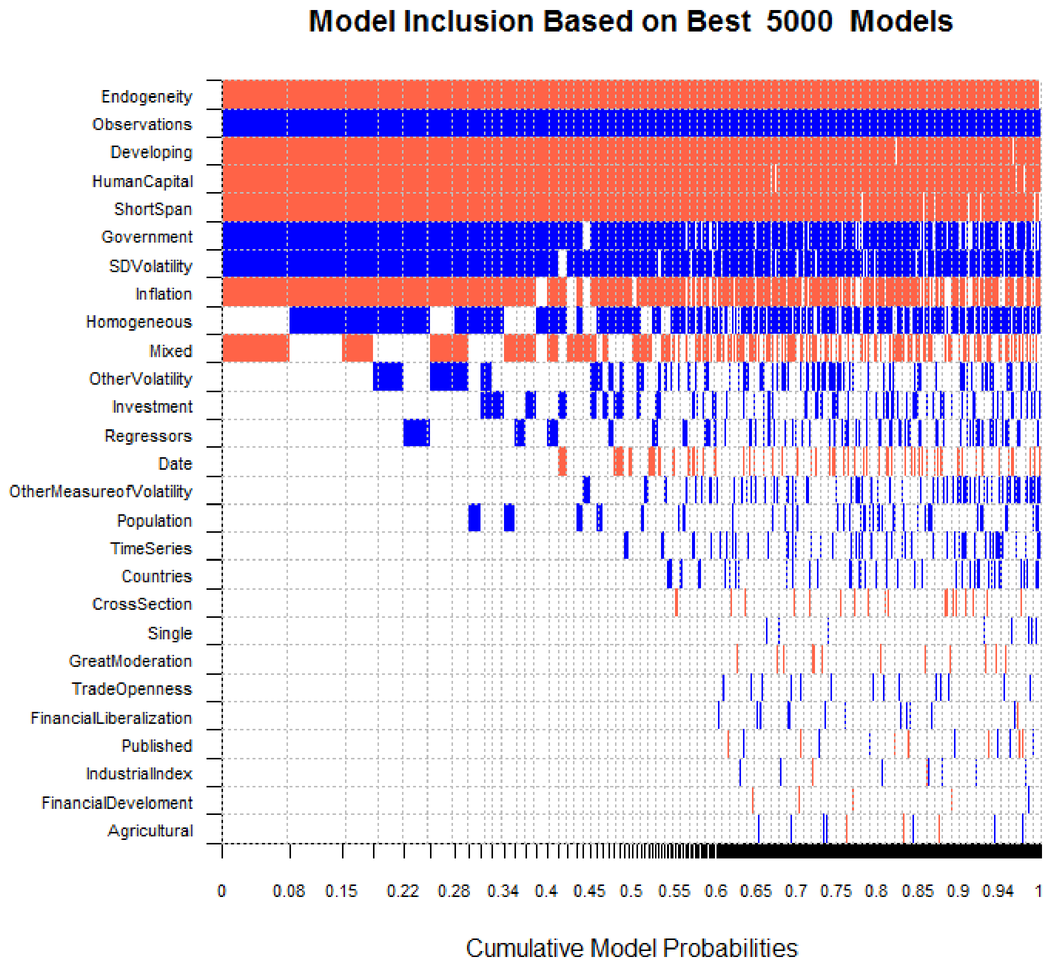
Notes: Presence of symmetry suggests the absence of publication bias and vice versa; an asymmetrical funnel plot indicates a possible publication bias. The dotted line shows the average effect (r = *-0.049*).
Source: Authors' calculations.

Figure 5: Bayesian Map I



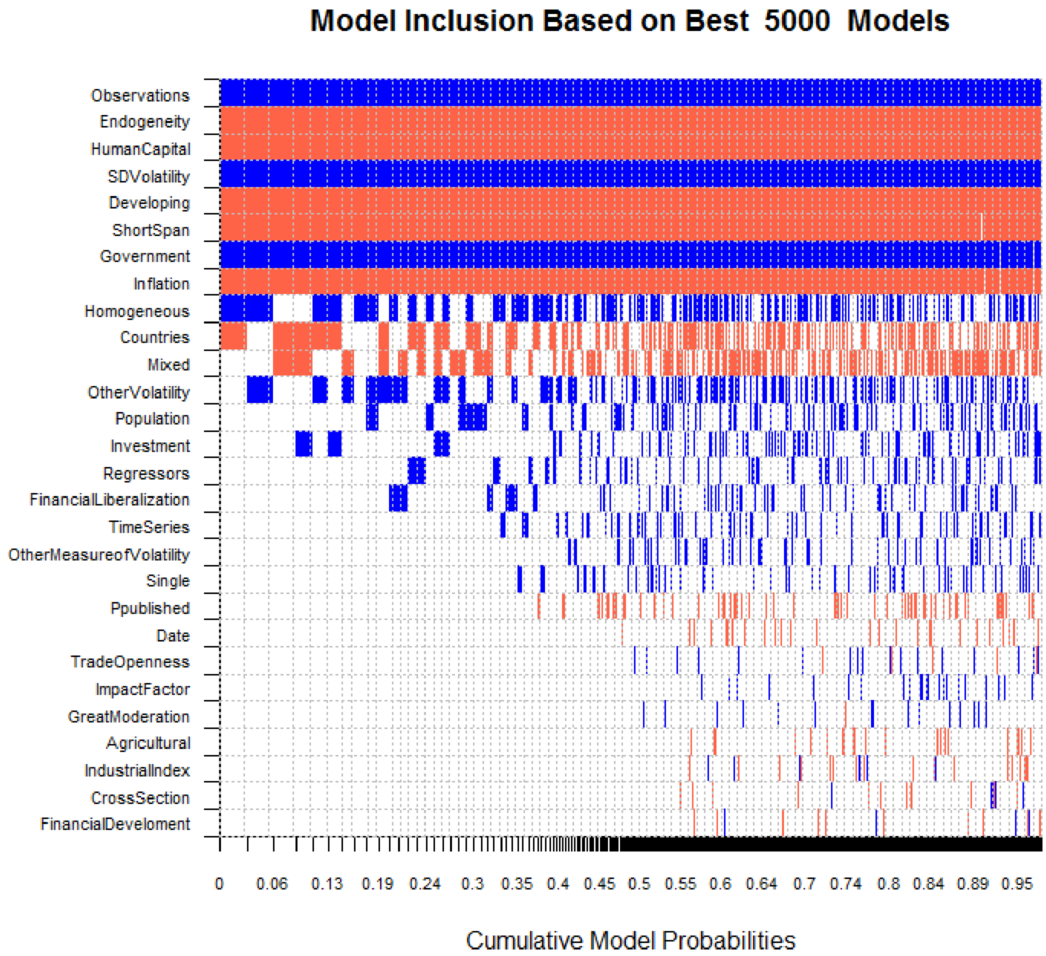
Notes: The horizontal axis measures the cumulative posterior model probabilities, while the vertical one depicts the moderator variables that are explained in Table 1. Each column shows different model. Each variable in the left axis is sorted according to posterior inclusion probability in descending order meaning that variables on the top appear more frequently across different models than the ones in the bottom. Red 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.
Source: Authors' calculations.

Figure 6: Bayesian Map II (Robustness: Alternative Priors)



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 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.
Source: Authors' calculations.

Figure 7: Bayesian Map III (Robustness: Only Published Papers)



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

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