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Research Article

Growth and Volatility Reconsidered: Reconciling Opposite Views

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Many contributions in the recent literature have investigated over the relationship between GDP growth and its volatility without getting a clear and unambiguous answer. Besides reassessing the well-known effect of output volatility on growth as benchmark analysis, this study aims at looking into the "black box" of the business cycle volatility by disentangling the impacts of volatility of GDP major components—that is, private consumption, private investment and government expenditure—on growth, simultaneously considered. Our empirical analysis unveils a remarkably robust and strong negative correlation of consumption volatility with mean growth and a positive one with volatility of investment and of public expenditure. If these findings shed some additional light on the (still controversial) relationship between economic fluctuations and growth, they will also make it possible to compare the relative impact of each component, with possibly relevant policy implications. Importantly, this might reconcile opposite views about the issue that different empirical results might originate from the relative importance across empirical studies of the various components of volatility.

1. Introduction

Among the issues economists largely debated upon over the recent decades, the relationship between the volatility of business cycle and output growth deserves a particular attention. Nonetheless, for a long time, long-run growth and business cycle were conceived of as independent phenomena to be analyzed by means of separated tools. This view was strongly supported by Lucas [1] who claimed that the trade-off between growth and business cycle fluctuations was pretty inexistent. Then, the Real Business Cycle (RBC) paradigm [2] pointed to the exogenous stochastic process driving the technological progress as the common root of both trend growth and cyclical fluctuations. However, once the endogenous technological progress hypothesis was introduced into the RBC framework [3, 4] the idea of a causal relationship between the instability of the business cycle and growth gained theoretical support, thereby prompting the subsequent empirical literature on volatility and growth (see Aghion and Saint-Paul [5] for a very interesting analysis of the theoretical evolution on this issue and Gaggl and Steindl [6] for a literature review on growth and cycle).

This paper is meant to contribute to the stream of literature which aimed at verifying both the existence of a statistically significant causal relationship between output volatility and growth and the sign of that relationship. Although no unambiguous evidence has been obtained on this topic so far—also due to the existing differences across studies with respect to the computation of volatility, the sample selections, and the estimation methodologies—the largest consensus suggests that volatility is detrimental for growth. It is worth mentioning the seminal work by G. Ramey and V. A. Ramey [7] which proved the existence of a negative robust relationship between output volatility and average growth, whereby volatility was built as a measure of forecast uncertainty. However, despite their findings were subsequently confirmed by an extensive literature (see, e.g., [8–11]), other relevant empirical studies pointed at a positive impact of output variability on growth [12–14] and, in general an inconclusive evidence comes out of the theoretical debate (from the theoretical point of view the *neo-Schumpeterian* view and the *arrovian* approach attain opposite conclusions on the issue. The former considers "*recessions as opportunities*" [15] because the opportunity cost of efficiency-enhancing activities is lower than in normal times, thus prompting optimizing firms towards engaging in those activities (see, e.g., [5, 16–18]). Therefore, downturns drive positive effects not only on output growth but also on productivity growth that turns out to be countercyclical. By contrast, according to the arrovian approach, as long as production is dominated by external learning [19] or *learning-by-doing*, economic booms stimulate productivity enhancement, whereas economic downturns negatively affect both the short-term and the long-term growth. As a consequence, productivity growth follows a procyclical path (see, e.g., [8, 20, 21])).

To our knowledge, most contributions to the previous literature have mainly aimed at empirically investigating the impact of the volatility of single macroeconomic variables on growth, as for example, government spending [22, 23], investment share of GDP, real exchange rate [24, 25], or inflation [26, 27]. However, notwithstanding the relevance of the results attained so far, it is still quite difficult to make a comparison among the different kinds of volatilities in order to identify the one relatively most detrimental to growth. The only attempt to fill this gap is Furceri's [28] that comparatively evaluates the impact of the volatility of investment, government, and exchange rate, simultaneously considered, onto long-term growth.

In a similar spirit, our purpose is to go beyond the traditional analysis of the relationship between business cycle volatility and growth; as we are confident that the impact of the former on the latter might change depending on the transmission channel considered. Hence, besides reassessing the well-known effect of output volatility on growth as benchmark analysis, this study aims at looking into the "black box" of the business cycle volatility by simultaneously verifying the statistical relevance of the volatility of some of the main components of GDP—private consumption (C), private investment (I), and government expenditure (G)—for growth (we skip net exports for reasons which will become clearer in the sequel). We believe that, by disentangling the impacts of the volatility of GDP main components on growth, not only additional aspects of the (still controversial) relationship between economic fluctuations and growth can be unveiled, but also the relative impact of each component volatility can be compared, with possibly relevant policy implications.

Indeed, there exist several theoretical arguments suggesting how volatility in consumption, private investment, and government expenditure can interact with growth. Concerning consumption and investment volatility, the literature on risk and optimal decisions predicts that *ceteris paribus* a higher degree of risk and volatility implies a higher economic growth rate, on average, because higher profitable investments are associated with more volatility, via a higher degree of technology specialization and a smaller degree of risks diversification [29]. However, as agents are assumed to be risk averse, the ultimate impact of risk on growth crucially depends on the degree of markets completeness: if they were complete, agents could hedge against risks and pursue higher rate-of-return investment plans; if they were incomplete this would not be possible, and a trade-off would emerge between volatility and growth. Hence, risk averse agents would invest in both high and low expected return sectors in order to ensure a larger diversification of their risk, thereby reducing economic volatility and also economic growth. On the other hand, to the extent that risk aversion and insurance market incompleteness induce agents to increase precautionary savings leading to higher capital accumulation rates [30], risk and volatility can be beneficial to growth. Concerning fiscal policy volatility, theory predicts ambivalent outcomes in terms of its impact on growth: if government expenditure comes in the form of automatic stabilizers (among others, see Sachs and Sala-i-Martin [31], Asdrubali et al. [32], and Afonso and Furceri [22]) that offset the negative effects of business cycle shocks, clearly one can expect a beneficial effect of more volatility to investment and growth; by contrast, if a balance discipline must be respected so that government expenditure tends to follow the business cycle rather than contrast it, the volatility of fiscal policy risks to exacerbate the negative effect of adverse shocks to the economy.

A large number of econometric procedures have been implemented throughout the literature to evaluate the relationship between growth and volatility. Although a pure time-series approach was followed by, for example, Caporale and McKiernan [14] and Grier and Perry (2000), several cross-country regressions [7, 33], (Martin and Rogers, 2000) and panel data estimations [8, 10, 11, 34, 35] have been performed to the same purpose. Here we resort to a panel data investigation but, unlike some more recent panel data exercises, we do not average our variables over intervals of time. Indeed, computing volatility as the standard deviation of nonoverlapping time spans leaves no choice but averaging the whole sample over the same time periods. Thus, in order to build our volatility measure, we will rather follow a "rolling windows" approach that yields time-varying variables and allows to preserve the original time dimension of our data set. In other words, GDP growth at time t will be regressed upon measures of volatility computed on the window $t - s$, t, where s is the width of the window. The underlying idea is that growth at time t is influenced by volatility (of the relevant macrovariables) perceived over a window of s years (we will use an $s = 5$ year interval). This assumption seems more reasonable than supposing that the average rate of growth of GDP, over a period of s years, is influenced by the volatility computed over the same spell of time.

This paper is organized as follows. Section 2 presents our dataset, some preliminary evidence emerging from the data, and the methodology employed for the estimation. Section 3 describes our empirical results, while some concluding remarks are drawn in Section 4.

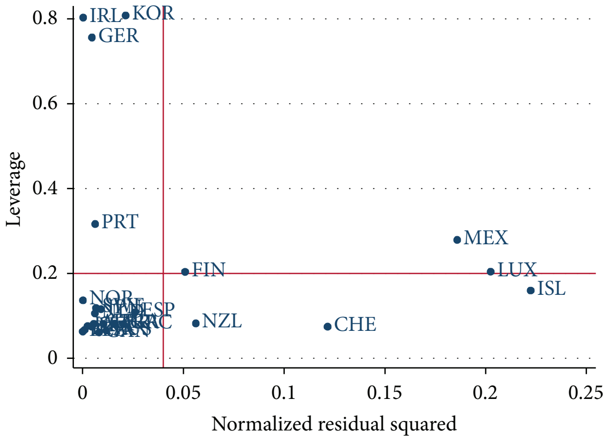

Figure 1: Average values of leverage and normalized residuals squared.

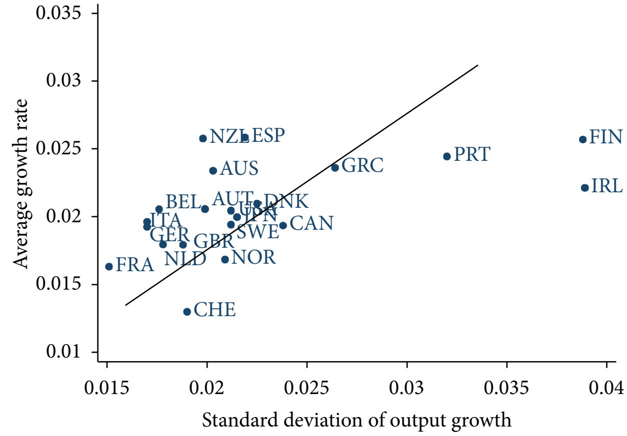

Figure 2: Simple correlation of growth and output volatility.

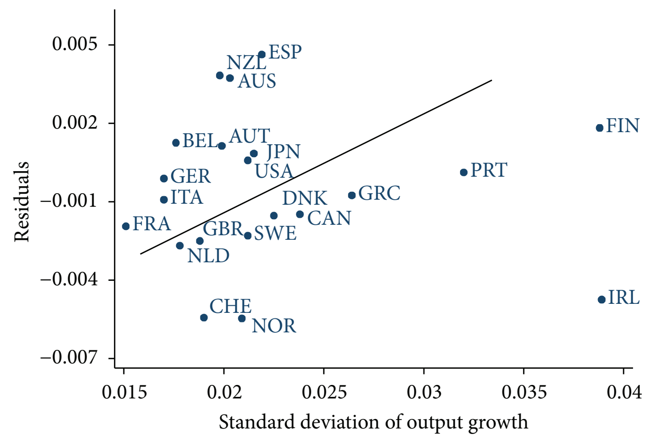

Figure 3: Partial correlation of growth and output volatility. (Controlling for the volatility of C, G, and I.)

2. Data, Models, and Methodology

2.1. Data. We use data from Heston et al. [36] and from the Barro-Lee data set [37], both consisting of annual observations (an exception is the schooling variable, which is only available on five-years intervals in the World's Bank data release. We applied a polynomial interpolation method to those series in order to get annual observations to be employed in our model). Our regression analysis focuses on a sample of 25 OECD countries and is performed over the time horizon 1978–2007 (our main sample consists of 25 countries out of the whole 34 OECD countries. Indeed, we retain those countries that joined the OECD before the 1990's in order to preserve a certain degree of homogeneity in terms of technology, development, and quality of data. Consistently, we do not include Turkey, whose data quality is graded "C" according to the Heston et al. [36] data quality scale ranging from A (best quality) to D (worst quality)). However, before turning to the empirical models specification and discussing the econometric strategy, we present some evidence based on some basic preliminary analysis of our data.

Table 4 shows the results of our outliers testing and inspecting procedure, that reveals some extreme values in the case of Iceland, Korea, Luxembourg, and Mexico. These results, combined with the evidence presented in Figure 1 (where the points above the horizontal line have higher-than-average leverage, and points to the right of the vertical line have higher-than-average studentized residuals, based on our benchmark regression), suggest that it may be worth testing our models on a second sample, that is, a subsample of the main one where the above mentioned countries are omitted. Hence, our cross-country dimension is equal to $N = 25$ in the benchmark sample and $N = 21$ for the restricted sample, while our time dimension is equal to $T = 30$.

In what follows we focus on a subsample of 19 OECD countries (compared to our 21-countries restricted sample, we additionally get rid of Ireland and Switzerland presenting outlier values in the government and consumption volatility series, resp.) over the period 1978–2007 and present the simple cross-country correlation between average output growth rate and, respectively, the standard deviation of output, consumption, investment, and government consumption growth rates. What Figures 2, 4, 6, and 8 clearly show is that growth positively correlates with the standard deviations of either GDP and GDP components. However, as simple correlation is likely to hide spurious linkages between variables, we also provide the (more robust) partial correlation measure in Figures 3, 5, 7, and 9, whose y-axes display the residuals of a cross-country population weighted estimation where average growth is regressed against the volatilities of all variables so far mentioned (i.e., GDP, C, I, and G) except the variable whose standard deviation is displayed on the x-axis. Partial correlation confirms the evidence of the positive linkage assessed by simple correlation only in the case of output and government consumption volatility. On the other hand, the sign of the relationship between consumption and investment volatilities to growth is reverted as a clear negative relationship emerges between their standard deviations and the correspondent regressions residuals. It should be noted, however, that partial correlations do not account for the effect of additional explanatory variables, that will be used in our regression analysis.

Table 1: List of countries in the main sample and averaged volatilities over the period 1978–2007.

Country	GDP growth	Output volatility	Consumption volatility	Investment volatility	Gov. consumpt. volatility
Australia	0.0234	0.0203	0.0132	0.0785	0.0153
Austria	0.0206	0.0199	0.0170	0.0592	0.0100
Belgium	0.0206	0.0176	0.0124	0.0745	0.0148
Canada	0.0193	0.0238	0.0177	0.0792	0.0161
Denmark	0.0210	0.0225	0.0232	0.0891	0.0169
Finland	0.0257	0.0388	0.0262	0.1030	0.0194
France	0.0163	0.0151	0.0107	0.0554	0.0139
Germany	0.0192	0.0170	0.0142	0.0547	0.0166
Greece	0.0236	0.0264	0.0209	0.0849	0.0402
Iceland	0.0414	0.0404	0.0499	0.1474	0.0197
Ireland	0.0221	0.0389	0.0287	0.1059	0.0408
Italy	0.0196	0.0170	0.0191	0.0502	0.0180
Japan	0.0200	0.0215	0.0160	0.0016	0.0120
Korea	0.0557	0.0519	0.0454	0.1162	0.0230
Luxembourg	0.0384	0.0306	0.0183	0.1010	0.0213
Mexico	0.0139	0.0428	0.0400	0.1404	0.0318
Netherlands	0.0180	0.0178	0.0186	0.0544	0.0189
New Zealand	0.0258	0.0198	0.0184	0.0902	0.0219
Norway	0.0168	0.0209	0.0232	0.0869	0.0158
Portugal	0.0244	0.0320	0.0241	0.1025	0.0282
Spain	0.0258	0.0219	0.0205	0.0629	0.0178
Sweden	0.0194	0.0212	0.0214	0.0887	0.0137
Switzerland	0.0130	0.0190	0.0090	0.0610	0.0176
United Kingdom	0.0179	0.0188	0.0194	0.0683	0.0116
United States	0.0204	0.0212	0.0142	0.0736	0.0163

Table 2: Descriptive statistics.

		Descriptive statistics			
Series	Obs	Mean	Std. dev.	Min	Max
GDP growth	750	0.0233	0.0287	−0.1302	0.11639
GDP volatility	750	0.0232	0.0147	0.0036	0.0957
Consumption volatility	750	0.0186	0.0142	0.0022	0.0987
Investment volatility	750	0.0798	0.0476	0.0079	0.323
Government consumption volatility	750	0.0162	0.0100	0.002	0.0646
Investment share of GDP	750	28.81	5.6367	16.0422	53.5848
Education	750	42.23	13.67	9.76	73.42
Population growth	750	0.006	0.0050	−0.0046	0.0241
Initial level of GDP	750	22541.93	8156.53	3980.23	66065.33

Finally, our preliminary data analysis is devoted to verify the time series properties of our panel data. Indeed, we test the stationarity of the series involved in our regressions by applying the [38] (IPS hereafter) test for unit root which seems particularly suitable for our data (the IPS test is based on heterogeneity of the autoregressive parameters of the tested equation, i.e., it allows for heterogeneity in the error variances and the serial correlation structure of the errors). The results of the IPS test, which is based on the well-known Dickey-Fuller procedure, are reported in Table 5. They are evidence that our main variables of interest—that is, the GDP growth rate and the volatilities of GDP components—are stationary, whereas some of our control variables are not. This holds in particular for the initial level of GDP series (cf. the results in Table 5 referring to the log level of GDP) and for education. The use of explanatory nonstationary variables as controls in equations with a stationary dependent variable has already been discussed in the literature [39–41]. However, when nonstationary variables are among the regressors in an expression where the dependent variable is stationary, one may reasonably argue that they are sharing a common trend, thus forming a stationary error correction term. This seems

Table 3: Data sources and descriptions.

Variable name	Definition and construction	Source
GDP growth rate	Percentage growth rate of real GDP per capita in constant prices. Reference year: 1996, Laspeyres index.	Penn World Tables 6.3
GDP volatility	Standard deviation of real GDP growth rate. Yearly series.	Penn World Tables 6.3
Consumption volatility	Standard deviation of real consumption growth rate (real GDP times consumption share of GDP). Yearly series.	Penn World Tables 6.3
Investment volatility	Standard deviation of real Investment growth rate (real GDP times investment share of GDP). Yearly series.	Penn World Tables 6.3
Gov. consumption volatility	Standard deviation of real public consumption growth rate (real GDP times government cons.share of GDP). Yearly series.	Penn World Tables 6.3
Investment share of GDP	Log level of the investment share of real GDP. Yearly series.	Penn World Tables 6.3
Initial GDP	Log level of GDP of the 1st year of the window of which the corresponding volatility is computed. Yearly series.	Penn World Tables 6.3
Population growth rate	Percentage growth rate of population. Yearly series.	Penn World Tables 6.3
Education	Logarithm of the percentage of secondary schooling attained in population aged 25 years and over.	Barro-Lee dataset (2010)

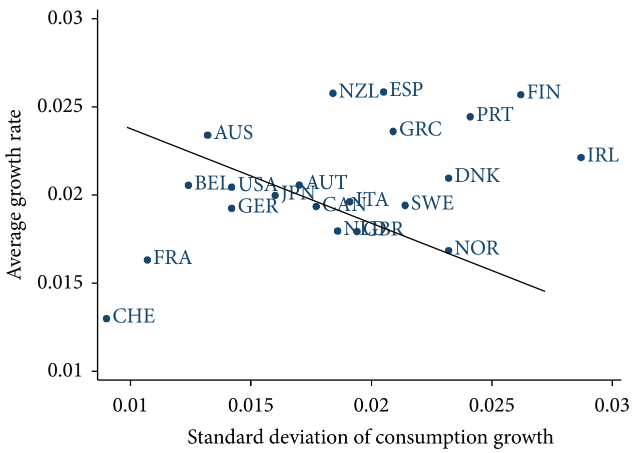

Figure 4: Simple correlation of growth and consumption volatility.

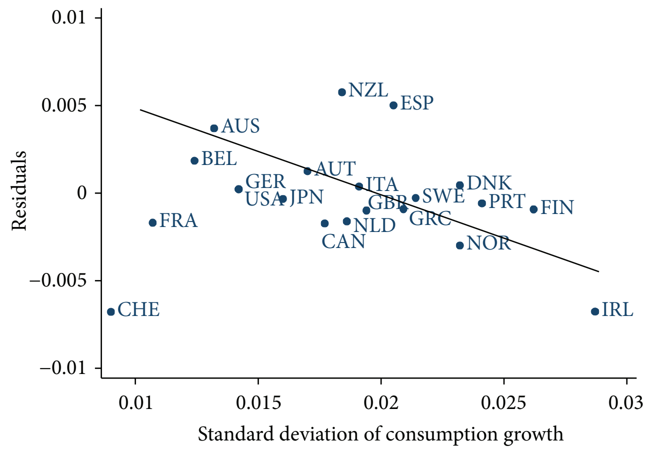

Figure 5: Partial correlation of growth and consumption volatility. (Controlling for the volatility of Y, I, and G.)

Table 4: Outlier testing.

Country	Residuals (|0.2|)	Leverage (0.4)	Cook's D. (0.16)	DFBETA (0.4)
Germany		0.76	0.24	
Iceland	2.61		0.21	0.83
Ireland		0.80		
Korea	1.54	0.81	1.87	2.41
Luxembourg	2.54		0.26	0.87
Mexico	−2.56		0.40	

Note: Studentized residuals, Levarages, Cook's Distance, and DFBETA influence measures are considered. Only countries reporting statistics besides the cutoff values are reported. Cutoff values for each indicator are in parenthesis.

to be the case in our analysis, as it is very likely that the level of education is related to the level of GDP. Moreover, any time-related common factor should be captured by the time dummies included in our models.

2.2. Growth and Volatility: A Static Regression Analysis. We start by estimating a benchmark model, in the spirit of G. Ramey and V. A. Ramey [7], where we regress GDP growth against the volatility of output growth along with a set of conditioning variables that are quite standard within the growth regression literature—documented by Levine and Renelt [42] to be relevant in the context of growth cross-country regressions—and where country and time-specific constants are also considered as follows:

$$g_{it} = \alpha_{i\cdot} + \tau_{\cdot t} + \beta\sigma^{y}_{it} + \theta' X_{it} + \varepsilon_{it},$$
$$\varepsilon_{it} \sim N\left(0, \sigma^2_{\varepsilon}\right), \quad i = 1, \dots, N, \; t = 1, \dots, T, \tag{1}$$

where g_{it} is the annual growth rate of per capita GDP of country i at time t; $\alpha_{i\cdot}$ and $\tau_{\cdot t}$ represent, respectively, a country and a time-specific fixed effect; σ^{y}_{it} is our measure of output growth volatility, and the vector X_{it} includes a set of control variables, namely, (i) the annual log-level of investment share

Table 5: Panel unit root test [38].

Variable	Level		First difference	
	Constant	Constant + trend	Constant	Constant + trend
Log of GDP	12.4454	0.78674	−13.409***	−9.96431***
GDP volatility	−4.9473***	−6.3950***	−19.0850***	−16.803***
Consumption volatility	−4.3329***	−4.0761***	−19.6400***	−16.336***
Investment volatility	−20.811***	−6.1437***	−4.4186***	−18.687***
Gov. consumption volatility	−5.6580***	−2.6002***	−20.813***	−17.653***
Investment share of GDP	−0.7502	−2.8268**	−17.7615***	−14.5888***
Log of population	6.6528	−1.0168	−4.4148***	−3.1863***
Education	−0.2669	1.5139	−3.1892***	−8.4E + 12***

***, ** Rejection of the null hypothesis of the presence of a unit root at 1% and 5% level of significance.
The choice of the optimal lag for the underlying autoregressive equation is based on the Schwarz identification criterion (SIC).

Table 6: Dependent variable: growth rate of per capita GDP. Regressors: volatility of GDP growth, consumption growth, investment growth, government consumption growth, and control variables. Sample: OECD countries (25 countries). Horizon: 1978–2007. Annual observations. All regressions include year dummies.

	Static models estimations					
Estimation	FE	FE	FE	FE-IV GMM	FE-IV GMM	FE-IV GMM
GDP volatility	−0.127		0.177	−0.417*		−0.981
	(−0.88)		(0.69)	(−1.93)		(−1.62)
Consumption volatility		−0.549***	−0.613***		−0.907**	−0.525***
		(−3.28)	(−3.46)		(−3.06)	(−2.50)
Investment volatility		0.049	0.012		0.154	0.334*
		(1.18)	(0.21)		(1.56)	(1.77)
Government consumption volatility		0.460***	0.443***		0.323*	0.442***
		(3.83)	(3.72)		(1.86)	(2.71)
Education	0.003	0.003	0.003	0.005	0.002	0.003
	(0.58)	(0.66)	(0.50)	(0.60)	(0.31)	(0.51)
Population growth	−0.736*	−0.823**	−0.863**	0.501	0.340	0.542
	(−1.72)	(−2.04)	(−2.21)	(0.89)	(0.67)	(1.00)
Initial GDP	−0.050***	−0.032**	−0.031**	−0.066***	−0.035**	−0.041**
	(−3.52)	(−2.23)	(−2.20)	(−4.15)	(−2.11)	(−2.58)
Investment share of GDP	0.084***	0.083***	0.084***	−0.106***	−0.084***	−0.082***
	(6.73)	(7.19)	(7.26)	(−3.28)	(−3.22)	(−3.25)
Observations	750	750	750	675	675	675
Instruments	no	no	no	yes	yes	yes
Hansen J statistic (P value)				0.321	0.76	0.87
Kleibergen-Paap Wald F statistic				69.231	41.711	27.638

Note: T-statistics in parenthesis, robust SEs. *Significance at 10%, **significance at 5%, and ***significance at 1%.

of GDP, (ii) the log-level of GDP per capita on the first year of the rolling window over which the corresponding observation of volatility is computed (see below), (iii) a measure for the initial human capital given by the log-percentage of population aged over 25 years who attained a degree of secondary school, and (iv) the annual growth rate of population (a detailed description of the series is provided in Tables 1, 2, and 3). Finally, ε_{it} is a standard error term.

The peculiarity of our model is that our measure of volatility is time varying, whereas previous panel studies on volatility and growth, such as, for example, Kose et al. [10], and Rafferty [34] measure volatility as the standard deviation over 5/10 yearly observations along with averaged observations over the same span for the rest of the variables, which implies a sharp shortening of the time dimension of their panel dataset. By contrast, our measure of volatility is computed as the standard deviation of a five-year rolling window of observations whose last year is contemporaneous to the dependent variable g_{it} (thus, 1974–1978 is the first rolling window and 2003–2007 is the last one). Our dependent variable, on the other hand, is not computed as a mean over a rolling window, but rather as a simple growth rate. This is also relevant from the statistic point of view, as it should prevent our results from being affected by serial correlation

Table 7: Dependent variable: growth rate of per capita GDP. Regressors: lagged growth rate of per capita GDP, volatility of GDP growth, consumption growth, investment growth, government consumption growth, and control variables. Sample: OECD countries (25 countries). Horizon: 1978–2007. All regressions include year dummies.

	Dynamic models estimations					
Estimation	LSDV IV 2sls	LSDV IV 2sls	LSDV IV 2sls	GMM-SYS	GMM-SYS	GMM-SYS
GDP volatility	−0.248		−0.931	−0.053		−0.392
	(−1.59)		(−1.43)	(−0.29)		(−0.56)
Consumption volatility		−0.769***	−0.396**		−0.470**	−0.304
		(−2.83)	(−2.16)		(−2.11)	(−1.26)
Investment volatility		0.169*	0.341*		0.13	0.195
		(1.78)	(1.66)		(1.66)	(0.92)
Government consumption volatility		0.252*	0.372***		0.330*	0.360**
		(1.85)	(2.70)		(2.05)	(2.12)
GDP growth ($t-1$)	0.365***	0.309***	0.299***	0.375***	0.340***	0.345***
	(4.95)	(4.33)	(4.02)	(4.44)	(4.24)	(4.33)
Education	0.004	0.003	0.004	0.007	0.008	0.009
	(0.66)	(0.48)	(0.68)	(0.66)	(0.83)	(0.77)
Population growth	0.100	−0.024	0.16	−0.440	−0.534	−0.522
	(0.22)	(−0.06)	(0.33)	(−0.92)	(−1.08)	(−0.98)
Initial GDP	−0.048***	−0.021	−0.028**	−0.015	−0.013	−0.015
	(−3.90)	(−1.64)	(−2.12)	(−0.77)	(−0.68)	(−0.65)
Investment share of GDP	−0.085***	−0.064**	−0.060***	−0.075**	−0.068**	−0.075**
	(−3.49)	(−3.14)	(−3.00)	(−2.37)	(−2.17)	(−2.24)
Observations	675	675	675	725	725	725
Country dummies	Yes	Yes	Yes	No	No	No
Instruments	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F statistic	140.47	56.569	23.352			
Hansen J/Sargan test (P value)	0.715	0.738	0.654	0.243	0.592	0.558
Arellano-Bond test (AR2)				0.837	0.707	0.752

Note: T-statistics in parenthesis, robust SEs. *Significance at 10%, **significance at 5%, and ***significance at 1%.

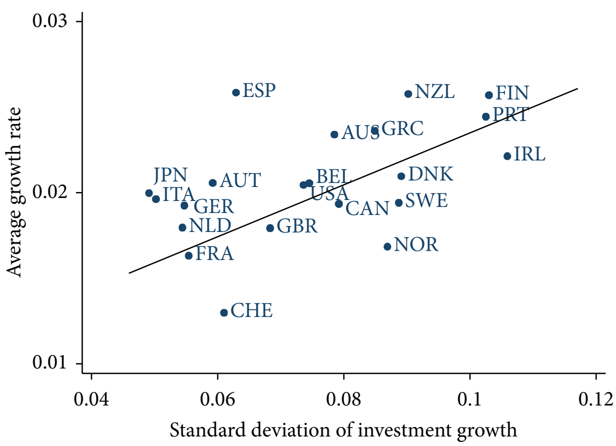

Figure 6: Simple correlation of growth and investment volatility.

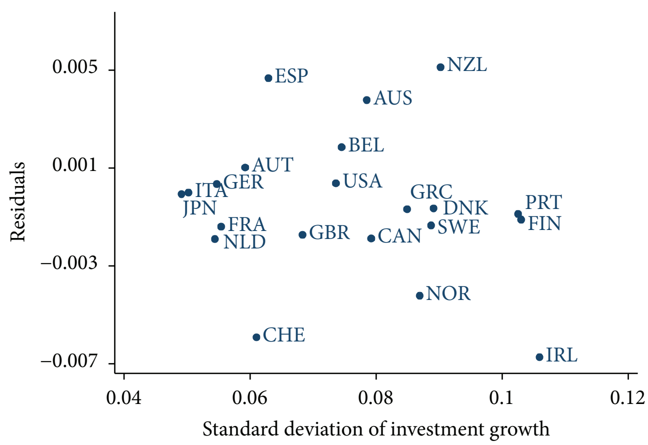

Figure 7: Partial correlation of growth and investment volatility. (Controlling for the volatility of C, G, and I.)

problems. The aim of this regression is to verify the existence of a causal relationship between the growth rate of GDP at time t and the volatility occurring over the previous interval, from $t-5$ to t.

The next step will be checking whether this global relationship is driven by some specific components or whether

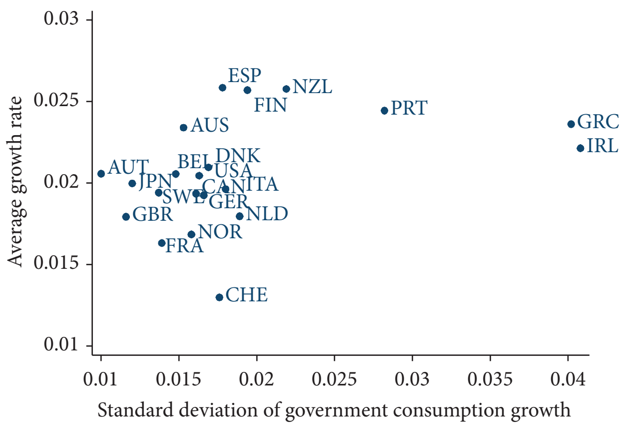

Figure 8: Simple correlation of growth and government consumption volatility.

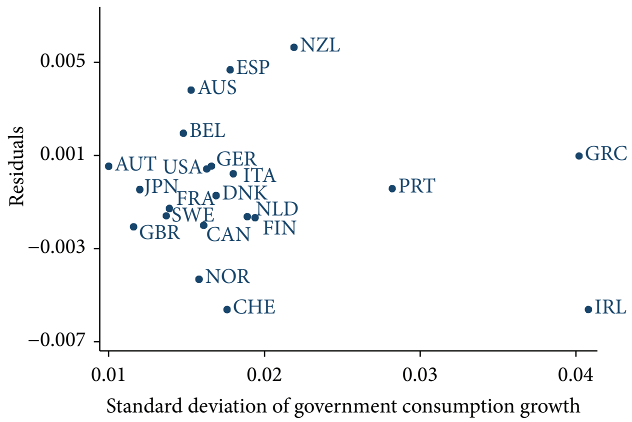

Figure 9: Partial correlation of growth and government consumption. (Controlled for volatility of Y, C, and G.)

all of them exert the same influence upon growth. In order to see this, we start from the fundamental accounting identity

$$\mathrm{GDP}_t = C_t + I_t + G_t + NX_t. \quad (2)$$

By dividing both members by GDP_{t-1} we get

$$\frac{\mathrm{GDP}_t}{\mathrm{GDP}_{t-1}} = \frac{C_t}{\mathrm{GDP}_{t-1}} + \frac{I_t}{\mathrm{GDP}_{t-1}} + \frac{G_t}{\mathrm{GDP}_{t-1}} + \frac{NX_t}{\mathrm{GDP}_{t-1}}. \quad (3)$$

Which can also be written as

$$\frac{\mathrm{GDP}_t}{\mathrm{GDP}_{t-1}} = \frac{C_t}{C_{t-1}} s_{t-1}^{C} + \frac{I_t}{I_{t-1}} s_{t-1}^{I} + \frac{G_t}{G_{t-1}} s_{t-1}^{G} + \frac{NX_t}{NX_{t-1}} s_{t-1}^{NX}, \quad (4)$$

where s_{t-1}^{C}, s_{t-1}^{I}, s_{t-1}^{G}, s_{t-1}^{NX} represent the GDP shares of consumption, investments, public expenditure and net exports, respectively. In what follows, we will assume that those shares are approximately constant for the (relatively short) spell of time over which volatilities are computed (the time subscript will thus be omitted). Under this assumption, elementary statistics yield

$$\begin{aligned}
\mathrm{Var}\left(\frac{\mathrm{GDP}_t}{\mathrm{GDP}_{t-1}}\right) = {} & \left(s^C\right)^2 \mathrm{Var}\left(\frac{C_t}{C_{t-1}}\right) + \left(s^I\right)^2 \mathrm{Var}\left(\frac{I_t}{I_{t-1}}\right) \\
& + \left(s^G\right)^2 \mathrm{Var}\left(\frac{G_t}{G_{t-1}}\right) \\
& + \left(s^{NX}\right)^2 \mathrm{Var}\left(\frac{NX_t}{NX_{t-1}}\right) \\
& + 2\left[s^C s^I \mathrm{Cov}\left(\frac{C_t}{C_{t-1}}, \frac{I_t}{I_{t-1}}\right)\right. \\
& \quad + s^C s^G \mathrm{Cov}\left(\frac{C_t}{C_{t-1}}, \frac{G_t}{G_{t-1}}\right) \\
& \quad \left. + s^C s^{NX} \mathrm{Cov}\left(\frac{C_t}{C_{t-1}}, \frac{NX_t}{NX_{t-1}}\right)\right] \\
& + 2\left[s^I s^G \mathrm{Cov}\left(\frac{I_t}{I_{t-1}}, \frac{G_t}{G_{t-1}}\right)\right. \\
& \quad + s^I s^{NX} \mathrm{Cov}\left(\frac{I_t}{I_{t-1}}, \frac{NX_t}{NX_{t-1}}\right) \\
& \quad \left. + s^G s^{NX} \mathrm{Cov}\left(\frac{G_t}{G_{t-1}}, \frac{NX_t}{NX_{t-1}}\right)\right].
\end{aligned} \quad (5)$$

Equation (5) shows that the variance of GDP growth can be decomposed into the sum of variances of its various components, multiplied by the square of the corresponding shares, plus the covariances between the components. In the following empirical analysis we are going to consider only the first three components of the overall volatility as expressed by (5)—namely, the volatility of private consumption, investment, and government consumption—as we decided to focus on the internal sources of volatility, and because the variance of net exports is extremely large. In doing so, we are capturing a sizeable portion of the variance of GDP less net exports (around 70%, rising to about 100% if we also take covariances into account, which implies that the impact of the variability of shares is negligible). On the other hand, the share of the first three components of overall GDP volatility over the GDP comprehensive of the trade balance component is slightly larger than one (about 1.11 in some computations), mainly due to the effects of covariances of the three components with net exports.

Hence, estimation of model (6) aims at detecting if the volatility of consumption, investment, and government expenditure influences mean growth in the same direction, or rather if some of them are detrimental and some beneficial to growth. In order to do that, we simply augment Model (1) by consumption (σ_{it}^{c}), investment (σ_{it}^{i}), and government expenditure (σ_{it}^{g}) volatility as separate control regressors, as in the following:

$$g_{it} = \alpha_{i\cdot} + \tau_{\cdot t} + \gamma\sigma_{it}^{c} + \delta\sigma_{it}^{i} + \epsilon\sigma_{it}^{g} + \theta' X_{it} + \varepsilon_{it}. \quad (6)$$

Finally, our last empirical specification (Model (7)) also includes a measure of the overall volatility of GDP growth which will possibly capture the effects of net exports growth volatility and of all the interactions between the various components, and possibly a size effect as follows:

$$g_{it} = \alpha_{i\cdot} + \tau_{\cdot t} + \beta\sigma_{it}^{y} + \gamma\sigma_{it}^{c} + \delta\sigma_{it}^{i} + \epsilon\sigma_{it}^{g} + \theta' X_{it} + \varepsilon_{it}. \quad (7)$$

Turning to the econometric methodology, as our sample of OECD countries represents the universe of countries more likely than a random sample taken from a larger universe of countries, we opt for a fixed-effects model specification. Therefore, we assume that the fixed country-specific ($\alpha_{i\cdot}$) and a fixed period-specific terms ($\tau_{\cdot t}$) are deterministic, respectively, for each country and period and that ε_{it} is a standard random component (an appropriate Hausman test of the fixed effects model versus random effects model was performed over all the model specifications, supporting our intuitive argument in favour of the former). Then, we account for the presence of both country and time effects, respectively, by applying a "within-group" transformation (i.e., we subtract the mean of each variable over time per country from itself) on all variables and by including time-specific dummies. Finally, we perform a robust least square (LS) estimation, which represents our benchmark estimation.

However, since growth equations are likely to be affected by reverse causality issues, we check for the endogeneity of the regressors (the endogeneity test that we perform is defined as the difference of two Sargan-Hansen statistics: one for the equation with the smaller set of instruments (where the suspect regressor(s) are treated as endogenous) and one for the equation (with the larger set of instruments) where the suspect regressors are treated as exogenous. See Baum et al. [43]). Test results show both the investment growth volatility and the investment share of GDP to be endogenous with respect to GDP growth, thus implying the inconsistency of the LS estimates. The lack of independence between the regressors distribution and the error term call for an instrumental variables (IV) approach. Concerning the choice of the instruments, we take advantage of the panel dimension of our data by using the lagged values of the endogenous variables as predeterminates, with respect to contemporaneous growth. A second concern is that a plain two-step least square (2SLS) IV estimator, though providing consistent coefficient estimates, implies a loss of efficiency and the inconsistency of standard errors estimates in the presence of heteroskedasticity, which might possibly affect the testing procedures and results in our models (both the Pagan-Hall and the Breusch-Pagan statistics indicate that the null hypothesis of homoscedasticity is rejected at the 1% level). However, the issue of inefficiency can be tackled by means of the generalized method of moments (GMM) that allows for an efficient estimation in the presence of heteroscedasticity, by resorting to linear orthogonality conditions (Baum et al. [43] provides a useful guide to IV and GMM estimation and their implementation in STATA). Our estimates of models (1), (6) and (7) are thus derived by a two-step efficient GMM estimator, where each variable found to be endogenous—namely, investment volatility and investment GDP share—is instrumented, respectively, by its second lag and its second and third lag (these regressions are performed using the *xtivreg2* program in STATA [44]). The validity of the instruments employed is tested by means of the Wald F-statistics based on the Kleibergen-Paap *rk* statistics which is robust in presence of heteroscedasticity. It excludes the hypothesis of weak instruments in both cases as it exceeds the rule of thumb, suggested by Staiger and Stock that the F statistic must be larger than 10. As for the exogeneity of the instruments, in both cases we rely on the Hansen-J statistics which strongly accept the exogeneity hypothesis of the instruments in both cases. (See Baum et al. [43] for a detailed explanation of test implementation in STATA and for references). Finally, it is worthwhile noticing that, besides being efficient, our estimation results are also consistent with respect to either heteroscedasticity or autocorrelation because of the Newey-West specification employed for the estimation of the long-run GMM covariance matrix (the Newey-West approach is based on the Bartlett kernel function (which enters the formula of the feasible long-run covariance matrix of moment condition) whose *bandwidth* is chosen according to the common criterion which sets it equal to $T^{1/3}$, where T is the panel time dimension. See Baum et al. [43] and the references therein).

2.3. Growth and Volatility: A Dynamic Panel Approach. Even though current growth rates are not likely to affect our measures of volatility (which is computed over the preceding 5-annual observations window), our results might be biased to the extent that persistent innovations to growth affect future growth rates, as it is argued, for example, in Fatàs and Mihov [23]. For this reason, we re-estimate our models (1), (6), and (7) including the lagged output growth rates as additional regressor as in a dynamic panel estimation framework as follows:

$$\begin{gathered} g_{it} = \alpha_{i\cdot} + \tau_{\cdot t} + \rho g_{it-1} + \beta\sigma_{it}^{y} + \theta' X_{it} + \varepsilon_{it}, \\ g_{it} = \alpha_{i\cdot} + \tau_{\cdot t} + \rho g_{it-1} + \beta\sigma_{it}^{y} + \gamma\sigma_{it}^{c} + \delta\sigma_{it}^{i} + \epsilon\sigma_{it}^{g} + \theta' X_{it} + \varepsilon_{it}, \\ g_{it} = \alpha_{i\cdot} + \tau_{\cdot t} + \rho g_{it-1} + \gamma\sigma_{it}^{c} + \delta\sigma_{it}^{i} + \epsilon\sigma_{it}^{g} + \theta' X_{it} + \varepsilon_{it}, \end{gathered} \quad (8)$$

where the previous notation holds.

However, estimating dynamic panel models with unobservable country fixed effects is not a straightforward task. Besides the well-known "dynamic panel bias" that would arise if a naive ordinary least square (OLS) approach was applied to a dynamic fixed-effects model—whereby the lagged dependent variable would turn out to be endogenous to the fixed effects in the error term—usual strategies employed to treat and estimate fixed-effects models, like the least square dummy variable (LSDV) or the "within-group transformation" estimators, are also well known to yield biased estimated coefficients. Anyway, the magnitude of such a bias was found to be inversely correlated with the time dimension of panel; that is, it approaches zero as T approaches infinity [45], implying that those estimators

Table 8: Dependent variable: growth rate of per capita GDP. Regressors: volatility of GDP growth, consumption growth, investment growth, government consumption growth, and control variables. Sample: OECD countries (21 countries). Horizon: 1978–2007. Annual observations. All regressions include year dummies.

Static models estimations—restricted sample						
Estimation	FE	FE	FE	FE-IV GMM	FE-IV GMM	FE-IV GMM
GDP volatility	−0.806		0.038	-0.583^{**}		−0.214
	(−0.41)		(0.15)	(−2.24)		(−0.66)
Consumption volatility		-0.941^{***}	-0.953^{***}		-0.881^{***}	-0.816^{***}
		(−4.63)	(−4.56)		(−4.07)	(−3.48)
Investment volatility		0.105^{**}	0.096^{*}		−0.025	0.016
		(2.37)	(1.74)		(−0.41)	(0.22)
Government consumption volatility		0.293^{***}	0.291^{***}		0.268^{*}	0.285^{*}
		(2.68)	(2.65)		(1.65)	(1.75)
Education	0.005	0.005	0.005	0.006	0.004	0.005
	(1.27)	(1.23)	(1.24)	(0.69)	(0.58)	(0.62)
Population growth	−0.497	−0.331	−0.335	0.761	0.922	0.920
	(−1.14)	(−0.86)	(−0.87)	(1.14)	(1.49)	(1.50)
Initial GDP	-0.066^{***}	-0.054^{***}	-0.054^{***}	-0.077^{***}	-0.065^{***}	-0.065^{***}
	(−3.32)	(−2.85)	(−2.84)	(−3.51)	(−3.18)	(−3.22)
Investment share of GDP	0.056^{***}	0.062^{***}	0.062^{***}	-0.089^{***}	-0.080^{***}	-0.079^{***}
	(4.79)	(5.82)	(5.82)	(−3.95)	(−3.00)	(−2.99)
Observations	630	630	630	567	567	567
Instruments	no	no	no	yes	yes	yes
Hansen J statistic (P value)				0.118	0.234	0.258
Kleibergen-Paap Wald F statistic				90.809	89.438	90.061

Note: T-statistics in parenthesis, robust SEs. *Significance at 10%, **significance at 5%, and ***significance at 1%.

perform well only when the time dimension of the panel is large enough—which is the case for most macropanel data (over the last two decades an extensive literature has delt with this issue especially in the context of microeconometrics—that usually deals with wide (large N) and short (small T) panel datasets—providing a number of alternative suitable econometric strategies). Judson and Owen [46] compare the performance of alternative estimators in the context of a dynamic fixed-effects model for narrow (small N) and long (large T) panels typical of macrodata (they run a Monte-Carlo approach experiment in the spirit of Kiviet [47] in order to compare the efficiency of the LSDV estimator, the LSDV corrected (LSDVC) estimator by Kiviet [47], the Anderson and Hsiao [48] IV difference estimator, and the Arellano and Bond [49] GMM difference estimator, according to different dataset dimensions and degrees of persistence of the lagged dependent variable). Among their findings, they also stress that (i) the difference in the efficiency of those estimators becomes quite small for "large enough" N and T and that (ii) when the outperforming corrected LSDV estimator by Kiviet [47] cannot be implemented (Bruno [50] provides a STATA routine able to implement a LSDVC estimator which, however, is not viable in presence of endogenous regressors other than the lagged dependent variable, which unfortunately is our case) and when $T = 30$, the LSDV represents a more than satisfactory alternative to the Anderson and Hsiao [48] and Arellano and Bond [49] GMM difference strategies, because the magnitude of the bias is relatively small (Harris and Mátyás [51] show that when N is small enough, the LSDV estimator performs just as well as the Arellano and Bond [49] GMM difference estimator). By relying on this evidence, in order to estimate our dynamic models (8) we resort to the LSDV approach. Moreover, in order to confer robustness to our LSDV estimates results, we repeat the estimation employing a restricted one-step "GMM system" estimator [52, 53] as other studies do, like for example, Edwards's [35]. The GMM system estimator belongs to the group of consistent estimators for dynamic panel fixed-effects models that have been proposed in the literature in order to tackle the inconsistency of LSDV in that context (these techniques share the common features of expunging fixed effects by first-differencing the data and of relying upon internal instrumentation of the lagged dependent variable that, once first-differenced, turns out to be correlated with the first-differenced error term. Anderson and Hsiao [48] exploit a simple 2SLS - IV approach using the second lags of the dependent variable (either in difference or in levels) as instruments; Arellano and Bond [49] resort to a GMM approach to derive a larger number ($T - 1$) of internal instruments (in levels) to instrument the endogenous lagged differenced term, which gains efficiency with respect to Anderson and Hsiao approach). Besides, the GMM system is particularly suitable to the extent that data used in the model suffer from some degree of persistence—whereby lagged level of persistent variables would be only weak instruments for the stationary first-differenced term, as it would be the case

Table 9: Dependent variable: growth rate of per capita GDP. Regressors: lagged growth rate of per capita GDP, volatility of GDP growth, consumption growth, investment growth, government consumption growth, and control variables. Sample: OECD countries (21 countries). Horizon: 1978–2007. Annual observations. All regressions include year dummies.

Dynamic models estimations—restricted sample						
Estimation	LSDV IV 2sls	LSDV IV 2sls	LSDV IV 2sls	SYS-GMM	SYS-GMM	SYS-GMM
GDP volatility	-0.339^{**}		-0.089	-0.135		0.700
	(-1.99)		(-0.40)	(-0.63)		(1.54)
Consumption volatility		-0.586^{***}	-0.560^{***}		-0.386^{**}	-0.562^{**}
		(-3.65)	(-3.14)		(-2.17)	(-2.15)
Investment volatility		-0.020	-0.001		-0.059	-0.222^{*}
		(-0.43)	(-0.02)		(-1.01)	(-1.79)
Government consumption volatility		0.235^{**}	0.242^{**}		0.291^{*}	0.289^{*}
		(2.04)	(2.06)		(1.79)	(1.72)
GDP growth ($t-1$)	0.478^{***}	0.430^{***}	0.428^{***}	0.473^{***}	0.432^{***}	0.451^{***}
	(7.30)	(6.92)	(6.89)	(4.14)	(3.58)	(3.53)
Education	0.004	0.004	0.004	-0.004	-0.001	-0.001
	(0.70)	(0.72)	(0.73)	(-0.32)	(-0.02)	(-0.13)
Population growth	0.220	0.267	0.268	0.111	-0.112	-0.007
	(0.50)	(0.63)	(0.63)	(0.16)	(-0.22)	(-0.01)
Initial GDP	-0.036^{**}	-0.032^{**}	-0.034^{**}	-0.012	-0.012	-0.012
	(-2.23)	(-2.23)	(-2.24)	(-0.56)	(-0.74)	(-0.62)
Investment share of GDP	-0.072^{***}	-0.063^{***}	-0.062^{***}	-0.135^{**}	-0.094^{*}	-0.117^{***}
	(-3.72)	(-3.40)	(-3.40)	(-2.47)	(-1.69)	(-2.66)
Observations	567	567	567	609	609	609
Country dummies	Yes	Yes	Yes	No	No	No
Instruments	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F statistic	212.340	202.231	201.867			
Hansen J/Sargan test (P value)	0.713	0.571	0.562	0.182	0.215	0.214
Arellano-Bond test (AR2) (P value)				0.862	0.745	0.768

Note: T-statistics in parenthesis, robust SEs. *Significance at 10%, **significance at 5%, and ***significance at 1%.

with the GMM difference estimator. However, when the time dimension of the panel is large, an evident drawback of the GMM approach is that it implies the proliferation of the number of instruments, which tends to explode in T. Using too many instruments can overfit the endogenous variables and bias the coefficient estimates, which is among the reasons both difference and system GMM are recommended for short (small T) and large (large N) panels, as argued in Roodman [54, 55]. Therefore, in order both to preserve the reliability of the estimates and to improve the performance of Sargan tests for the joint validity of the instruments, our strategy aims at the limitation of instruments proliferation by both limiting the number of lags used as instruments in the GMM system regressions and resorting to a "collapsed" form of the instrumenting matrix [54].

3. Results

3.1. Main Regressions. Tables 6–9 contain the results of our main regressions' estimates. In particular, Tables 6 and 7 contain results relative to the whole panel, whereas Tables 8 and 9 contain results relative to the restricted sample of countries. In fact, from the descriptive statistics and from the diagnostic analysis of our main sample, the presence of some extreme outlier countries can be easily detected (see Tables 1 and 4). Thus, in order to verify the robustness of our benchmark results, we exclude these countries from our OECD sample, thus resorting to a restricted sample over which we test again our empirical models. Results of the static and dynamic models estimations are displayed, respectively, in Tables 6, 7, 8, and 9. Hansen-J and Sargan tests output for the exogeneity of the instruments employed in either 2SLS and GMM estimations is always provided when IV regressions results are presented, whereas the Arellano and Bond [49] tests for autocorrelation in the error structure are provided only when GMM system estimations output is presented. It is worth noticing that the null hypothesis for all these tests should be accepted for valid estimations, which is always the case in our regressions.

First of all, we can see from our tables that the Ramey and Ramey type of result is confirmed both in our static and in our dynamic models, either on the complete or on the restricted sample, although the (negative) coefficient of volatility is sometimes not statistically significant. In particular, it is worth stressing that, regardless of the sample chosen, GDP

TABLE 10: Dependent variable: growth rate of per capita GDP. Regressors: volatility of GDP growth, consumption growth, investment growth, government consumption growth, and control variables. Sample: OECD countries (25 countries). Horizon: 1978–2007. Annual observations. All regressions include year dummies. All regressions are population weighted.

	Static models weighted estimations					
Estimation	FE	FE	FE	FE-IV 2sls	FE-IV 2sls	FE-IV 2sls
GDP volatility	−0.073		0.311	−0.476***		−1.790**
	(−0.89)		(1.55)	(−3.94)		(−2.84)
Consumption volatility		−0.687***	−0.766***		−1.337***	−0.882***
		(−5.75)	(−5.90)		(−6.79)	(−4.68)
Investment volatility		0.086***	0.116		0.202***	0.625***
		(2.83)	(0.21)		(3.08)	(3.11)
Government consumption volatility		0.066	0.036		−0.058	0.136
		(0.57)	(0.753)		(−0.34)	(0.73)
Education	0.006	0.007*	0.008**	0.003	0.006	0.006
	(1.45)	(1.94)	(2.03)	(0.55)	(0.95)	(0.99)
Population growth	−0.048	−0.203	−0.223	1.332***	1.05**	1.297***
	(−0.15)	(−0.65)	(−0.72)	(2.88)	(2.38)	(2.70)
Initial GDP	−0.042***	−0.016**	−0.017**	−0.057***	−0.100	−0.022*
	(−5.63)	(−2.21)	(−2.05)	(−5.18)	(−0.81)	(−1.69)
Investment share of GDP	0.115***	0.110***	0.110***	−0.132***	−0.108***	−0.119***
	(11.44)	(11.07)	(11.05)	(−5.19)	(−4.44)	(−4.28)
Observations	750	750	750	675	675	675
Instruments	no	no	no	yes	yes	yes
Sargan statistic (P value)				0.807	0.514	0.852
Kleibergen-Paap Wald F statistic				133.016	87.75	40.079

Note: T-statistics in parenthesis, robust SEs. *Significance at 10%, **significance at 5%, and ***significance at 1%.

volatility coefficient always turns out to be significantly negative in the context of the static IV regressions; that is, once we properly account for endogeneity which is found to affect investment volatility and the investment share of GDP. According to these estimates, an increase by 10% in the volatility of GDP brings about a reduction in mean growth by 0.09% in the main sample and by 0.13% in the restricted sample. What we infer from this evidence is that disregarding endogeneity would imply a substantially downward biased significance of coefficient estimates. On the other hand, volatility of GDP always fails to be statistically significant within the dynamic regression context, regardless of the estimation strategy employed. Then, we also observe that when volatility of GDP is included in addition to volatility of consumption, investments, and public expenditure, it is never statistically significant at standard significance level, although the sign of its coefficient is always negative.

Concerning the sign of the impact of the different components of volatility on mean growth, the most striking and seemingly very robust result is the negative and almost always statistically significant coefficient attached to the volatility of consumption. It is also worth stressing that the magnitude of its negative impact onto growth is slightly above that implied by (mean) output volatility, as a 10% increase in consumption volatility determines a 0.12% and a 0.16% drop in average GDP growth, respectively, in the two sample considered in the static context (as for this parameter we observe statistically significant estimated coefficients across the models (cf. Tables 6–9); we discuss the average of these estimates). As for the dynamic regression framework, we note that the negative influence of consumption volatility growth is somehow mitigated in both the samples as, on average, the estimated impacts of a 10% increase of consumption volatility onto average GDP growth drop to 0.08% and 0.09%, respectively. As we argued in the introduction, this might be taken to mean that what is really harmful to economic growth is market incompleteness, revealed by the fact that volatility of production and income cannot be dampened by real or financial markets and spill over to consumption. Moreover, volatility in consumption directly affects agents and makes them more vulnerable and less prone to accept additional risks, which might endanger their willingness to engage in more risky and on average more profitable investment opportunities.

On the same ground, the result concerning the impact of public expenditure volatility on mean growth is also quite remarkable. The sign of the coefficient is positive and almost always statistically significant across model specifications, estimations strategies, and samples, suggesting in a fairly robust way that volatility in public expenditure is not harmful, but rather beneficial for growth. The magnitude of the estimated impact of a 10% change in public expenditure volatility ranges between 0.07% and 0.05% for the main sample and between 0.045% and 0.042% for the restricted sample, respectively, in the static and dynamic models. This result lends some support to the view that public expenditures

Table 11: Dependent variable: growth rate of per capita GDP. Regressors: lagged growth rate of per capita GDP, volatility of GDP growth, consumption growth, investment growth, government consumption growth, and control variables. Sample: OECD countries (25 countries). Horizon: 1978–2007. Annual observations. All regressions include year dummies. All regressions are population weighted.

Dynamic models weighted estimations						
Estimation	LSDV	LSDV	LSDV	LSDV IV 2sls	LSDV IV 2sls	LSDV IV 2sls
GDP volatility	−0.042		0.396*	−0.271***		0.436*
	(−0.46)		(1.92)	(−2.71)		(1.76)
Consumption volatility		−0.583***	−0.683***		−0.515***	−0.630***
		(−4.67)	(−5.06)		(−3.51)	(−3.85)
Investment volatility		0.074***	−0.200		−0.120	−0.114
		(2.38)	(−0.34)		(−0.31)	(−1.64)
Government consumption volatility		0.013	−0.030		−0.075	−0.122
		(0.11)	(−0.20)		(−0.49)	(−0.79)
GDP growth ($t-1$)	0.183***	0.142***	0.142***	0.430***	0.399***	0.399***
	(4.70)	(3.59)	(3.61)	(8.65)	(7.92)	(7.92)
Education	0.004	0.005	0.005	0.005	0.005	0.005
	(0.86)	(1.19)	(1.28)	(0.88)	(1.00)	(0.98)
Population growth	−0.282	−0.378	−0.414	0.518	0.360	0.346
	(−0.87)	(−1.17)	(−1.28)	(1.32)	(0.92)	(0.77)
Initial GDP	−0.032***	−0.139	−0.120	−0.036***	−0.019*	−0.017
	(−4.07)	(−1.59)	(−1.34)	(−3.68)	(−1.80)	(−1.56)
Investment share of GDP	0.092***	0.093***	0.093***	−0.096***	−0.099***	−0.096***
	(8.20)	(8.30)	(8.30)	(−4.96)	(−4.98)	(−4.99)
Observations	725	725	725	675	675	675
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Instruments	No	No	No	Yes	Yes	Yes
Kleibergen-Paap Wald F statistic				275.699	269.17	268.73
Sargan test (P value)				0.136	0.166	0.208

Note: T-statistics in parenthesis, robust SEs. *Significance at 10%, **significance at 5%, and ***significance at 1%.

become more volatile when it is used to dampen economic fluctuations, originating from both idiosyncratic and aggregate shocks.

On the other hand, the results concerning volatility in the investment component of GDP growth are less clear cut, at least in terms of statistical significance of the estimated coefficients. If in the case of the benchmark sample the investment volatility coefficients become statistically significant only once we control for endogeneity in the context of the IV regressions and are not statistically significant in the non-IV case, the opposite occurs in the case of the restricted sample (cf. Tables 6 and 8). Hence, we argue that unobserved characteristics imply a downward bias of the coefficient's significance in the former case, whereas a spurious relationship—that we eliminate by resorting to the IV strategy—occurs in the latter. However, across most model specifications, except for the dynamic model estimated on the restricted sample, volatility of investments exerts a positive impact on mean growth. If we recall that volatility of investment *demand* is what we are really talking about, then more volatility can be interpreted as a larger sensitivity of investments to aggregate economic fluctuations, which is a necessary condition for the efficient working of such mechanisms as the ones advocated by neo-Schumpeterian's opportunity cost argument (see e.g., [5, 16, 18, 56]).

Finally, the sign of the other regressors, which we added as control variables following Levine and Renelt [42], meets our prior expectations though with some exceptions that will be duly stressed in the following paragraph. First of all, as expected, dynamic models estimations show that lagged GDP growth is always strongly and significantly correlated to current growth. Then, the negative and statistical significant estimated coefficient of the initial level of GDP can be interpreted as a proof of the betaconvergence hypothesis. Moreover, as all models specifications adopted are endowed with structural variables and country-specific fixed effects, we can interpret that result as verifying the conditional betaconvergence hypothesis. We interpret the fact that the coefficient attached to the initial level of GDP estimated within the static models is slightly higher than its counterpart estimated within the dynamic models, as evidence that the presence of the lagged growth rate term might partially capture the "catching-up" effect.

According to our results, a higher level of education fosters more growth, though the estimated coefficient never achieves standard statistical significance. However, it is likely

Table 12: Dependent variable: growth rate of per capita GDP. Regressors: volatility of GDP growth, consumption growth, investment growth, government consumption growth, and control variables. Sample: OECD countries (21 countries). Horizon: 1978–2007. Annual observations. All regressions include year dummies. All regressions are population weighted.

	Static models weighted estimations—restricted sample					
Estimation	FE	FE	FE	FE-IV 2sls	FE -IV 2sls	FE-IV 2sls
GDP volatility	0.319***		0.513**	0.224		0.859***
	(2.99)		(2.48)	(1.55)		(3.15)
Consumption volatility		−1.038***	−1.09***		−1.165***	−1.25***
		(−7.43)	(−7.78)		(−6.53)	(−7.02)
Investment volatility		0.139***	0.017		0.089**	−0.107
		(4.68)	(0.29)		(2.27)	(−1.44)
Government consumption volatility		0.003	−0.020		−0.052	−0.106
		(0.03)	(−0.19)		(−0.36)	(−0.73)
Education	0.004	0.007**	0.007**	−0.002	0.002	0.002
	(1.33)	(2.11)	(2.22)	(−0.41)	(0.48)	(0.31)
Population growth	0.623*	0.626*	0.620*	2.36***	2.079***	2.059***
	(1.85)	(1.92)	(1.91)	(5.00)	(4.60)	(4.62)
Initial GDP	−0.039***		−0.023**	−0.0452***	−0.029**	−0.024**
	(−4.00)		(−2.45)	(−3.56)	(−2.38)	(−1.99)
Investment share of GDP	0.085***		0.080***	−0.097***	−0.091***	−0.089***
	(8.44)		(8.56)	(−4.91)	(−4.83)	(−4.80)
Observations	630	630	630	567	567	567
Instruments	no	no	no	yes	yes	yes
Hansen J statistic (P value)				0.339	0.541	0.560
Kleibergen-Paap Wald F statistic				170.679	171.291	175.060

Note: T-statistics in parenthesis, robust SEs. *Significance at 10%, **significance at 5%, and ***significance at 1%.

that the slow-moving behavior of this variable is absorbed by the country fixed effects which are always included in the regressions presented, as they capture any unobservable slow-moving country characteristic by construction. Indeed, we proved that carrying out OLS regressions that do not account for country specific effects provides positive and significant coefficients estimates for education in almost all models specifications and for both samples (the results of these estimations are available upon request).

As for the estimates of the impact of population growth rates on GDP growth, results are quite nonrobust across estimation strategies, models, and samples employed. In fact, the expected negative sign of the estimated coefficient is verified only by static non-IV regressions, showing statistical significance only when the complete sample is considered. Turning to dynamic models estimations, population growth coefficient reverts to positive sign but never appears statistically significant at standard levels.

Eventually, another unexpected result comes from the estimated coefficient of investment share of GDP in the context of the IV static and dynamic regressions, as it appears to be significatively negative. By contrast, the expected positive and statistically significant sign is only provided by the non-IV estimates. However, as this variable is verified to be endogenous across all models specifications and samples, we tend to rely on the (counterintuitive) results provided by the instrumented estimates, possibly generated by a convergence-like mechanism.

3.2. Population-Weighted Regressions. The results so far are obtained from models that assign all countries equal weights, regardless of their relative size. In other words, results are equally influenced by, for example, the USA and Sweden notwithstanding the substantial differences in their population size. Therefore, as additional robustness check, we run a set of population-weighted regressions for both static and dynamic models and for both complete and restricted samples. The estimations strategies do not differ from those employed in our benchmark not-weighted regressions. However, since the GMM approach is not allowed when weights are employed, we resort to the 2SLS-IV method when we need to run instrumented variables regressions in order to account for endogeneity. This experiment is intended to verify whether the evidence provided by our main regressions is driven by small countries, and the corresponding results are presented in Tables 10, 11, 12, and 13. Broadly speaking, we see that the impact of overall GDP volatility on growth is more ambiguous and seems to crucially depend on the sample: significantly negative for the overall sample, while being significantly positive for the restricted sample. Moreover, unlike in the unweighted regressions, the impact of overall GDP volatility often plays a statistically significant role—with a positive sign—when the three distinct sources of volatility are included. At this point, it is maybe useful to remember the interpretation of this coefficient, which should capture the impact of volatility in net trades and, though probably to a lesser extent, the impact of covariances among the various

Table 13: Dependent variable: growth rate of per capita GDP. Regressors: lagged growth rate of per capita GDP, volatility of GDP growth, consumption growth, investment growth, government consumption growth, and control variables. Sample: OECD countries (21 countries). Horizon: 1978–2007. Annual observations. All regressions include year dummies. All regressions are population weighted.

Dynamic models weighted estimations—restricted sample						
Estimation	LSDV	LSDV	LSDV	LSDV IV 2sls	LSDV IV 2sls	LSDV-IV IV 2sls
GDP volatility	0.197*		0.511**	0.006		0.584**
	(1.78)		(2.40)	(0.04)		(2.40)
Consumption volatility		−0.825***	−0.889***		−0.731***	−0.800***
		(−5.61)	(−5.97)		(−4.46)	(−4.84)
Investment volatility		0.094***	−0.026		0.019	−0.113*
		(2.95)	(−0.44)		(0.53)	(−1.69)
Government consumption volatility		−0.052	−0.070		−0.124	−0.159
		(−0.47)	(−0.63)		(−0.96)	(−1.23)
GDP growth ($t-1$)	0.331***	0.272***	0.267***	0.497***	0.457***	0.445***
	(7.95)	(6.43)	(6.34)	(10.16)	(9.14)	(8.96)
Education	0.001	0.003	0.003	0.002	0.005	0.004
	(0.21)	(0.86)	(0.87)	(0.55)	(1.04)	(0.90)
Population growth	0.104	0.161	0.187	0.58	0.525	0.549
	(0.29)	(0.46)	(0.54)	(1.42)	(1.30)	(1.36)
Initial GDP	−0.025**	−0.017*	−0.146	−0.021*	−0.013	−0.011
	(−2.51)	(−1.73)	(−1.50)	(−1.89)	(−1.22)	(−0.95)
Investment share of GDP	0.049***	0.053***	0.052***	−0.063***	−0.064***	−0.063***
	(4.66)	(5.12)	(5.05)	(−4.17)	(−4.23)	(−4.20)
Observations	609	609	609	567	567	567
Country dummies	yes	yes	yes	yes	yes	yes
Instruments	no	no	no	yes	yes	yes
Hansen J/Sargan test (P value)				0.178	0.196	0.200
Kleibergen-Paap Wald F statistic				348.850	344.011	346.559

Note: T-statistics in parenthesis, robust SEs. *Significance at 10%, **significance at 5%, and ***significance at 1%.

components of volatility. Investment volatility is still linked to more growth, except in the case of the dynamic estimation on the restricted sample. On the other hand, the volatility in public expenditure ceases to be significant for all model specifications and all samples. Once again, the most robust and clear cut relationship remains the negative one between consumption volatility and mean growth.

4. Concluding Remarks

This paper tries to complement the existing empirical literature on volatility and growth by decomposing volatility of GDP and using some of the components (consumption, investment, and public expenditure) in standard growth equations *à la* G. Ramey and V. A. Ramey [7] that are estimated by a variety of econometric methods, on an OECD cross country panel dataset, in order to assess the robustness of the results. The underlying idea is that key to understanding the reasons why GDP volatility should influence mean growth in either way is an assessment of the drivers of such a volatility (in other words whether it is consumption, investment, or public expenditure that makes GDP unstable should really make a difference).

We suggest that attaching a positive or negative sign to the impact of the various components of GDP volatility could also help solving the apparent lack of unanimity affecting the results presented in the recent empirical literature, whose contributions make clear that different estimation techniques and, above all, different samples, may yield different results.

Among the various components of overall GDP growth volatility we focus on consumption, investments, and public expenditure volatility, leaving out volatility in net trades and the covariances between all of these variables. The most striking result we obtain is a remarkably robust and strong negative relationship between consumption volatility and mean growth. This we interpret as evidence that lack of markets completeness discourage riskier and more profitable investments and depress consumption, by fostering more precautionary savings. On the other hand, once we control for this particular factor, investment volatility is often positively associated to mean growth, as well as volatility in government expenditures.

It is worth recalling that our measures of volatility relate to the demand side of the economy. It would also be interesting, as a future extension of this work, to relate mean growth to other measures of volatility, computed from variables related to the supply side of an economy, such as the volatility in the returns of labour and capital, and productivity.

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