Uncertainty and economic growth: evidence from Latin America

Daniel Aromí, Cecilia Bermúdez and Carlos Dabús

Abstract

This paper explores the effect of uncertainty on economic growth in Latin American from 1960 to 2016. Uncertainty is found to be positively correlated to inflation and the volatility of three macroeconomic variables: inflation rate, GDP and the real exchange rate. The empirical evidence indicates that uncertainty is detrimental for growth, particularly at higher levels. In line with existing consensus in the literature, the results appear to show that macroeconomic instability has been a major hindrance explaining the poor economic performance of the region. Economic policy recommendations include applying more stringent countercyclical policies to stabilize prices and output fluctuations.

Keywords

Economic conditions, uncertainty, economic growth, macroeconomics, inflation, gross domestic product, foreign exchange rates, Latin America

JEL classification

E32, O47, E31

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I. Introduction

The determinants of economic growth have been widely studied in the literature. Since the key contribution of Levine and Renelt (1992), more recent evidence has been presented, inter alia, in Caporale and McKiernan (1996), Hall and Jones (1999), Doppelhofer, Miller and Sala-i-Martin (2000), Kneller and Young (2001), Crespo Cuaresma (2003), Bhattacharyya (2004), Hoover and Perez (2004), Minier (2007), Jones (2011), Bittencourt (2012), Kremer, Bick and Nautz (2013), Salahodjaev (2015), Brueckner and Kraipornsak (2016), Teixeira and Queirós (2016) and Vedia-Jerez and Chasco (2016). These works show several factors that can promote or damage growth processes. The factors that can promote growth include investment as a proportion of GDP, human capital accumulation, degree of economic openness and so forth. On the other hand, the main variables that can be harmful to economic growth include income inequality, volatility of output growth rate and high inflation.

In particular, the relationship between instability and economic growth is very relevant in a highly unstable region like Latin America. Along these lines, De Gregorio (2007) shows that macroeconomic instability was a limiting factor to sustained growth in Chile. The empirical literature also associates economic instability with output volatility. In a cross-country study, Ramey and Ramey (1995) show a strong negative relation between output growth variability and economic growth. Subsequently, Martin and Rogers (2000) presented evidence about countries and regions with higher standard deviations of the growth rate presenting lower economic growth. Hnatkovska and Loayza (2005) show a negative relationship between output growth rate volatility and long-term economic growth, particularly in developing countries. Similarly, Macri and Shina (2000) find a negative relationship between output variability and growth in the case of the Australian industrial sector. More recently, in a wide sample study of 93 countries, Fatás and Mihov (2013), state that policy volatility, proxied by government spending unrelated to business cycles, generates lower economic growth. Similarly, Bermúdez, Dabús and González (2015) find that high inflation and growth rate volatility are the main factors behind Latin American stagnation during the 1950-2009 period. In more general terms, Fanelli and Jiménez (2010) present a survey of the main stylized facts on economic volatility and economic performance in the region.

Predictably, the mechanism through which output growth rate fluctuations negatively affect economic growth is the adverse response of investors to future uncertainty related with those fluctuations. According to Fischer (1993b), the usual emphasis on the stability of the macroeconomic framework suggests that uncertainty is particularly harmful. There are two main channels through which uncertainty could affect negatively economic growth. First, policy-induced macroeconomic uncertainty reduces the efficiency of the price mechanism. This kind of uncertainty, associated with output growth rate variability, reduces the level of productivity, and then economic growth. In turn, temporary uncertainty about the macroeconomic context tends to reduce the rate of investment, because potential investors will wait for uncertainty to reduce before carrying out investment plans. This suggests that investment would be lower at higher uncertainty. Once again, lower investment can be expected to lead to a reduction in the economic growth rate.

Similarly, inflation is also a proxy for macroeconomic instability. Indeed, inflation is a useful indicator of general price level instability (Dabús, González and Bermúdez (2012)). A negative inflation-economic growth relationship can be found in Kormendi and Meguire (1985), Barro (1997), Fischer (1993a and 1993b), Bruno and Easterly (1998), and more recently in Bermúdez, Dabús and González (2015), who find that particularly high inflation has a strikingly damaging effect on long-term growth in Latin America. Moreover, according to Fischer (1993b), an increase in inflation and inflation variability, which create macroeconomic uncertainty and distort information, would adversely affect economic growth through at least three mechanisms. First, uncertainty reduces the efficiency of the price system, which brings down the level and the rate of productivity. Second, uncertainty also reduces the rate of private investment by increasing the option value of waiting, as potential investors wait for resolution before committing themselves, and reduces expected profits (Fischer, 1993b). In turn, this increases capital flight, which lowers capital accumulation and economic growth.

Finally, a rise in exchange rate variability creates higher uncertainty, which then brings down investment. In turn, it may also lead to a high degree of dollarization and hence result in a loss of seigniorage revenue, which reduces public capacity to carry out public investment expenditures, and once again harms economic growth. All in all, there seems to be a general consensus that higher variability of the real exchange rate is harmful for growth. Indeed Cottani, Cavallo and Khan (1990) present evidence for a sample of less developed countries indicating an inverse relationship between higher exchange rate instability and economic growth. Bleaney and Greenaway (2001), for a panel of 14 sub-Saharan African countries during the period 1980–1995, present evidence that economic growth is negatively affected by terms of trade instability, while exchange rate volatility reduces investment (and then growth). More recently, in a wide sample of the small open economies at the periphery of the European Monetary Union (EMU), Schnabl (2008) identifies a negative relationship between real exchange volatility and economic growth for countries in the economic catch-up process with open capital accounts. Similarly, Tarawalie (2010), Rapetti, Skott and Razmi (2012), Vieira and others (2013), Janus and Riera-Crichton (2015) and Bermúdez and Dabús (2018) find that real exchange rate volatility negatively affects economic growth.

The literature states that developed countries present less macroeconomic instability than developing countries. In fact, advanced economies show a history of lower inflation and a more stable output growth rate evolution. On the other hand, developing regions show greater economic instability, with periods of high inflation and a more erratic economic growth rate. In turn, the evidence indicates that both variables are detrimental for growth. The study of the relationship between economic instability and growth in unstable countries therefore deserves special attention. In this framework, the goal of this study is to determine the effect of uncertainty on economic growth in Latin America during the 1960-2016 period, for the total sample as well as at higher and lower uncertainty levels. These levels are obtained by using the k-median clustering algorithm. Regressions are then run on each uncertainty cluster to establish whether economic performance changes at different levels of the uncertainty index. The contribution of this paper is twofold. First, a measure of uncertainty is obtained by means of text mining techniques in a region that has historically experienced episodes of high uncertainty due to political and economic crises, high inflation and devaluation and significant output growth rate volatility. Second, the study determines the effect of uncertainty on economic growth at low and high uncertainty levels, which sheds some light on the relationship between the two variables in different macroeconomic environments.

Unsurprisingly, the evidence indicates that uncertainty, and particularly high uncertainty, was harmful for economic growth in Latin America during the period in question.

The following section presents the data and variables used in the study. Section III develops the methodology by means of the uncertainty index and the clusters of high and low levels of this index. Section IV characterizes the information captured by the uncertainty indices. Section V shows the empirical results. Finally, section VI presents the conclusions.

II. Data and variables

This study uses a sample of seventeen Latin American economies and nineteen consecutive and non-overlapping three-year periods from 1960 to 2016. The countries included in the sample are Argentina, Bolivarian Republic of Venezuela, Brazil, Chile, Colombia, Costa Rica, Ecuador, El Salvador, Honduras, Guatemala, Mexico, Nicaragua, Panama, Paraguay, Peru, Plurinational State of Bolivia and Uruguay.

Table 1 summarizes information about the variables of interest. Those that capture the volatility of a variable were calculated as the (rolling) standard deviation of three-year subperiods. In turn, for the uncertainty variable, this study uses text from the economic press to generate an index of uncertainty. More specifically, an uncertainty metric is calculated using a selection of text published in *The Wall Street Journal* between 1900 and 2011. For each article published in the newspaper, the website provides access to the headline, the lead and some of the text.[1]

Table 1
Variable definition and source

Variables	Definition	Source
gpd_pc	GDP per capita (constant 2010 US$)	World Bank - World Development Indicators [online] http://data.worldbank.org/data-catalog/world-development-indicators
vol_gdp	Standard deviation of GDP per capita (three-year average)	Authors' calculations based on World Bank gdp_pc data
ini_gdp	Initial GDP (of each three-year subperiod)	Authors' calculations based on World Bank gdp_pc data
gpd_pc_growth	Growth rate of GDP per capita	World Bank - World Development Indicators
vol_growth	Standard deviation of GDP per capita growth rate (three-year average)	Authors' calculations based on gdp_pc data
invest_gdp	Gross capital formation (% of GDP)	World Bank - World Development Indicators
Infla	Inflation, consumer prices (annual %)	World Bank - World Development Indicators
infl_vol	Standard deviation of Inflation (three-year average)	Authors' calculations based on inflation data
vol_rer	Standard deviation of real exchange rate (three-year average)	Authors' calculations based on nominal exchange rates (Penn World Table 9.0 (R. C. Feenstra, R. Inklaar and M. P. Timmer, "The next generation of the Penn World Table" *American Economic Review*, vol. 105, No. 10, 2015)) and inflation rates (World Bank)
Uncertainty	Uncertainty index	Authors' calculations

Source: Prepared by the authors.

It is important to mention that not all the above variables are used in the regressions, because the small panel size only allowed for the introduction of a few control variables. This study includes the control variables habitually used in the literature on economic growth: initial GDP and the investment-to-GDP ratio. In turn, in order to determine which social and economic variables are behind uncertainty, the rest of the variables are used to conduct two kinds of correlation approaches. The first is the classical Spearman or pairwise correlations, shown in table 2. Secondly, partial and semi-partial correlations between the uncertainty index and a set of variables that might also capture uncertainty are presented in table 3. These are inflation and the volatility of three macroeconomic variables: inflation rate, GDP, GDP growth rate and the real exchange rate. The results indicate that uncertainty is significantly correlated with the inflation rate (with the expected sign), as well as the volatility of inflation, GDP and the real exchange rate. These factors can therefore be seen as potentially causing the kind of uncertainty that discourages investment and reduces economic growth.

Table 2
Spearman correlations

Variables	gdp_pc_gr	vol_growth	vol_gdp	Infla	inf_vol	invest_gdp	vol_rer	uncertainty
gdp_pc_gr	1							
vol_growth	-0.0293	1						
vol_gdp	0.0849	0.074	1					
infla	-0.2642	-0.037	-0.0112	1				
inf_vol	-0.2463	-0.0322	-0.0139	0.9715	1			
invest_gdp	0.15	0.0848	0.1706	-0.0283	-0.0399	1		
vol_rer	-0.0985	-0.0382	-0.0405	0.0466	0.0368	0.0144	1	
uncertainty	-0.1506	-0.0308	0.2828	0.1406	0.1279	-0.0513	0.0931	1

Source: Prepared by the authors.

[1] The text was downloaded from a public website (http://pqasb.pqarchiver.com/djreprints/) using the "readLines" command in platform R. The website was unavailable at the time of writing.

Table 3
Partial and semi-partial correlations – uncertainty index and other uncertainty indicators

Variables	Partial correlations	Semi-partial correlations	Squared partial correlations	Squared semi-partial correlations	p-value
gdp_pc_gr	-0.0671	-0.0612	0.0045	0.0037	0.2776
vol_growth	-0.0570	-0.0520	0.0033	0.0027	0.3561
vol_gdp	0.3048	0.2913	0.0929	0.0849	0.0000
infla	0.1922	0.1783	0.0370	0.0318	0.0017
inf_vol	-0.1714	-0.1584	0.0294	0.0251	0.0052
invest_gdp	-0.0983	-0.0899	0.0097	0.0081	0.1110
vol_rer	0.1164	0.1067	0.0136	0.0114	0.0589

Source: Prepared by the authors.

III. Methodology: uncertainty index construction and the estimation method

1. The uncertainty index

The construction of the indicator is described as a two-step process. First, a large corpus is used to compute word vector representations. These representations allow for the identification of words related to uncertainty. In the second step, national uncertainty indices are computed using the list of uncertainty-related words indicated by word vector representations.

(a) Word vector representations

The first step involves representing words through vectors using an algorithm known as GloVe and presented in Pennington, Socher and Manning (2014). This type of representation has been shown to efficiently summarize semantic (and syntactic) information corresponding to each word. It can be understood as a linear structure of meaning. This quantitative representation can be used to measure relatedness between different words. For example, given the word "uncertainty", closely related words can be identified by computing the distance between the respective vectors. Also, information provided by multiple words can be aggregated by adding their respective word vector representations. While GloVe is not the only method that computes vector representations of words, it has been shown to perform better than alternative methods in multiple natural language processing tasks (see Pennington, Socher and Manning, 2014).

The inputs used to train the vector are a corpus (a collection of texts) and a list of words (a vocabulary). Given a window size parameter (such as +/- 5), the first computation involves counting the number of co-occurrences for each possible pair of words. In this way, a term co-occurrence matrix can be constructed. Next, a loss function that depends on word vector representations is proposed. The loss function is such that it decreases as the vector representations reflect more information contained in the term co-occurrence matrix. In this way, by minimizing the loss function, a rich set of information is reflected in a multidimensional portrayal.

More formally, let X represent a matrix of word co-occurrence counts. Its entries X_{ij} indicate the number of times word j occurs in the context of word i. The vectors w_i are computed to minimize the following loss function:

$$L = \sum_{i,j \in W} f(X_{ij})\left(w_i^T w_j + b_i + b_j - log\left(X_{ij}\right)\right)^2$$

Where W is the vocabulary, $f(X_{ij})$ is an increasing concave weighting function and b_i is the bias of word i. This is the weighted least squares problem. The vector representations are formed using a stochastic gradient descent (Duchi, Hazan and Singer, 2011). More details can be found in Pennington, Socher and Manning (2014).

Typical vector dimensionality used in implementations is between 100 and 300. In the current implementation, the vector dimensionality is 100 and the window size used to compute term co-occurrence is 5. The vocabulary used in the implementation is made up of words with a frequency of at least 100 in the previously described corpus. Vector representations of words were computed using package text2vec in platform R. The same package was used in other related computations (such as tokenization and the term co-occurrence matrix).

The corpus used to train the vectors is a selection of text published in *The Wall Street Journal* between 1900 and 1989. For each article published in the newspaper, this website provides access to the headline, the lead and some of the text.

A small set of words is defined as unambiguously related to the topic of interest: uncertainty, uncertain and uncertainties. These three words are used as seeds to obtain a larger set of relevant words. With that objective, the "uncertainty vector", which represents the concept of uncertainty, is constructed by adding the vectors corresponding to the three seed words. The relatedness of a given word w with the concept of uncertainty is given by the cosine distance between the vector representation of w and the "uncertainty vector". The set of 500 closest words are selected to form the set of words U.

An informal inspection of the selected words indicates that the associations are mainly driven by semantic associations with the seed words. These are words describing adverse cognitive states (confusion, doubts, unclear), forward-looking terms (future, prospects) and related subjective responses (worries, nervousness, fear). In addition, there are some words that point to concepts that seem to be mentioned in times of high uncertainty. These concepts include: economy, political, inflationary and shortages.

(b) Indices of uncertainty

In the second step, given a set of words related to uncertainty (U), the index is constructed computing the frequency of these words for each period of the analysis. Let n_{wt} denote the number of times word w is observed on day t and let W denote the set of words in the vocabulary (or dictionary). Then, the value of the uncertainty index (UI) corresponding to day t is given as:

$$UI_t = \frac{\sum_{w \in U} n_{wt}}{\sum_{w \in W} n_{wt}}$$

That is, the index is given by the number of occurrences of words in U as a fraction of the total number of occurrences of dictionary words.

In this work, the previously described method is used to compute indices for each country in the panel. This requires selecting text associated to each country. In a straightforward approach, the selected text relates to portions of the corpus that are close to a keyword associated with the respective country. More specifically, country keywords are given by name of country, capital city and demonym. The text selected to compute country uncertainty indices is made up of the parts of the corpus that are located 50 words before or 50 words after a keyword for the corresponding country.

(c) Use of the uncertainty index

The uncertainty index is used to test for the presence of asymmetric effects of high and low uncertainty on the economic performance of Latin American economies. In order to determine the robustness of the results, the estimates of such effects are carried out by clustering the sample into two "categories" of uncertainty, namely "high" and "low", as well as by using a dummy of higher uncertainty levels. In relation to the clustering, the algorithm used is based on the median instead of the mean of each cluster, which avoids the effect of outliers that might be present in the sample.

The k-median algorithm used can be written as:

$$argmin\sum_{i=1}^{k}\sum_{x_j\in S_i}\| x_j-\mu_i \|$$

where μ represents the median of each cluster.[2] The inner sum represents the sum of squares of the difference between observation x (the uncertainty index) in cluster s and the median of cluster s. Meanwhile, the outer sum indicates that the sums of all clusters from i to k are totalled to obtain a single number that will be minimized.

The algorithm is composed of the following steps:

(i) Place k points into the space represented by the objects that are being clustered. These points represent initial group centroids.

(ii) Assign each object to the group that has the closest centroid. This study uses the Euclidean distance.

(iii) When all objects have been assigned, recalculate the positions of the k centroids.

(iv) Repeat steps 2 and 3 until the centroids no longer move. This produces a separation of the objects into groups to calculate the metric to be minimized.

Following these steps, two clusters are created with a satisfactory and similar number of observations, which allows separate regressions to be run for each one.[3]

Table 4 presents the descriptive statistics for the uncertainty index in each cluster. This shows that its mean value is considerably higher in the high uncertainty cluster.

Table 4
Descriptive statistics for the uncertainty index by cluster

Clusters	Observations	Mean	Standard deviation	Min.	Max.
High uncertainty	168	0.0593241	0.0100961	0.0448681	0.092615
Low uncertainty	154	0.0258786	0.0163166	0.0000000	0.0444065

Source: Prepared by the authors.

[2] This method was chosen over hierarchical clustering techniques because of the prohibitive computational burden of analysing 1,660 observations and at least two variables.

[3] Given the small size of the panel, it was decided to work with two distinct clusters, while the Calinski-Harabasz rule might determine a higher optimal number of clusters.

2. Estimation methodology

In line with the considerable literature on economic growth, a dynamic endogenous growth specification is estimated. The baseline model can be written as:

$$y_{i,t} - y_{i,t-1} = \propto y_{i,t-1} + \beta X_{i,t} + \gamma Z_{i,t} + \psi_{i,t}$$

where $y_{i,t}$ is the natural logarithm of output per capita for country i at time t (non-overlapping triannual averages), and $y_{i,t} - y_{i,t-1}$ is the growth rate of output per capita. In addition, $X_{i,t}$ and $Z_{i,t}$ are the vectors of two explanatory variables. The first contains the initial GDP per capita of each three-year subperiod and the investment level as a share of GDP. $Z_{i,t}$ is the vector of the uncertainty index.

A lagged dependent variable of the growth rate is also included, which makes the regression dynamic in nature. The generalized method of moments (GMM) estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998) is used in its two versions: the difference GMM and the system GMM. These models use lagged values of regressors (in levels and in differences) as instruments for right-hand side variables, and also allow lagged endogenous (left-hand side) variables as regressors in short panels, as used in this study. The estimation of growth models using the GMM approach for linear panel data was introduced by Levine, Loayza and Beck (2000), and has now become common practice.

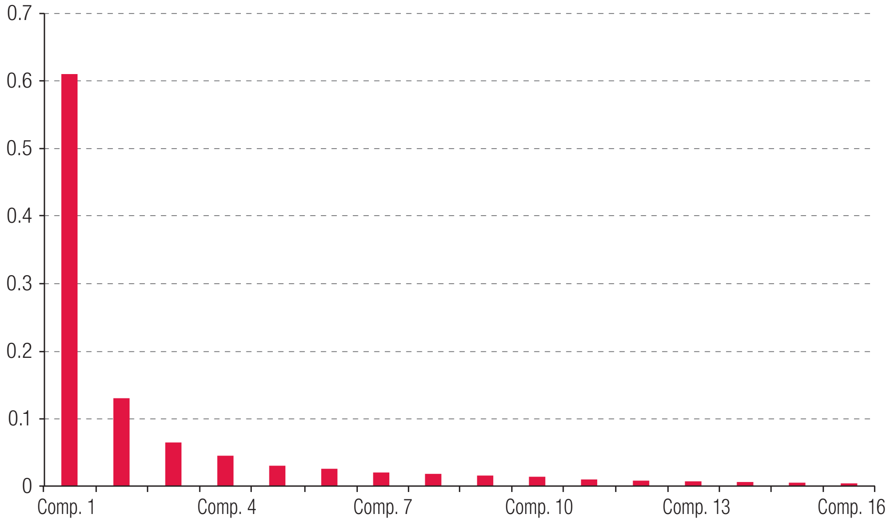
In order to address the issue of ‘too many instruments’ that can result in biased estimators, Roodman’s (2009) approach is followed. This consists of limiting the lag depth to one or two instead of using all available lags for instruments. This strategy has been adopted by several researchers in the economic growth field (Levine, Loayza and Beck, 2000; Giedeman and Compton, 2009; Demir and Dahi, 2011). In addition, as the panel is small, this may produce a downward bias of the estimated asymptotic standard errors. Windmeijer’s correction procedure (Windmeijer, 2005) avoids this inconvenience.

IV. Characterization of the uncertainty indices

The uncertainty indices are a novel metric proposed in this study. Considering its nontraditional nature, a characterization of the information captured by these indicators could be useful to interpret the results. Two exercises are implemented with this in mind. First, principal component analysis will be carried out to identify the fraction of the variation in the uncertainty indices explained by common factors. Second, this section evaluates the associations between the uncertainty indices and variables that describe the global economic environment.

Principal components were computed for the set of indices associated with each country. In the methodology used, the first principal component is the linear combination of the indicators that maximizes the fraction of the explained variability. Each subsequent factor then maximizes the fraction of explained residual variability. Figure 1 shows the fraction of the variance explained by each component. The first principal component explains approximately 60% of the variance of the indices. As expected, all loadings corresponding to this factor are positive and display similar absolute values. With just one exception, loadings are between 0.17 and 0.30. This substantial fraction of the variance explained by the first principal component can be linked to the existence of important common factors.

Figure 1
Fraction of variance explained by each component



Source: Prepared by the authors.

To understand the economic effects of these factors, a collection of economic variables associated with the global economic scenario is analysed. The set of variables are: real global GDP growth, a price index for commodities and real interest rate. Global real GDP growth corresponds to information provided by the World Bank (n.d.). The general price index for a broad group of commodities is from the United Nations Conference on Trade and Development (UNCTAD, n.d.). The real interest rate is the difference between the effective United States Federal Funds Rate minus the variation of the implicit deflator of United States GDP. This information is provided by the Federal Reserve Bank of St. Louis.

Table 5 gives the correlations between the uncertainty metric and the selected indicators of global economic environment. As expected, average country uncertainty indices are negatively associated with growth and commodity prices and positively associated with real interest rates. In a way that suggests these indicators can explain a substantial fraction of the variability of the uncertainty indices, the absolute value of the average correlations range between 0.3 and 0.64. The strongest association is found for commodity prices. A similar but stronger pattern is found for the correlations with the first principal component of the uncertainty index. Notably, the correlation between the first principal component and the commodity index reaches -0.84.

Table 5
Correlation between uncertainty indices and global economic indicator

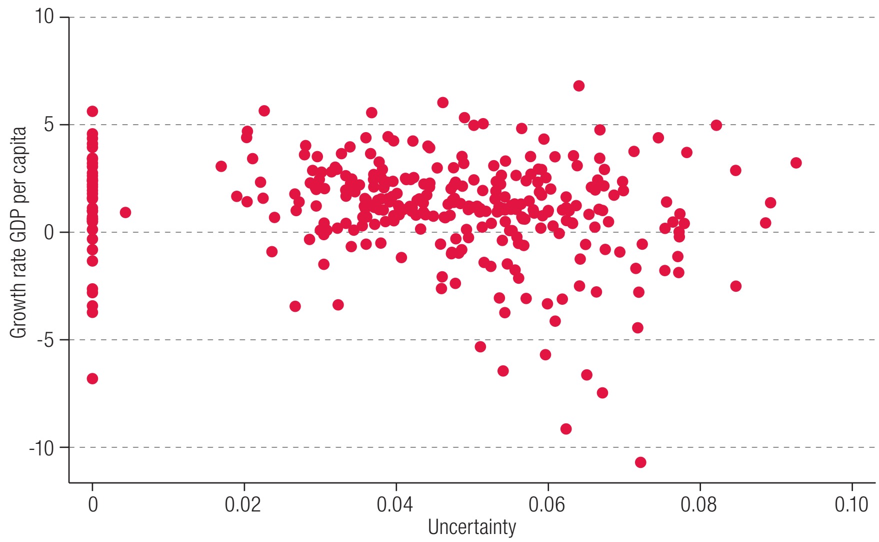
	Global GDP growth	Commodity price index	Real interest rate
Country uncertainty indices (Average correlation)	-0.32	-0.64	0.31
First principal component	-0.44	-0.84	0.35

Source: Prepared by the authors.

V. Uncertainty and economic growth in Latin America: empirical evidence

In order to assess the influence of uncertainty on economic performance more accurately, this section presents the empirical evidence between uncertainty and economic growth - both for the total sample and for the clusters of low and high uncertainty. To estimate the relationship between these variables, a dot graph is provided in Figures 2 and 3, while tables 6 and 7 show the estimation results. Figures 2 and 3 present these results for the total sample and for both the clusters of low and uncertainty, and tables 6 and 7 introduce a dummy variable for high uncertainty.

Figure 2
Economic growth and uncertainty, total sample, 1960–2016



Source: Prepared by the authors.

Figure 3
Economic growth and uncertainty by clusters, 1960–2016

Source: Prepared by the authors.

Table 6
Uncertainty and economic growth, total sample and clusters of low and high uncertainty levels

Variables	Total sample		Difference GMM by clusters		Sys GMM by clusters	
	(1)	(2)	(3)	(4)	(5)	(6)
	Diff Gmm	Sys GMM	High uncertainty	Low uncertainty	High uncertainty	Low uncertainty
Laggegdp_pc_gr	-0.218[a]	-0.0816	-0.209[b]	-0.199[b]	-0.0944	-0.0733
	(0.0189)	(0.376)	(0.0278)	(0.0339)	(0.514)	(0.749)
ini_gdp	-0.00115[a]	0.0000	-0.00146[a]	-0.00123[a]	0.0000	0.000124
	(0.000)	(0.291)	(0.000001)	(0.000001)	(0.825)	(0.278)
Invest_gdp	0.100[b]	0.359	0.150[b]	0.0283	0.0911	0.0116
	(0.0435)	(0.413)	(0.0219)	(0.641)	(0.246)	(0.878)
uncertainty	-123.6[a]	-60.73[a]	-98.43[a]	-70.63[a]	-63.35[c]	-48.71
	(0.000)	(0.0191)	(0.00162)	(0.00136)	(0.0640)	(0.151)
Constant		2.769[c]			2.708	2.405
		(0.0656)			(0.279)	(0.152)
Observations	275	291	155	120	160	133
Number of groups	17	17	16	16	16	16
Number of instruments	36	7	36	35	7	7
AR1 Test (p-value)	0.000	0.000934	1.97e-08	0.00754	0.0172	0.0522
AR2 Test (p-value)	0.945	0.918	0.407	0.0129	0.932	0.947
Hansen Test (p-value)		0.385			0.0512	0.0291

Source: Prepared by the authors.
Note: p-values are in parentheses.
[a] $p<0.01$.
[b] $p<0.05$.
[c] $p<0.1$.

Table 7
Uncertainty and economic growth, total sample with a dummy for uncertainty

Variables	Difference GMM	System GMM
Lagged gdp_pc_gr	-0.165[a]	-0.0613
	(0.0162)	(0.284)
ini_gdp	-0.00111[b]	0.0007
	(0.000)	(0.139)
invest_gdp	0.193[b]	0.0285
	(0.00013)	(0.359)
dummy_uncert	-3.65[b]	-2.96[a]
	(0.000000154)	(0.0113)
Constant		-1.290[c]
		(0.0863)
Observations	275	293
Number of groups	17	17
Number of instruments	36	7
AR1 Test (p-value)	0	0.00083
AR2 Test (p-value)	0.355	0.858
Hansen Test (p-value)		0.693

Source: Prepared by the authors.
Note: p-values are in parentheses.
[a] $p<0.05$.
[b] $p<0.01$.
[c] $p<0.1$.

At first glance, both figures suggest no clear link between the two variables at low uncertainty levels. Nonetheless, this relationship seems to be negative at higher uncertainty levels. In this sense, the regressions results presented below tend to confirm this evidence.

Table 6 shows that the control variables have the expected signs (in the differences estimates, both in the total and clusters samples). Initial GDP negatively affects economic growth, while the ratio of investment/GDP favours it. In turn, in table 1 the results presented for the total sample in regressions (1) and (2) indicate that the uncertainty index is very significant and negative for growth in Latin America in both difference and system GMM regressions. More interestingly, in order to determine if this index is more relevant to the economic performance of the region in different macroeconomic environments, the total sample was divided in two clusters of lower and higher uncertainty. In general, this reduces economic growth and, unsurprisingly, is more harmful at higher uncertainty. In fact, this has a higher and more significant coefficient into each estimation method at high uncertainty levels (regressions (3) and (5)), and is not only significant for the cases of lower levels when the system GMM method is applied (regression (6)).

In order to perform a robustness check of the empirical results obtained with the clustering technique, table 7 presents the estimation of the same model (using difference and system GMM) with the introduction of a dummy variable to capture both uncertainty levels (high and low), as defined by the k-median algorithm.

The main difference between running estimations for both clusters separately and the estimation model with a dummy is that the first implies that there are two different "structures" for groups of countries with high and low uncertainty, as the coefficients of the regressors are allowed to vary from one to the other. The use of a dummy variable is interpreted in the customary way: all countries in the sample are supposed to share the parameters that promote economic growth, and they only differ in the way it is affected by uncertainty. In this sense, the models estimated with the dummy variable show that countries with high uncertainty grow annually on average less than countries with low uncertainty by between 2.96% (with system GMM estimates) and 3.65% (with difference GMM estimates).[4] Hence, the results are robust for both cluster and dummy estimation techniques.

Tables 2 and 3 above indicate that uncertainty is significantly and positively correlated with inflation, as well as the volatility of inflation, GDP and the real exchange rate. As stated above, these factors therefore seem to cause higher uncertainty and also lower economic growth. In turn, uncertainty here seems to be an indicator that encompasses the behaviour of the variables usually associated with macroeconomic instability.

In short, the evidence presented above indicates that macroeconomic uncertainty, particularly at higher levels, is damaging for growth in the region. The suggestion is that higher inflation and volatility in real exchange rate, output and inflation are associated with higher uncertainty levels of the economic environment perceived by the society. This, in turn, discourages investment and then reduces economic growth.

These results are compatible with previous findings. In particular, they are similar to the evidence present in De Gregorio (2007), Bermúdez, Dabús and González (2015) and Fanelli and Jiménez (2010), who find that macroeconomic instability harms economic performance in the region. Economic policy recommendations must therefore contain measures destined to reduce overall macroeconomic uncertainty. According to the evidence from this study, this implies the need for tighter countercyclical policy to avoid sharp output fluctuations, as well as deeper and more effective price stabilization plans.

4 The base category (with value zero) is "low uncertainty".

VI. Conclusions

This study examines the relationship between uncertainty and economic growth in Latin America from 1960 to 2016. This period was defined by periods of social unrest, as well as high political and economic instability. In general, these phenomena are associated with social uncertainty, approximated here by the uncertainty index. The aim of this study was to determine the impact on economic performance. In this sense, the results indicate that uncertainty is harmful for growth, and particularly at higher levels. Besides, the correlations suggest that factors like price and output instability seem to underlie uncertainty, which makes sense intuitively.

Therefore, higher inflation and volatility of output and inflation promote an atmosphere of uncertainty that discourages productive long-term investments, and then reduces economic growth. The evidence presented here seems to indicate that the perception of a social environment of uncertainty could reflect the existence of high macroeconomic instability. This is important for implementing economic policy. The evidence suggests that the region's policymakers could reduce instability and improve economic performance by implementing more stringent counter cyclical policies, in order to stabilize prices and output fluctuations more successfully.

This research could be expanded to explore other factors associated with uncertainty, or to build an index of uncertainty that includes social and political aspects, as well as external events that could cause instability in the region. This could allow for a more comprehensive measure that would explain the poor long-term economic performance of Latin America in relation to other more dynamic and successful emerging areas such as South-East Asia.

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